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An Empirical Analysis of European Credit Default Swap Spread Dynamics

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Abstract

I analyze the dynamics of European credit default swap spreads by estimating CDS spreads via an extension of the structural credit risk models by Black and Cox (1976) as well as Leland (1994), the so called CreditGrades model proposed by Finger et al. (2002). Using two different procedures in approximating the asset volatility surface of obligors, the models are calibrated by means of historical equity volatility and volatility extracted out of at-the-money options. I discover that model performance strongly depends on the distribution of input parameters clustered by economical sectors. Model spreads exhibit significant correlation with market spreads and seem to predict market spreads contingent on sectors and model calibration techniques. The gap between model and market spreads, derived model spreads and empirical market spreads are analyzed by running panel regressions in fashion of Collin-Dufresne and Goldstein (2001) and Bedendo, Cathcart, and El-Jahel (2011). These show that times of disconnectedness between credit and equity markets, model inherent misspecifications as well as possible market inefficiencies can contribute to the inability to estimate spreads reliably. Robustness checks show that determinants of gap, model and market spreads are sector specific, time varying and tenor dependent.

Keywords: Credit Risk; Credit Risk Modelling; Structural Models; Credit Risk Management; Quantitative Finance.

1. Introduction

Credit risk is among the most fundamental economical risks. It emerges from the act of lending and borrowing capital as one of the main objectives of the financial system and allows for an efficient allocation of capital from surplus sectors to sectors in demand for capital, increasing economical welfare. In this context, the financial system fulfills two major functions: a reduction in information and transaction costs as well as the enhancement of trading, diversification and risk management. Since financial intermediation and their institutions facilitates the allocation of capital within an economy mainly due to asymmetric information and accompanying comparative advantages in associated monitoring costs, banks have typically the largest exposure to credit risk (Allen & Santomero, 1997; Diamond, 1984). Due to this fact, banks and other financial institutions are in constant need to quantitatively manage risk via mathematical models, thus limit the downside of lending not only by internal risk thresholds, but also regulatory requirements, such as Basel III and accounting loss allowance as well as risk appetite rules. With the rise of credit derivatives in the 1990s, the need for assessing the risk and deriving fair value pricing emerged. Financial institutions came up with quantitative models to control risk in new markets. One of those models is the CreditGrades model that was developed in the early 2000's by investment banks to establish an industry standard open source quantitative credit risk model for publicly traded firms. Besides the commercial use of those models, the academic world became more and more interested in their performance. Up to the year 2010, a lot of researchers considered commercial credit risk models in academic settings. Since then, commercial credit risk models decreased in popularity because the market of credit derivatives matured over time, so that financial institutions relied more on well tested and experienced models. Here my thesis steps in and tries to shed light onto the CreditGrades model and its performance, as it was primarily tested only in the North American derivatives market in the early 2000's with short observation windows. The aim of my study is to estimate the CreditGrades model for a sample of European Credit Default Swap (CDS) contracts with long observation windows, covering multiple crisis and tranquil periods in order to assess its performance in various economical conditions. Furthermore I employ different model calibration procedures using information from European equity as well as option markets to test the hypothesis if the model performs better with forward-looking information extracted from option markets as often cited in the literature covering

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the North American market. After the estimation and performance evaluation, I proceed with analyzing the gap between model and market spreads. To do so, I employ panel regressions in order to identify drivers of divergence and shedding light onto possible model misspecifications. Furthermore I try to identify drivers of model and market spreads in the spirit of Collin-Dufresne and Goldstein (2001), who consider credit spreads on corporate bonds. Related to that, I test if the CG Model entails predictive behavior, which is exploited by capital structure arbitrage trading strategies. Additionally I employ time period panel regressions to reveal whether the determinants are time invariant or if certain factors are more influential in specific economical environments.

To the best of my knowledge I provide the largest study that tests the performance of the CreditGrades model in its respective specifications and determinants of credit default swap spreads considering the European credit market. Furthermore I am the first who considers the performance of the CreditGrades model in the Corona crisis of 2020 and its determinants of the gap, empirical CDS spreads and model spreads both on a European and international level.

My thesis is structured as follows. Section 2 deals with credit risk and associated derivatives. Then, section 3 provides an overview of the importance of structural credit risk models and its implication for identifying determinants of CDS spreads. Afterwards, section 4 outlines the methodology of my study, including my model choice, the model calibration procedures as well as the subsequent correlation and pricing analysis and the multi-factor model CDS determinants estimation procedure. Section 5 introduces the data used in my thesis. My empirical analysis is located in section 6 and starts with descriptive statistics on my sample composition involving respective summary statistics, followed by the results of my correlation and pricing analysis, showing that model performance strongly depends on the distribution of input parameters clustered by economical sectors. These results are then analyzed in more detail by means of panel regressions covered in subsections 6.3 to 6.6. I proceed with robustness checks in chapter 7 where I control my results for different tenors and time periods, finding that determinants of gap, model and market spreads are sector specific, time varying and tenor dependent. Finally section 8 concludes.

2. Credit Risk and associated Credit Derivatives

Credit risk describes the possibility that the borrower cannot meet his/her financial obligations, thus defaults on the capital amount outstanding. Credit risk is hence not driven in an aggregate, but consists of individual factors and drivers which are called mathematical components of credit risk in the following analysis. The Bank for International Settlements (BIS) depicts these components as credit risk parameters in their principles for the management of credit risk (BIS (2000)) which coincide with Basel regulation as follows. Probability of Default (PD): the statistical likelihood a default occurring within the lifetime of the loan contract. The default is defined by a default event, which is typically measured in delinquency days or days past due of 90 days. Exposure at Default (EAD): the amount of capital outstanding and thus at risk. Loss given Default (LGD): the actual loss contingent on the default of the obligor measured in percentage points of the exposure. LGD is typically smaller than 1, since the proceeds from repossessing, required collateral as well as other guarantees can mitigate the loss risk and thus the LGD largely depends upon the type of default and the subsequent settlement. The inverse of the LGD is called Recovery Rate (RR) and is defined as 1 - LGD. The resulting credit risk is then a function of all mathematical components

$$CreditRisk = f(PD, EAD, LGD).$$

One could assume that credit risk has to be accepted once a loan is granted, thus if a loan or bond would be issued, the risk of failing repayment could not be mitigated ex-post and hence has to be compensated by either high interest rates or high coupons ex-ante. The role of risk management would be constrained to the instruments of limited exposure, ex-ante time invariant low PDs and high RRs. This situation was largely present up to the 1990s, since at that time, financial innovation led to the emergence of so called credit derivatives (Brandon & Fernandez, 2005). These instruments allow the financial market to allocate and distribute pure isolated credit risk to those parties, who have risk bearing capacities and to those who would like to reduce their credit risk appetite. This aspect marks a fundamental difference to tradeable debt of entities with corresponding credit risk exposure (e.g. corporate bonds), since credit derivatives enable the pure/isolated credit risk to be tradeable as they eliminate the necessity to hold the asset subject to credit risk itself. Hull (2012) classifies credit derivatives in two main categories, which are the following: single-name and multi-name credit derivatives. Since my study considers the dynamics of CDS spreads, I will not give a detailed overview of multi-name credit derivatives such as Collateralized Debt Obligation (CDO) or basket CDS, but rather focus on the single-name branch of credit derivatives. The most common single-name instrument is the CDS, which was first introduced by J.P. Morgan in 1997 (Chan, Guo, Lee, & Li, 2019). CDS offer protection against the default of corporations or sovereigns. Corporations are called reference entities upon which the CDS is issued. These reference entities are not directly part of the derivatives contract, since they are bilateral negotiated between the issuer of the CDS (most often investment banks or insurance companies) and the buyer of the CDS (most often hedge funds or other banks). This setup allows for credit risk to be discretely traded and shifted across financial market participants. The typical CDS contract consists of two sides, the buyer and the seller side. The buyer side obtains credit protection for the issued reference entity in case of default by paying period premiums to the seller of the CDS, the so called CDS spread, which is measured in Basis Points (bps) of the notional amount. The seller of the CDS, however, has to settle the contract in case of an occurring credit event either physically or in cash. Thus, the CDS buyer is entitled to sell the underlying bonds at their notional amount, whereas the CDS seller has to buy the bonds at the notional amount. These payment streams boil down to exchanging streams of cashflows wherefore this product is considered as a swap agreement. The face value of the debt that the CDS buyer is entitled to sell is called the notional principal. The debt itself is called the reference obligation (Hull (2012)).

Moreover, CDS products are defined by their maturity or tenor for which the protection will last. A typical maturity for a CDS is five years. Thus if the reference entity would experience a credit event within five years, the buyer of the CDS would be entitled to receive credit protection by the mechanism described above. Another crucial aspect is the definition of a default event. The International Swaps and Derivatives Association (ISDA) defines three main types of credit events: filing for bankruptcy, defaulting on payment and the restructuring of debt. This differentiation has material impact on CDS valuation in markets, since they carry different degrees of default risk profiles dependent on the inclusion of specific credit events. Berndt, Jarrow, and Kang (2007) find that the premium for exposure to restructuring risk amounts on average between 6% and 8% of the value of protection against non-restructuring default events.

As any derivative, credit derivatives fulfill the three central functions of hedging, arbitrage and speculation. The function of hedging considers CDS as an insurance type product for mitigating the exposure to credit risk by paying periodic premiums with the aim to transfer the risk. In a more precise manner, this allows for instance to create positions of risk-free corporate bonds since the investor can buy the bond with its time to maturity and match this by buying a CDS written on the same bond issuer with the corresponding tenor. The aspect of arbitrage covers a specific strategy called capital structure arbitrage. Capital structure arbitrage is based on the idea that there exists mispricing between equity and credit markets and the subsequent exploiting of this divergence from an equilibrium state by applying trading strategies (Wojtowicz, 2014). This type of arbitrage was very popular during the early 2000s, since at that time hedge funds started to explore credit derivatives and their applications in trading strategies. In accordance to the attention in the practitioners world, the academic sphere also took capital structure arbitrage under closer consideration. The most influential study was performed by Yu (2006) who have considered the risk and return profile of capital structure arbitrage by calibrating a structural credit risk model, the CreditGrades Model (CG Model), to a sample of 261 North American industrial obligors between 2001 and 2004. He implements trades by selling CDS and buying equity when the model predicts that CDS are overpriced and buying CDS and shorting equity when the model predicts that CDS are undervalued. He assumes that the trades eventually convergence when the model spread is equal to the market spread. Yu (2006) finds that individual trades are very risky resulting in complete drawdowns of capital. The convergence rate of trades are found to be as low as 10% and annualized trading returns for a 30 day holding period are negative or close to zero. If a 180 day holding period is implemented, the mean return is at its maximum 2.78%. Yu (2006) tests his results for statistical arbitrage using the procedure described in Hogan, Jarrow, Teo, and Warachka (2004) and has to conclude that in his setting, there are no significant arbitrage returns existent. The work of Yu (2006) was afterwards extended by the study of Bajlum and Larsen (2008) who use an advanced version of the CG Model calibrated to one month at-the-money (ATM) put option implied volatilities. Cao, Yu, and Zhong (2011) later support the findingy of Bajlum and Larsen (2008). Bajlum and Larsen (2008) achieve higher and statistical significant trading returns, in case for speculative grade obligors up to 4.61%. Huang and Luo (2016) use call option implied volatilities and derive a persistent trading strategy that produces significant risk adjusted excess returns, hence supporting the finding of Bajlum and Larsen (2008). Duarte, Longstaff, and Yu (2007) take a different approach in testing an array of different trading strategies, including capital structure arbitrage. They use the CG Model and are able to create positive and significant excess returns after trading costs. Imbierowicz and Cserna (2008) calculate CDS spreads using the CreditGrades model, the structural credit risk model by Leland and Toft (1996) as well as the model by Zhou (2001) and test capital structure arbitrage between 2002 and 2006 on 808 obligors and can support the findings of Duarte et al. (2007). As with any other structured financial product, speculation can be one field of application. If a speculator concludes that the true PD is higher than the market implied PD, he can buy default protection at a discount that pays a positive yield in case of default. On the other hand, if the speculator believes that the true PD is lower than the market implied PD, he can sell credit protection at a premium and collect the overvalued spread thereafter.

Regarding the valuation of CDS spreads, there are many theories, models and methodologies. However there exists one quantitative approach based on a fair value pricing mechanism widely regarded as the main pricing methodology of individual plain vanilla CDS, called the Hull-White Model. Hull and White (2000) base their approach of deriving CDS spreads on the present value of the so called fixed and floating/contingent leg of the CDS cashflow stream. The fixed leg represents the periodic spread payments transferred from the buyer to the seller. The floating/contingent leg represents the seller side, since the seller has to buy the underlying bonds in case of default. Thus, the cashflow transferred from the seller to the buyer is contingent on the reference entity experiencing a credit event. The main idea of the model is that the present value of all premiums payed should equal the present value of the expected payoff of the CDS for both participants, resembling no arbitrage conditions. Hull and White (2000) assume that default events, the risk free rate and the recovery rate are mutually independent from each other and that the claim in case of default is defined to be the notional amount additional to accrued interest. The risk neutral probability of no credit event happening during the lifetime of the swap is one minus the probability that a credit event will occur up to time T,

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

with $q(t)$ the risk neutral default probability density at time t. The expected present value of the fixed leg is determined by the payments until a credit event happens or until the maturity of the contract at time T in case no credit event occurs. If the default occurs at $t < T$, the Present Value (PV) of the payments is $w[u(t) + e(t)]$, with w the total payments per year made by the CDS buyer, $u(t)$ the PV of payments at the rate of \$ 1 per year on payment dates between $t = 0$ to t and $e(t)$ the PV of an accrual payment at time $t - t*$ with $t*$ as the preceding payment date after t. Hence the expected PV of all payments is given by

$$w\int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T). \tag{2}$$

The market value of the reference obligation just after the reference entity has defaulted is the recovery rate multiplied with the sum of the notional amount plus accrued interest

$$P - RP[1 + A(t)] = P[1 - R - A(t)], \tag{3}$$

with P as the notional principle, R the recovery rate and $A(t)$ as the accrued interest up to time t measured in percentage of the notional amount. If the above described assumptions apply, the risk neutral expected payoff can be written as

$$1 - [1 + A(t)]\hat{R} = 1 - \hat{R} - A(t)\hat{R}, \tag{4}$$

with $\hat{R}$ as the expected recovery rate in the risk-neutral world. Then the present value of this expression indicating the expected payoff is equation (4) integrated over the lifetime of the CDS

$$\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt, \tag{5}$$

with $v(t)$ as the present value of \$ 1 received at time t. The present value of the CDS to the protection buyer is the present value of the expected payoff in case of default (equation (5)) after subtraction of the present value of the periodic payments made by the buyer in equation (2)

$$\begin{aligned}&\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt \\ &- w\int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T).\end{aligned} \tag{6}$$

Hull and White (2000) conclude that the CDS spread s is the value of w that is setting equation (6) to zero

$$s = \frac{\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt}{\int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T)}, \tag{7}$$

such that the spread is defined as the total amount of payments within a year measured as an annualized percentage of the notional amount of the CDS reference entity.

3. Literature Overview

Chapter 3 gives an overview of the most prominent credit risk models cited in the academic literature. Since my thesis considers the use of an extension of a structural credit risk model, I proceed in outlining the main differences to so called reduced-form models and provide pricing implications for credit risk thereafter. Afterwards I shed light into the implications of these models providing guidance for the empirical determinants of CDS spreads cited in the literature so far, setting up the rational for the model choice in my empirical part closer assessed in chapter 4.

3.1. Structural Credit Risk Models and their extensions

In the academic literature, credit risk modeling can be split into two fundamental types of models. The first type, called the *structural credit risk model*, establishes a relationship between the capital structure of a firm and the corresponding default probability. The main intuition of these models is that corporate liabilities can be viewed as contingent claims on the firm assets (Lando, 2009). The second strain of credit risk models are called *reduced-form models*. They are based on the idea that credit risk is driven by exogenous variables, such as hazard intensity rates or credit migration and model it by a random stochastic Poisson processes that is independent of the capital structure of firms (Kliештik & Cúg, 2015). The main advantage of these types of models is that they do not require to obtain information on the capital structure of individual firms (Kliештik & Cúg, 2015). However, this is also the the biggest drawback of reduced-form models since they do not allow for interpretation using economic theory. These types of models deliver mathematical tractable solutions, but lack the depth and economical background needed to derive and identify economical drivers and determinants of default risk. For this reason, I will not cover these types of models in detail. The most prominent reduced-form models are formulated by Duffie and Singleton (1999); R. Jarrow and Protter (2004); R. A. Jarrow and Turnbull (1995) and Madan and Unal (2000).

The first and arguably most important structural model was developed by Merton (1974). He was the first who applied modern option pricing theory developed by Black and Scholes (1973) to credit risk modeling by establishing the methodology that a company's equity can be modeled as a call option written on the firm's assets. Thus model implied probabilities of default are endogenous to the capital structure of the firm and are not driven by exogenous shocks or hazard rates. Since the Merton model relies on option pricing theory, the so called Black-Scholes assumptions apply (see appendix A). The main idea of Merton (1974) is that the capital structure of a company consists out of equity and debt. Debt is modeled as a single zero-coupon bond outstanding D_t with face value K and maturity T. Equity is defined as the market value of equity E_t. The assets of a company are derived by the balance sheet identity equation $V(t) = E_t + D_t$. Merton adjusts the assumptions of Black and Scholes (1973) that the value of equity follows a Geometric-Brownian Motion, since now the assets of a company follow a Geometric Brownian Motion[1]

$$dV(t) = rf_t dtV(t) + \sigma V(t)dW_t, \quad (8)$$

with rf_t as the continuously compounded risk-free interest rate determining the asset drift, σ the asset return volatility determining the firm asset diffusion and dW_t a Wiener process stochastically driving the asset value over time. If $v(t) \geq K$ then debtholders are payed in full and the residual value of $v(t)$ is $v(t)-K$ and thus is distributed among equity holders. In case of $v(t) < K$, the debtholders can only be partially payed and the equity holders receive nothing. The company has defaulted on its debt at maturity T. This yields the payoff profile of a European call option written on the firm assets $v(t)$ with strike K and maturity T

$$E_t = max(V(t) - K; 0). \quad (9)$$

Now the Black-Scholes formula for a European call can be applied, giving

$$E_t = V(t)\Phi(d_1) - Ke^{-rf_t(T-t)}\Phi(d_2) \quad (10)$$

with

$$d_1 = \frac{ln(\frac{V(t)}{K}) + (rf_t + \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}} \quad \text{and}$$

$$d_2 = \frac{ln(\frac{V(t)}{K}) + (rf_t - \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}. \quad (11)$$

The default event now describes the possibility that the European call of equity holders matures out-of-the-money, which yields the risk-neutral default probability[2]

$$PD_t = Prob(V(t) < K) = \Phi(-d_2). \quad (12)$$

A common problem addresses the calibration of the Merton model, since the value of assets $v(t)$ and the corresponding asset volatility are both unobservable parameters. Merton (1974) solves this by assuming that E_t is also driven by a Geometric Brownian Motion and by applying Ito's Lemma, the identity between observable equity volatility and unobservable asset volatility are given as follows

$$V(t)\sigma\frac{\partial E_t}{\partial V(t)} = E_t\sigma_e. \quad (13)$$

By inserting the call delta expression using Black-Scholes in (13), obtaining

$$E_t\sigma_e = \Phi(d_1)\sigma V(t). \quad (14)$$

Equation (10) and equation (14) can both simultaneously solved for $v(t)$ and σ to derive probabilities of default by inserting the asset value and asset volatility in equation (12). The described model setup above relies on an number of simplifying assumptions that do not correspond to the real-world environment in which firms operate and default risk emerges. Thus various follow-up models address these shortcomings by implementing different aspects as follows.

Point of default. The Merton model assumes that a company can only default on its debt at maturity T. Black and Cox (1976) relax this assumption by implementing a so-called exogenous default barrier, active throughout the lifetime of the company. The barrier is derived by exploiting the fact that there exists a probability distribution with a corresponding Laplace transformation explicitly known for the Brownian Motion first hitting a certain level (the default barrier) assuming time invariant parameters for the asset drift and diffusion (Duffie & Singleton, 2003). If the firm assets fall under this barrier, the company is considered to have defaulted. Hence, this model is frequently referred to as first passage time model. The default barrier has to be only hit once to constitute a default event. In Collin-Dufresne and Goldstein (2001) this first passage model is extended by modeling a stochastic default barrier which is still exogenous but time-dependent. The amount of debt is conditional on the changes in firm value which results in a stochastic mean-reverting debt-to-equity ratio. Leland and Toft (1996) are the first who attempted to derive an endogenous structural credit risk model by considering optimal capital structures of a firm to maximize the market value of equity E_t in order to optimize the amount and the maturity of its debt.

Debt structure. To characterize the entire debt of firms as one zero-coupon bond outstanding rarely meets the actual debt structure of firms. Thus the structural model proposed by Geske (1977) addresses this aspect and models debt as a coupon bond, where each coupon is viewed as an option on the firm value. This enables the firm to default not only at maturity, but at any coupon date. Since the assumption that a stable debt structure is maintained throughout the lifetime of the firm holds, equity is issued to settle the coupon payments. The firm defaults, if equity holders do not issue new equity due to unfavorable investor conditions, resulting in a failing coupon payment defined as a credit event.

Stochastic processes for asset values and interest rates. The standard structural model by Merton (1974) is derived by using a Geometric Brownian Motion to drive the asset value process. A standard GBM cannot account for sudden jumps in the firm value by construction. Hence, a firm never defaults due to unexpected short term changes in its firm value. This aspect was empirically criticized by the assessment of model estimated short term credit spreads being too low, especially for low rated companies. Merton (1976) adjusted the standard GBM asset value process, introducing a jump diffusion process in form of a Poisson process. This type of model is often called hybrid credit risk model, since it combines the economical foundations of structural models and extends those by Poisson processes, also found in reduced-form models,

[1] Because Black-Scholes derive their formula in a risk-neutral world under the risk-neutral measure Q, the asset drift is now determined by the risk free rate, thus μ is replaced with rf_t.

[2] Whereas the risk-neutral probability is always smaller than the physical probability of default, if and only if $rf_t < \mu$.

in order to obtain mathematical tractable results that better match the empirical data. Zhou (2001) applied the extension by Merton (1976) to model credit spreads of corporate bonds and concludes that by incorporating a compound Poisson jump diffusion process, the performance of the Merton model improves significantly. This improvement is especially achieved by accounting for different term-structures of credit spreads unique to obligors. The work of Boyarchenko (2000) as well as Hilberink and Rogers (2002) build on the work of Zhou (2001) by introducing Lévy jump processes. Besides the assumptions of the stochastic asset values process, the assumption of a constant interest rate does not seem realistic, since market rates are typically not time invariant. Kim, Ramaswamy, and Sundaresan (1993) are the first who considered stochastic interest rates explicitly by using the influential CIR short rate model proposed by Cox, Ingersoll Jr, and Ross (1985). Longstaff and Schwartz (1995) consider the same methodology but rely on a Gaussian one-factor model derived by Vasicek (1977) for the short rate.

3.2. Determinants of Credit Default Swap Spreads

The literature covering the empirical analysis of determinants of credit default swap spreads has its roots in the analysis of credit spreads. Credit spreads are defined as the difference in yield of corporate bonds and a risk-free benchmark yield, such as government bonds (Collin-Dufresne & Goldstein, 2001). Credit risk models propose that this difference emerges due to the exposure to credit risk in accordance to different credit risk factors consistent with theoretical models. However, empirical research assesses this assumption by testing other factors driving credit spreads. This field of research was initiated by the seminal work of Collin-Dufresne, Goldstein, and Martin (2001) who analyzed the determinants of changes in credit spreads for different credit rating groups, leverage groups and maturity groups. They base their analysis on variables from structural credit risk models, such as the risk-free rate, slope of the yield curve, leverage, volatility, the probability of a downward jump in firm value and business climate. They then regress changes in credit spreads from 1988 to 1997 on these proposed factors and conclude that the explanatory power of the regressions are in general rather low, explaining only 25% of the variation in credit spreads. Even if other control variables, such as financial and economic variables, are introduced, the results do not significantly change relative to the initial model setting. An afterwards conducted Principal Component Analysis (PCA) of the regression residuals shows that the model lacks a common risk factor, since the first component accounts for 76% of left over variation in credit spreads. Collin-Dufresne et al. (2001) conclude that local supply and demand shocks, independent between treasury and equity markets, can be one feasible explanation for the missing common aggregated systematic risk factor.

Tsuji (2005) was the first who called the findings of Collin-Dufresne et al. (2001) the *credit spread puzzle*. He conducts the same econometric analysis for Japanese bonds considering determinants implied by theoretical models, illiquidity, risk aversion and expectations, credit ratings, business cycle and other bond characteristics. Despite this extensive approach, he mostly confirms the puzzle. Campbell and Taksler (2003) explicitly consider the effect of firm-level volatility, but employ regressions to explain levels of credit spreads. They conclude that the idiosyncratic equity volatility can explain variation in credit spreads comparable to credit ratings. Thus, idiosyncratic risk has significant explanatory power (Campbell & Taksler, 2003). Cremers, Driessen, Maenhout, and Weinbaum (2008) support this finding as they consider option-implied volatilities as the level of implied volatility and the implied volatility skew seem to matter for the explanation of credit spreads.

In the subsequent years after the credit spread puzzle was discovered, the focus of the academic literature considering determinants of credit risk shifted from analysing credit spreads to investigating credit default swap spreads. As outlined in chapter 2, credit derivatives have some advantages regarding investors/speculators/arbitrageurs when comparing them with their underlying bonds. But also for researchers CDS entail advantages when assessing them in econometric settings. While CDS spreads are comparable to credit spreads of corporate bonds, they do not require to specify a risk-free yield curve since the observable price for a CDS is already expressed as the spread itself. Thus by choosing CDS spreads as the dependent variable, possible effects arising from the choice of the risk-free rate can be mitigated. Houweling and Vorst (2005) show that the choice of a risk-free rate has substantial impact on the estimation of credit risk premia. In their study only the usage of swap or repo rates results in reliable estimation of credit risk premia. Ericsson, Jacobs, and Oviedo (2009) also mentions the aspect of accounting for coupon payments and possible effects triggered by choosing the corresponding framework to remove coupon payments. Another favorable argument for declaring CDS spreads as the subject of analysis are liquidity reasons. Due to the fact that derivatives are in general more frequently traded, higher observation frequencies (e.g. daily) with a better data quality favor CDS spreads. In addition, Blanco, Brennan, and Marsh (2003) show by assessing the rate of spread change in both markets conditioned on a change in the credit rating, that a change in credit quality is faster incorporated in the credit derivative markets than in the corresponding corporate bond market. This hints at a more efficient incorporation of new information in derivative markets when considering the likelihood of a credit event. Additionally, Di Cesare and Guazzarotti (2010) state that CDS are inherently more standardized than bonds due to missing aspects like coupon structure, callability, convertability and other bond specific factors. Hence, increasing the level of comparability and standardization within a study design improves the implementation and interpretation of subsequent empirical results.

The first study considering determinants of CDS spreads was performed by Aunon-Nerin, Cossin, Hricko, and Huang (2002). Their study was motivated by the work of Collin-Dufresne and Goldstein (2001) published in the previous year. By considering so called "structural variables" motivated by credit risk pricing theories and applying the same methodology as Collin-Dufresne et al. (2001), Aunon-Nerin et al. (2002) find significant explanatory power reaching 82% in R^2 for the cross-sectional variation in level CDS spreads. Furthermore, variables used as proxies for equity market information (e.g. stock prices and its variance) as well as stochastic interest rates and credit ratings deliver robust results when pricing credit risk in the cross-section. The work of Skinner and Townend (2002) was the first paper officially published in an academic journal that empirically examines CDS spreads. The study contains 29 US dollar denominated CDS spread time series observed between 1997 to 1999 and thus also captures the Asian Currency Crisis in 1997. Skinner and Townend (2002) apply the same methodology as Aunon-Nerin et al. (2002) by analyzing CDS spreads in an OLS regression framework. They propose five factors motivated by option pricing models and test those in their subsequent regression analysis. They find that four factors, the risk-free rate, interest rate volatility, time to maturity and the yield on the underlying bonds are statistically significant, whereas the exercise price, defined as the payable amount by the CDS seller in case of default, does not appear to be significant. Ericsson, Reneby, and Wang (2006) use a set of structural models to predict CDS spreads and afterwards regress the residuals on default and non-default proxies, concluding that there are little or no significant factors driving the residuals. In consequence, credit risk models seem to adequately price the credit risk in credit derivatives markets.

Besides structural models that identify structural variables as determinants of CDS spreads, some researchers also considered volatility and jump risk as factors that contribute to the explanatory value of the dynamics in credit derivatives markets. These studies are mainly motivated by the findings of Campbell, Lettau, Malkiel, and Xu (2001), Campbell and Taksler (2003) and Goyal and Santa-Clara (2003). Benkert (2004) was the first to consider the effect of equity volatility on default risk in CDS markets. Benkert (2004) follows Campbell and Taksler (2003) in relying on fixed effects panel regression analysis that control for time and firm effects. His final sample includes spreads for 120 reference entities between January 1999 and May 2000, totaling to 26.478 quotes. In his regression model, he controls for liquidity, interest coverage, firm leverage, profitability, credit rating, annualized historical equity volatility over 180 calendar days and Black-Scholes option implied volatility derived from at-the-money stock options. In their setting, option implied volatilities show high statistical significance, contributing 5 to 10 percentage points to the R^2 in reference to the setting where no volatility control variable is employed. Furthermore, Benkert (2004) confirm the results of Campbell and Taksler (2003) that historical volatilities are also significant and have the expected sign. In comparison to implied volatility, however, the associated R^2 is significantly smaller, indicating higher efficacy of implied volatility in the explanatory value of CDS premia. The importance of jump risk was considered by Zhang, Zhou, and Zhu (2009) who employ OLS regressions and confirm the results of Benkert (2004). In their study, volatility risk accounts for 48% of the variation in CDS spread levels, whereas jump risk alone accounts for 19%. Hence volatility and jump risk are both the most important factors driving CDS spreads. Zhang et al. (2009) also use factors such as credit ratings, macroeconomic factors and firm specific balance sheet information and are able to explain up to 73% of CDS spread levels, both valid for investment grade and sub-investment grade reference entities.

A number of empirical studies assess the role of liquidity in credit derivative markets, mainly motivated by the seminal work of Amihud (2002) and Pástor and Stambaugh (2003) who identified liquidity risk as an important risk factor in the context of equity asset pricing. Besides illiquidity in equity markets, debt markets also contain priced illiquidity risk factors as shown by De Jong and Driessen (2012) and Bongaerts, De Jong, and Driessen (2017). Regarding CDS markets, Tang and Yan (2007) are the first who examined the role of liquidity in credit derivatives markets. The CDS data used in their study cover the period from June 1997 to March 2006, including 27 industries of U.S. corporate senior unsecured CDS, denominated in US Dollar with a maturity of 5 years. They perform panel regressions with robust standard errors and monthly time dummies to control for issuer clustering in time series correlation's. As a result, they find that liquidity effects arsing from liquidity characteristics account for 13.2 bps in the cross-section, whereas in a beta pricing framework, the liquidity risk premium is estimated to be about 10.9 bps (Tang & Yan, 2007). In later studies performed by Chen, Fabozzi, and Sverdlove (2010), Bongaerts, De Jong, and Driessen (2011) and Junge and Trolle (2015), the role of liquidity in CDS markets was further analyzed, providing additional evidence on the fact that liquidity risk has an influence on CDS valuation.

Another obvious CDS determinant that can be controlled for is the credit rating of the obligor. Hull, Predescu, and White (2004) consider the effect of rating announcements on changes in CDS spreads before and after the change in credit rating. They obtain 233.620 individual CDS spread observations between 1998 and 2002 and conclude that the review for a downgrade in credit status contains significant information, whereas counter intuitively the downgrade itself and negative outlooks do not. Positive rating changes do not exhibit the same significance in the CDS dynamics compared to negative reviews. Given these findings, Hull et al. (2004) subsume that the CDS market anticipates negative credit reviews before the actual downgrade happens. Thus, CDS spreads entail predictive characteristics when the likelihood of a downgrade is considered.

Besides firm-specific factors like volatility, illiquidity and the usage of structural variables indicating credit risk, also macroeconomic factors play an important role in the determination of factors driving CDS spreads. General market conditions and the overall state of the economy can provide meaningful information about the environment in which firms operate and default risk emerges. Due to this fact, a number of studies exist that consider the explicit explanatory power of macro factors such as inflation, GDP growth, unemployment rate, business climate, consumer confidence and overall market sentiment. The role of macroeconomic factors are predominantly considered in studies that analyze credit spreads, most prominently in Collin-Dufresne and Goldstein (2001).

The above mentioned determinants need not be time invariant. In consequence, several studies examined so-called regime dependent determinants of CDS spreads. They typically define specific time periods, such as crisis periods, in which specific factors contribute more or less to the explanation in CDS dynamics than others. Alexander and Kaeck (2008) most prominently assess time dependencies in delta spreads of iTraxx Europe CDS indices by employing a Markov regime switching regression model. They find that spread changes exhibit severe regime dependent as well as sector specific behavior. In times of high turbulence, spreads are very sensitive to stock volatility, whereas in times of tranquility, spread changes are more sensitive to stock returns. In the volatile regime, the size of regression coefficients are significantly higher in comparison of the tranquil regime, contributing to previously unexplained parts of variation in credit spreads, e.g. in Collin-Dufresne and Goldstein (2001). In line with Benkert (2004), they conclude that structural variables of credit risk can contribute to the explanatory power of the model.

4. Methodology and Model Choice

The following section outlines the methodology used throughout my study. Section 4.1 starts with the selection and introduction of a structural credit risk model that is used as the reference point for the estimation of CDS spreads with structural input variables. Section 4.2 describes the different model calibration procedures employed to fit the model to market observables. Then section 4.3 assesses the performance of my fitted CG model by means of a conditional correlation analysis and popular forecasting measures. Section 4.4 sheds light on my selected econometric procedures employed to identify drivers and determinants of credit default swaps spread dynamics.

4.1. The CreditGrades Model

As outlined in section 3.1, structural credit risk models have the advantage of economical interpretability and allow for identification of the drivers and determinants of credit risk justified by economic theory. As my study aims to identify drivers of European CDS spread dynamics, I rely on structural credit risk models. Furthermore, I consider the availability of data and overall tractability of model implementation, given the time frame and overall setting of this thesis. When looking into structural credit risk models used to identify drivers of credit default swap spreads in more detail, one model is frequently cited and implemented by researchers. The so-called CreditGrades model (CG Model hereafter), was developed in the early 2000's by the RiskMetrics Group (now MSCI) in cooperation with the three major investment banks JPMorgan, Goldman Sachs and Deutsche Bank, to establish an industry standard open source quantitative single-name credit risk model for public traded firms. The CG model has to be seen as a complimentary addition to other commercial structural credit risk models that provide the same tractability and performance like the CreditMetrics model introduced in 1997 by JPMorgan. The main difference to other commercial structural credit risk models is that the CG model derived credit risk is determined on the base of CDS spreads and not probabilities of default. Thus, the model was among the first to address the need for a framework to capture credit risk in the credit derivatives market in the early 2000s. It was also motivated by increased regulation and capital requirements in that time. In addition to that, 2001 was the year of the burst of the dotcom bubble with resulting high default rates and the prominent default of Enron, further increasing the need for a framework of credit risk management open to any market participant (Thomas, 2002).

The authors describe the model setup and its implementation in the technical document by Finger et al. (2002), outlining that the CG model belongs to the group of structural credit risk models that link credit with equity markets. The model can be seen as an extension to the first passage time models of Black and Cox (1976) as well as Leland (1994), by modeling a default event as the market value of firm assets falling under a defined default barrier. The asset value process progresses as a geometric Brownian motion, however, Finger et al. (2002) assume that the asset drift term is zero, thus the firm is assumed to maintain a constant leverage ratio over time. The asset value process is defined as follows:

$$dV(t) = \sigma V(t) dW_t. \tag{15}$$

The authors note that for pricing credit risk through first passage time models, not the asset drift itself is relevant, but the asset drift relative to the default barrier. The constant leverage is obtained by either issuing more debt or pay dividends such that the drift of the debt and the drift of equity is the same. By no-arbitrage conditions, the asset drift should then also have the same dynamics as the debt and equity drift. This allows for the conclusion, that the "asset drift relative to the default barrier is zero."[3] The CG model defines the default barrier as the amount of firms assets that remain in case of default, which is the recovery value that debtholders receive. It is defined as $L \cdot D$, with L beeing the average recovery rate on debt and D the firms debt-per-share (Finger et al., 2002).

Another aspect that differs from standard structural models is that the CG model assumes a random default barrier. This stochastic threshold addresses the main problem of estimating artificially low short-term spreads when using classical Merton style default models, because asset processes that start above the barrier cannot cross the default threshold by pure diffusion in very short time intervals. This circumstance is most prominently documented in

[3] Finger et al. (2002), p.11.

Jones, Mason, and Rosenfeld (1984) and Eom, Helwege, and Huang (2004), who conduct extensive empirical work on comparing the performance of different structural credit risk models regarding their ability to estimate credit spreads for different maturities. Even though, Anderson and Sundaresan (2000) as well as Ericsson and Reneby (2001) use various extensions to the original Merton model, they still conclude a systemic underestimation of short-term credit spreads. The methodology of the CG model to introduce randomness to the average recovery rate L prevents the authors from using complex jump diffusion asset value processes or other advanced adjustments, but yields the same tractable estimations for short term spreads. Finger et al. (2002) justify the introduction of uncertainty to recovery rates based on empirical studies of recovery rates like the one of Hu and Lawrence (2000). Hu and Lawrence (2000) find large variability in recovery rates and contingencies depending on whether the default is due to financial and operational reasons or if the firm will be liquidated or restructured. Based on that, Finger et al. (2002) assumes that the recovery rate L is log normally distributed with mean $\bar{L}$ and corresponding standard deviation λ

$$\bar{L} = \mathbb{E}[L] \quad \text{and} \quad \lambda^2 = Var(log(L)). \tag{16}$$

The recovery rate is then denoted by

$$L = \bar{L}e^{\lambda Z - \lambda^2/2} \tag{17}$$

and the recovery value is given by equation (17) multiplied with the firms debt-per-share

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2}, \tag{18}$$

where λ and $L \in \mathbb{R}^+$ and Z is a standard normally distributed random variable that is independent from the Brownian motion and equation (18) describes the stochastic default barrier. Z is considered to be unknown at $t = 0$, revealed only in case of default. Hence, Z can capture uncertainty in the level of debt-per-share and in its default barrier. Finger et al. (2002) conclude that there is some true time-invariant value of L that is not directly observable. This uncertainty in recovery rate allows that the default barrier can be hit suddenly, thus, implementing the same effect as a jump type diffusion asset value process (Finger et al., 2002). Figure 1 illustrates the described asset process and the stochastic default barrier in a condensed manner.

In summary, the firm will not default for the initial asset value V_0, if the following condition holds $\forall t$

$$V_0 e^{\sigma W_t - \sigma^2 t/2} > D\bar{L}e^{\lambda Z - \lambda^2/2}. \tag{19}$$

Finger et al. (2002) proceed in deriving the survival probability, i.e. the probability that the asset value in equation (15) will not hit the barrier defined in equation (18) until time t by introducing a process X

$$X_t = \sigma W_t - \lambda Z - \frac{\sigma^2 t}{2} - \frac{\lambda^2}{2} \tag{20}$$

to be able to transform equation (19) to

$$X_t = log(\bar{L}D/V_0) - \lambda^2 \tag{21}$$

which is normally distributed with

$$\mathbb{E}[X_t] = -\frac{\sigma^2}{2}(t + \lambda^2/\sigma^2) \quad \text{and} \quad Var(X_t) = \sigma^2(t + \lambda^2/\sigma^2). \tag{22}$$

Finger et al. (2002) then approximate the process X by a Brownian motion $\hat{X}$ with drift $-\sigma^2/2$ and diffusion σ^2. This step exchanges the uncertainty in the default barrier by the uncertainty in the asset value level at $t = 0$ to implement the methodology that the distance-to-default (DD)dd, i.e. the distance between asset value and default barrier, drives the credit risk in the model setup. The authors note that for $t \geq 0$, the moments of the original process X coincide with the moments of $\hat{X}$ and hence provide a valid approximation. In the next step, the distribution for first hitting time Brownian motions in the process form of $Y_t = at + bW_t$[4] is applied (e.g. in Musiela and Rutkowski (1998))

$$Prob(Y_s > y, \forall s < t) = \Phi\left(\frac{at - y}{b\sqrt{t}}\right) - e^{2ay/b^2}\Phi\left(\frac{at + y}{b\sqrt{t}}\right) \tag{23}$$

by inserting the drift term of $\bar{X}$ into $a = -\sigma^2/2$, setting equation (21) as y and shifting the time from t to $t + \lambda^2/\sigma^2$. The closed-form formula for the survival probability up to time t is given by

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{log(d)}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{log(d)}{A_t}\right), \tag{24}$$

with

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D} \tag{25}$$

and

$$A_t^2 = \sigma^2 t + \lambda^2. \tag{26}$$

The survival probability expressed in equation (24) implies that there exists the possibility that the firm defaults prior to $t = 0$ in the interval $(-\Delta t, 0]$, which is implied by the assumption that the default barrier is log-normal distributed and that the uncertainty in the default barrier is shifted to the Brownian motion starting value (Cao et al., 2011). This aspect results in the artefact that the probability of default in $t = 0$ is not zero. Finger et al. (2002) provide an alternative estimation of the survival probability addressing this aspect by integrating over the default barrier distribution which yields a survival probability expressed by a cumulative bivariate normal distribution. The closed form solution of the

[4] With constant a and b.

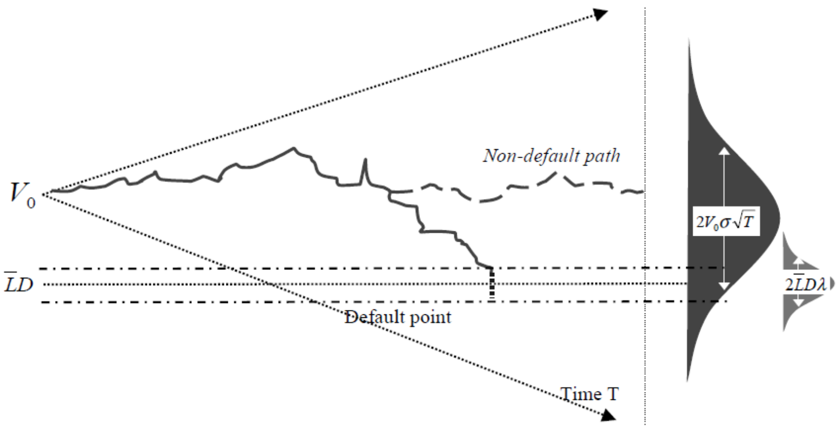

Figure 1: Illustration of CreditGrades Model, Finger et al. (2002).

exact survival probability was later derived by Kiesel and Veraart (2008). However, Finger et al. (2002) state that the numerical differences between the two approaches are small enough, such that for practical purposes, the initial implementation provides reasonable estimates.

To derive credit default swap spreads, the estimated survival probabilities must be transformed into a credit price. This is achieved by introducing two parameters, the risk-free rate r and the recovery rate of the underlying credit R. The important difference between $\bar{L}$ and R is that $\bar{L}$ describes the global average recovery rate across all debt classes and obligors and R depicts the individual recovery rate for the specific underlying asset subject to credit risk (e.g. the concrete bond issued by the obligor). A credit default swap is now priced by using the introduced methodology of Hull and White (2000) in chapter 2, requiring that the present value of the expected premium payments by the CDS buyer has to equal the present value of the expected payouts by the CDS seller in case of default.[5] Given the interest rate r and the survival probability derived in equation (24), the continuously compounded par credit default swap spread with maturity t estimated by the CG model equates to

$$s^* = r(1-R)\frac{1-P(0)+e^{r\xi}(G(t+\xi)-G(\xi))}{P(0)-P(t)e^{-r\xi}-e^{r\xi}(G(t+\xi)-G(\xi))}, \quad (27)$$

where $\xi = \lambda^2/\sigma^2$ and the G function is given by Rubinstein and Reiner (1991) as follows

$$G(t) = d^{z+1/2}\Phi\left(-\frac{log(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}\right) + d^{-z+1/2}\Phi\left(-\frac{log(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}\right) \quad (28)$$

and $z = \sqrt{\frac{1}{4}+\frac{2r}{\sigma^2}}$.

[5] For the complete derivation see appendix A of Finger et al. (2002).

The ability to price credit risk by the above described CG model is assessed by a hand full of researchers that predominantly consider the US CDS market. Byström (2006) was the first who considered the CG model for the European market. He uses the CG model to calculate CDS spreads on an aggregated level for eight iTraxx indices that cover the European area. All indices consist of 5 year maturity CDS contracts and are grouped into seven sectors (investment grade obligors) and one crossover index containing sub-investment grade obligors. He finds that model spreads are highly correlated with empirical spreads and constitutes that the CG model has predictive abilities since theoretical spreads tend to lead market spreads. This is mostly due to equity markets being faster in incorporating news than the CDS market (Byström (2006)). Furthermore he tests for autocorrelation and finds that market spreads exhibit severe autocorrelation, whereas model spreads do not. Byström (2006) states that this result provides reason for possible inefficiencies in the credit derivatives market, though equity markets seem to be more efficient. On this basis, Byström (2006) employs simple trading strategies that yield positive returns before transaction costs. The second most prominent study was performed by Yu (2006) as already outlined in chapter 2. In addition to that, Wagner (2008) assess CDS pricing via the CG model and compares it to the trinomial tree model proposed by Das and Sundaram (2001). They use a sample of 54 individual CDS extracted from the Markit CDX investment grade index covering the US market and the time period between May 2004 to July 2006. They find that both models' out-of-sample performance is poor with a low mean correlation in CDS spread deltas. However, when firm stock prices and CDS spreads highly correlate with the entire CDS market, the structural model fits better to empirical spreads and thus provides evidence on the fact that "model spreads fit better to market spreads given that less company specific credit risk is involved."[6]

[6] Wagner (2008), p. 26.

Bedendo et al. (2011) fit the CG model to 80 North American non-financial obligors between 2002 and December 2005 and analyse the resulting gap by running panel regressions for each sector on weekly deltas in the difference between model and market spreads. They choose to employ an advanced version of the CG model resting on the extraction of, not only option implied volatility, but also option implied estimates of asset volatility and the financial leverage of the firm using the implied volatility skew as the model input, taking option implied jump risk into consideration. Their main contribution is that the gap between model and empirical spreads tends to widen especially in crises times with high volatility. Especially the dynamics in equity implied volatility and volatility skew are major determinants of weekly gap deltas. Furthermore, liquidity factors and periods of a general disconnect between equity and credit markets result in high gaps. In line with Byström (2006) and Yu (2006), Bedendo et al. (2011) find that model spreads can act as predictors for changes in market spreads and contribute to the evidence that the CG model exhibits predictive abilities in credit markets.

Cao et al. (2011) employ two specifications of the CG model, one with option implied volatilities and the other with historical volatility of a 252-day horizon. Their sample consist out of 332 single name US credit default swaps observed between January 2007 until October 2009 and therefore also covering the global financial crisis in 2008. In order to assess the pricing performance of the CG model in respect to the different volatility estimations, Cao et al. (2011) conduct a pricing error analysis in which a pricing error ratio, calculated as the ratio of the implied volatility RMSE and the historical volatility RMSE, is analyzed. Afterwards they perform cross-sectional regressions with this ratio as the dependent variable in order to investigate if firm-level characteristics, such as spread volatility, credit rating, option volume and open interest, can provide some explanatory value. Their analysis shows that obligors with a high degree of spread volatility, option volume and lower credit ratings exhibit significantly lower pricing error ratios. This illustrates that implied volatility yields more credit market relevant information as when using historical volatility. They also tested the robustness of this finding by implementing different historical volatility estimators ranging from 22 to 1000 day horizons.

4.2. Model Calibration

In order to estimate CDS spreads using the CG model, model variables need to be calibrated to market observables. These observables cover the initial asset value of firms V_0, the asset volatility σ, the debt-per-share D, the global average recovery rate $\bar{L}$, the individual bond specific recovery rate R and the volatility of the default barrier λ.

Debt-per-share (DPS) is obtained by extracting liabilities from consolidated financial statements and dividing the liabilities by the number of shares outstanding. I follow Finger et al. (2002) and define liabilities as all debt issued that contributes in the financial leverage of a company. Hence all long- and short-term interest bearing financial obligations are included, whereas accounts payable do not enter my DPS calculation as they do not contribute to the financial leverage of the firm. Furthermore, I account for using consolidated financial statement data by adjusting the total debt for debt held by subsidiary companies. Since consolidated financial statements aggregate all debt, even though the subsidiary is not necessarily held a 100% by the parent company, I subtract the minority debt defined as $k \cdot MinorityInterest$ from the total debt, assuming that the debt-to-equity ratio k is equal to 1 and limiting the total amount of minority debt by not exceeding more than 50% of the total consolidated financial debt. The number of shares consist out of common shares outstanding plus preferred shares. As the number of preferred shares cannot be retrieved easily, I calculate them by retrieving the amount of preferred equity and divide it by the current equity price. Finally, debt-per-share is calculated by dividing the total debt, corrected for minority debt with the total amount of shares consisting of common and preferred shares. To avoid a look-ahead bias of the model, I update each parameter only when its information becomes available to the market. Hence, I keep the yearly consolidated financial data, such as total debt, minority interest and preferred equity, constant for the respective fiscal year. Common shares are retrieved quarterly, but are interpolated to obtain daily values since market participants can back out the number of common shares on a daily basis by dividing the current market capitalization by the current stock price. This way of estimating debt-per-share assures that the model provides an ex-ante view on the pricing ability of CDS spreads.

The instantaneous asset value V_0 and the asset volatility σ are both calibrated by assessing how the asset value behaves close to and far from the default barrier, relating the equity volatility to the asset volatility using Ito's Lemma:

$$\sigma_e = \sigma \frac{V}{S} \frac{\partial S}{\partial V}, \tag{29}$$

with the equity price of the firm denoted S and the corresponding equity volatility σ_e. The distance-to-default is given by η and is measured as the number of annualized standard deviations that separates the firms current equity value from the default barrier

$$\eta = \frac{1}{\sigma} log\left(\frac{V}{LD}\right) = \frac{V}{\sigma_e S} \frac{\partial S}{\partial V} log\left(\frac{V}{LD}\right). \tag{30}$$

The first boundary condition considers how V behaves close to the default barrier LD by assuming that the value of equity converges to zero when default becomes more probable. The value of the firms' assets then equal the contingent claim of debtholders in case of default defined as the default barrier itself

$$V|_{S=0} = LD \tag{31}$$

and close to the barrier adding the marginal rate of change in V based on a change in S

$$V \approx LD + \frac{\partial V}{\partial S} S. \tag{32}$$

The distance-to-default measure can now be expressed by substituting equation (32) into equation (30) in order to see how η behaves near the default barrier

$$\eta \approx \frac{1}{\sigma_e}. \tag{33}$$

The second boundary condition considers how V behaves far from the default barrier. Finger et al. (2002) assume that the asset value increases with the same speed as the equity value $S/V \rightarrow 1$. If this relation is substituted into equation (30), it follows that

$$\eta \simeq \frac{1}{\sigma_e} log\left(\frac{S}{LD}\right). \tag{34}$$

Finger et al. (2002) conclude that the most simple expression considering V and $e(t)aa$ that simultaneously satisfy the two boundary conditions is that $V = S + LD$. Hence, the value of assets consists of the value of equity plus the contingent claim of debtholders in times of default. The initial asset value V_0 is then given by

$$V_0 = S_0 + \bar{L}D, \tag{35}$$

with S_0 as the initial stock price and the corresponding volatility of assets given in equation (29)

$$\sigma = \sigma_e\left(\frac{S}{S+\bar{L}D}\right). \tag{36}$$

The estimation of σ is performed by a local approximation of the volatility surface, scaling the equity volatility σ_e by a gearing-ratio that accounts for leverage in the assets relative to equity only (Cao et al., 2011). The estimation of equity volatility is dependent on the research design. I employ two estimation procedures for equity volatility in order to be able to compare the pricing implications of using information from equity markets with forward-looking information extracted from derivative markets. The first procedure relies on historical volatility calculated from a 1000-trading-day moving average of daily equity returns that are afterwards scaled by $\sqrt{252}$ to obtain yearly volatility estimates. The choice of the length of the MA window is motivated by the studies of Duarte et al. (2007), Finger et al. (2002) and Yu (2006). For the other approach I obtain equity option implied volatilities derived from put and call options of the specific reference entities trading at 100% moneyness (at-the-money) with a remaining time to maturity of one year. This procedure is motivated by the work of Cao et al. (2011) and Wagner (2008) who find that the using option implied volatilities improves the fit of the CG model estimated spreads to market spreads in comparison to the CG model that uses an historical volatility estimator. Previous researchers addressed option implied information in linear settings by regressing option market variables on corporate bond credit spreads. They implicitly assume that the relation of equity volatility is inherently linear to observable market spreads (see e.g. Cremers et al. (2008) or Cao, Yu, and Zhong (2010)). My study design deviates from these studies by accounting for non-linear dependencies of forward-looking option market information and resulting CDS spreads within the CG model framework. My work also relates to the study of Stamicar and Finger (2006) who consider a case-study research design and price CDS written on Vivendi, General Motors, Ford and Boeing. However, my study incorporates a larger sample of reference entities and hence provides a higher degree of cross-sectional granularity using option implied volatilities. Stamicar and Finger (2006) conclude that using option implied volatilities improves the performance of the model, especially in crisis times, by providing credit warning signals backed out of option markets.

The parameters $\bar{L}$, R and λ cannot directly be observed in the market and therefore lead to difficulties in the model calibration process. Finger et al. (2002) assess the estimation of the global average recovery rate $\bar{L}$ by relying on the proprietary Portfolio Management Data and Standard & Poor's database also considered by Hu and Lawrence (2000). This database contains historical recovery rates for 300 non-financial US firms issued bonds and loans that defaulted in the period 1987 to 1997. From this data, Hu and Lawrence (2000) estimate $\bar{L} = 0.5$ and $\lambda = 0.3$. Since these estimates seem realistic and are by definition time invariant and global, I proceed by applying the same estimates in my study considering European non-financial firms.

The calibration of R poses the difficulty, that the recovery rate on the specific underlying bond cannot be observed, since default of the bond did not (yet) occur. The authors of the original model and researchers like Yu (2006) use the methodology of leaving R as a free parameter and calibrate the model to market spreads by minimizing the pricing errors of some pre-defined goodness-of-fit measure G. For this purpose I choose the squared pricing deviations as goodness-of-fit measure defined as:

$$\min_R G = \sum_{i=1}^{n}\left(s_i^{Model} - s_i^{Empirical}\right)^2. \tag{37}$$

Using this methodology and minimizing G over the first 25 trading days, I find unreasonable values for R most of the time. As a consequence I follow Yu (2006) who finds similar values and thus sets $R = 0.5$ leaving $\bar{L}$ as the free parameter to fit the model. However, following Yu (2006), I also find unreasonable values for $\bar{L}$. Consequently, I fit the model to sector specific recovery rates as given in Gambetti, Gauthier, and Vrins (2019). They publish sector recovery rates extracted from the proprietary Moody's Analytics Default and Recovery Database. I provide more recovery rate specific details in chapter 5.

The risk-free rate was initially considered to be the short end of the Euro yield curve using the 3-month EURIBOR offered rate in line with recommendations in the existing literature for selecting a Euro risk-free reference asset (Remolona, Wooldridge, et al., 2003). When I have employed this measure as a risk-free rate, the model sometimes did not produce any values. Upon closer examination, equation (28) demands that the risk-free rate embedded into $z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma^2}}$ does not necessarily have to be positive, but cannot be arbitrarily negative, such that the expression in the square root becomes negative. As this is the case for some observations, I have to choose an alternative risk-free rate that exhibits an overall higher interest rate level. A reasonable alternative is to select the US government bond rate since the general interest rate level is typically higher for the US market than for the European market mainly due to the European sovereign debt crisis and resulting monetary policy measures taken by the ECB. Since in the academic literature the US rate is typically used as a reference risk-free asset, I opt for using the 5 year constant maturity treasury bond middle rate to match the duration on constant 5 year maturity CDS contracts as described in chapter 5 in more detail. My selection of the risk-free asset poses the contextual difficulty that the geographical location does not match. On the other hand, it can be argued that international capital mobility can be taken as a given and thus European market participants can obtain exposure to the US risk-free asset, providing economical justification of employing the US government rate as the reference risk-free rate.

4.3. Correlation and Pricing Analysis

After calibrating the model to market observables using historical equity and option implied volatility as a proxy for asset volatility, I assess the pricing performance of each model specification by means of a correlation analysis and frequently cited forecast metrics. Similar to the study of Bedendo et al. (2011), the correlation analysis of model and empirical spreads is conditioned on sectors in order to obtain a sector specific view on the pricing performance of each model specification. I choose parametric as well as non-parametric methods for measuring the relationship between market and model spreads to capture linear as well as non-linear relationships. First, I calculate the Pearson-product moment correlation coefficient for each time series. In order to obtain average sector specific correlations, I transform individual Pearsons r to the Fisher z-transform by $Z = \frac{1}{2} ln\left(\frac{1+r}{1-r}\right)$. This procedure boils down to normalizing the sampling distribution with the aim to mitigate the effect of distribution skew to be able to take the average of all sector specific z-transformed $\bar{Z} = \frac{1}{n}\sum_{i=1}^{n} Z_i$. Afterwards, the average z-transformed variable is converted back using $\bar{r} = \frac{e^{2\bar{Z}}-1}{e^{2\bar{Z}}+1}$ to an average Pearson product-moment correlation coefficient. This way of obtaining average sector specific correlations appears to posses superior reliability compared to taking the simple time series average as proposed by Hunter and Schmidt (1990) (see e.g. Corey, Dunlap, and Burke (1998)). This transformation step is then performed for the Spearman rank-order correlation to capture possible monotonic non-linear dependencies.

I proceed by assessing possible autocorrelation within the empirical as well as calculated model CDS spreads for each obligor in the spirit of Byström (2006) to investigate whether my sample of reference entities is subject to inefficiencies in the CDS market. My methodology contributes to the study of Byström (2006) by analysing single name CDS instead of considering CDS indices as well as covering different time periods and obligors. Furthermore, I consider autocorrelations in model CDS spreads when using option implied volatility and thus again contribute to the study of Byström (2006). I calculate Ljung-Box test statistics with 5 and 10 lags respectively, closely following the recommendation of choosing $ln(T)$ as the optimal choice of lags to obtain good power properties in finite samples.

For the performance analysis, I calculate three forecasting metrics: Bias, the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE). The bias for the time series i and number of observations n is defined as the average error following:

$$bias_i = \frac{1}{n}\sum_{n} e_{i,t} \quad \text{with} \quad e_{i,t} = s_{i,t}^{Model} - s_{i,t}^{Empirical}$$

and captures the general tendency of the model to deliver feasible estimates. However, since negative and positive deviations can offset each other, a model can provide a very low bias but be imprecise at the same time. Thus, I also calculate the mean absolute error that corrects this issue by taking the mean of the absolute values of the errors. It is calculated as follows:

$$MAE_i = \frac{1}{n}\sum_{n} |e_{i,t}|.$$

In addition, I calculte the root mean squared error (RMSE) as it provides information on the standard deviation of the error and thus is a good model accuracy measure. In my study the RMSE is calculated as follows:

$$RMSE_i = \sqrt{\frac{1}{n}\sum e_{i,t}^2}.$$

In order to obtain sector cross sectional pricing metrics, I average the metric for each time series i within one sector. The performance of each model specification for each sector and time period can then be assessed and compared to other studies that deal with the pricing performance of the CG model. This comparison provides insight on how the model behaves for European CDS spreads accordingly.

4.4. Multi-factor Model CDS Determinants Estimation Procedure

After assessing the model performance, I proceed with analyzing the gap between theoretical and market CDS spreads using a regression-based analysis. The study I use as reference point in this section is published by Bedendo et al. (2011). They analyse the resulting gap by running panel regressions for each sector on weekly deltas in the difference between market and model CDS spreads. Following Bedendo et al. (2011), I calculate weekly gaps for both the standard CG model calibrated with 1000-day equity volatility and the calibrated CG model using option implied volatilities. Regarding the observation frequency, I opt for weekly observations, since daily observations could be too noisy and would enable possibilities for statistical inconsistencies and distorted estimates. Then I employ a one-way fixed effects panel regression model with the obligor as the reference index. A one-way fixed effects model is used here, since I assume that there exists obligor specific fixed effects that are captured by the individual-specific error component. Thus, I am able to account for unobserved effects that are unique to individuals, but are also time invariant. Furthermore, I do not employ a two-way fixed effects model, because I control for time variant regression estimates by performing panel regressions grouped according my pre-defined time periods covering the financial crisis, the European sovereign debt crisis, the tranquil period and the corona crisis.

I conduct my regression analysis in three different ways. My first approach considers the gap between model and empirical spread as the dependent variable. This approach tries to identify economical drivers of the variation in the error term, hence providing insights into possible missspecifications and shortcomings of the CG Model in its respective specifications as well as reveal what drivers move market and model spreads apart. With this approach I follow Bedendo et al. (2011) using an updated dataset as well as a different geographical regions. These regions are described in more detail in section 5. The second approach considers the CG Model spread itself as the dependent variable. This econometric setting allows to identify common characteristics and variables that contribute to the total explanatory power of the variation in models spreads. The third approach considers the weekly changes in the empirical CDS spread as dependent variable, thus providing additional insights into variables that explain the variation in weekly market spread independent from my model selection. Thus, I also shed light into possible model misspecifications and shortcomings using this approach. For the selection of the independent variables, I follow the the literature discussed in section 3 and employ firm specific (individual) as well as macroeconomic (common) variables in the panel regression framework.

As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002). The Amihud (2002) is defined as follows:

$$ILLIQ = \frac{1}{N}\sum_{t=1}^{T}\frac{|r_t|}{€\ VO_t}, \tag{38}$$

with $|r_t|$ the weekly absolute return and $€\ VO_t$ the weekly equity turnover euro volume from time $t-1$ to time t. The rational behind the inclusion of equity volatility is the connection between the model calibration procedure in section 4.2 and the interconnectedness and spillover effects between equity and credit markets. The same holds true for equity returns, since equity returns provide important information for equity markets with implications for credit markets and its credit quality. The credit curve is incorporated in my regression analysis, because it captures the variation in obtaining or providing credit protection for different tenors, indicating that the spread is dependent on how long the protection will last. The slope of the credit curve captures market sentiment, because when credit curves are upwards sloping, the likelihood of experiencing a credit event increases due to a greater degree of credit quality uncertainty in the future. If the credit curve is flat, the market does not anticipate that the occurrence of the credit event is more probable in the near future, nor the distant future and vice versa. A downward sloping credit curve indicates that the spreads for the near future are higher than for the distant future due to low anticipated survival rates in earlier periods. The common shape of the credit curve is the upward sloping curve as survival rates mostly decreases over time and the probability of the occurrence of a credit event increases. As I calculate weekly changes in the slope of the credit curve, I capture market sentiment dynamics that can contribute to the overall explanation of the dynamics in the European credit derivatives market. Additionally, Bedendo et al. (2011) as well as Bedendo, Cathcart, El-Jahel, and Liesch (2005) show that the inclusion of the slope of the credit curve can provide meaningful contributions in predicting future changes in credit spreads with short forecasting horizons.

The illiquidity factor derived by Amihud (2002) enters the regression specification because it provides information regarding illiquidity constraints on equity markets with possible spillover and contagion effects on credit markets (Bedendo et al. (2011)). Therefore, I calculate the weekly absolute return of the reference entity $|r_t|$ and the corresponding weekly euro turnover volume $€\ VO_t$ to derive the illiquidity measure in equation (38).

Regarding the common macroeconomic variables, I specify the weekly change in the risk-free rate, defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve, defined as the 12 month EURIBOR minus the one month EURIBOR and the weekly change of the VSTOXX index in my regression analysis. The risk-free rate is included in my regression framework because influential studies like the one of Collin-Dufresne and Goldstein (2001) find that changes in the spot rate are important determinants of the credit market. They argue that the spot rate is theoretically motivated by mechanics of the inherent risk-free asset drift firm value process described in chapter 3.1. An increase in the risk-free rate, increases the asset drift and thus the distance-to-default. In consequence it the likelihood of experiencing a credit event decreases. Thereby, most studies that contribute to this field of research include the risk-free interest rate as a baseline determinant in their regression methodology. The variation in the slope of the yield curve also provides additional information on the inherent default probability because Collin-Dufresne and Goldstein (2001) argue the dynamics in the slope of the yield curve can also influence the interest rate level itself, thus also driving the asset value process. Consequently an inverse relationship between an increase in the slope of the yield curve and a lowering of credit risk in the overall economy emerges (Collin-Dufresne and Goldstein (2001)).

As an additional aspect, I try to capture the effect of counterparty credit risk in my study. This aspect is predominantly motivated by the work of Arora, Gandhi, and Longstaff (2012) who find that counterparty credit risk is significantly priced in the cross-section of non-financial credit default swap spreads, becoming more statistically significant after Lehman Brothers defaulted. To be able to depict counterparty credit risk in my regression framework, I derive and calculate a counterparty credit risk index (CRI) which closely resembles the CDR counterparty risk index first introduced in 2008 by Credit Derivatives Research. The CDR index consists of the largest 15 equally weighted CDS 5 year mid-quotes for CDS sellers such as Barclays Bank, J.P.Morgan and Goldman Sachs and is depicted in basis points. I replicate this index with an updated dataset suitable for the largest CDS dealers selling European credit derivatives such as Commerzbank, Deutsche Bank and others closer described in appendix F. Besides the weekly change in the CRI, I further take the change in the slope of the CRI into account by calculating the weekly change in the difference between 10-year and 1-year mean cross-sectional CDS spreads for all index constituents. The change in the slope acts in the same way it does for the sample entity CDS slope as an indicator for market sentiment, but now focusing on the credit protection seller side. This allows to capture market sentiment not as an aggregate, but segmented into protection seller and protection buyer side.

In order to address possible autocorrelation, I include one week and two-week lags of the dependent variable. This methodology is in line with common regression model specifications found in the literature such as Bedendo et al. (2011). I do not include a broad stock market index due to collinearity issues arising from individual equity returns that are also included as firm-specific explanatory variables.

Finally, my fixed effects regression model in its three approaches regarding the gap, the CG model spread and the empirical CDS spread is estimated as follows:

$$\begin{aligned}\Delta GAP_{it} &= \alpha + \beta_1 \Delta rf_t + \beta_2 r_{it} + \beta_3 VOL_{it} + \beta_4 \Delta SLOPE_{it}^{CDS} \\ &+ \beta_5 ILLIQ_{it} + \beta_6 \Delta CRI_t + \beta_7 \Delta SLOPE_t^{CRI} + \beta_8 \Delta SLOPE_t^{Yield} \\ &+ \beta_9 \Delta VSTOXX_t + \beta_{10} \Delta GAP_{it-1} + \beta_{11} \Delta GAP_{it-2} + u_{it}\end{aligned} \tag{39}$$

$$\begin{aligned}\Delta CG_{it}^{Model} &= \alpha + \beta_1 \Delta rf_t + \beta_2 r_{it} + \beta_3 VOL_{it} + \beta_4 \Delta SLOPE_{it}^{CDS} \\ &+ \beta_5 ILLIQ_{it} + \beta_6 \Delta CRI_t + \beta_7 \Delta SLOPE_t^{CRI} \\ &+ \beta_8 \Delta SLOPE_t^{YIELD} + \beta_9 \Delta VSTOXX_t \\ &+ \beta_{10} \Delta CG_{it-1}^{Model} + \beta_{11} \Delta CG_{it-2}^{Model} + u_{it}\end{aligned} \tag{40}$$

$$\begin{aligned}\Delta CDS_{it} &= \alpha + \beta_1 \Delta rf_t + \beta_2 r_{it} + \beta_3 VOL_{it} + \beta_4 \Delta SLOPE_{it}^{CDS} \\ &+ \beta_5 ILLIQ_{it} + \beta_6 \Delta CRI_t + \beta_7 \Delta SLOPE_t^{CRI} \\ &+ \beta_8 \Delta SLOPE_t^{YIELD} + \beta_9 \Delta VSTOXX_t \\ &+ \beta_{10} \Delta CDS_{it-1}^{Empirical} + \beta_{11} \Delta CDS_{it-2}^{Empirical} + u_{it},\end{aligned} \tag{41}$$

with $u_{it} = \psi_i + v_{it}$, ψ_i indicating the individual-specific effect in the variation regarding the dependent variable which remains constant across time for each individual. v_{it} depicts the stochastic disturbance term that varies across individuals and time. I estimate each equation in (39), (40) and (41) on the sector level to account for sector specific idiosyncratic aspects and to compare the model specifications within my sample clustered by economical activity. Thus, I am able to identify sector specific drivers of the independent variable within each regression setup.

Afterwards I proceed with analyzing the error term of each regression by performing a principal component analysis (PCA) in fashion of Collin-Dufresne et al. (2001), Cremers et al. (2008) and Bedendo et al. (2011) to be able to identify any common variables that are not included in my regression specification and are potentially driving variations in the error term. For this I follow Bedendo et al. (2011), who define the number components used by the cumulative explained variance. They incorporate principal components until the cumulative explained variance reaches a level of more or equal to 80%. This procedure gives a standardized view on how many components drive the remaining variation in the error term and can thus indicate any misspecifications of my regression analysis. I deviate from Bedendo et al. (2011) by not only assessing the error term of empirical CDS spreads, but also on the error term of gap and CG model regressions in equation (39) and (40). With this extension I am able to examine the regression approach at a broader level.

After the main regression analysis and the subsequent PCA is performed, I proceed with testing the predictive ability of the CG model to forecast market spreads by implementing a sector specific fixed effects model that considers the regression of weekly changes in market spreads on weekly changes in model spreads with one and two lags and weekly deltas of market spreads with lag of one week accordingly defined in equation (42). This approach is related to the study of Bedendo et al. (2011), who also consider the forecasting ability of the CG model via this approach. The economical interpretation is based on the empirical finding "that relevant information is usually revealed and absorbed faster in the equity market rather than in the credit market."[7] Studies like Norden and Weber (2009) and Longstaff, Mithal, and Neis (2005) support this idea by providing evidence on lead-lag relationships between equity and credit markets. Thus, CDS spreads estimated from structural credit risk models should

[7] Bedendo et al. (2011), p. 673

be able to exhibit subsequent predictive behavior in the credit default swap market. Predictive regressions are performed as follows:

$$\Delta CDS_{it}^{Empirical} = \alpha + \beta_1 \Delta CDS_{it-1}^{Model} + \beta_2 \Delta CDS_{it-2}^{Model} + \beta_3 \Delta CDS_{it-1}^{Empirical} + u_{it}. \quad (42)$$

Along the regression estimation process described above, I compute diagnostic statistics to ensure that the aspect of stationarity, multicollinearity and heteroscedasticity are addressed properly and regression estimates are not biased. To quantify stationarity, I calculate the unit root test for panel data of Levin, Lin, and Chu (2002) that considers pooling cross-section time series data for testing the unit root hypothesis. This methodology is still in line with my fixed-effects model as I test each regression variable individually for stationarity using the entire dataset. In a second step, I test for multicollinearity by first estimating a pooled panel regression for each fixed-effects panel regression I estimate. As again only the independent regression variables are assessed, the pooled model does not interfere with the subsequent fixed-effects estimation procedure. I calculate the Variance Inflation Factor (VIF), since multicollinearity between the predictors is typically indicated by the predictors VIF value above some pre-defined threshold. The VIF measures the increase in variance of regression coefficients due to collinearity and provides an index measure of the inflation in standard errors emerging from correlations with other predictor variables. A typical threshold that is often cited in the literature is 3, such that I also use a VIF reference value of 3 to identify whether multicollinearity is existent in my regression specifications. Furthermore, I always correct the standard errors for heteroscedasticity and spatial correlation by estimating heteroscedasticity robust standard errors for panel regressions with cross-sectional spatial dependence. I rely on Driscoll and Kraay (1998), who derive a nonparametric covariance matrix estimator that yields heteroscedasticity and autocorrelation consistent estimates for standard errors which are corrected for robustness to forms of any spatial and temporal dependence. The often cited and popular Newey-West standard errors are also feasible for panel data regressions, but do not correct for possible autocorrelation between individuals, which is especially important for panel data regressions. Therefore I report regression estimates with Driscoll-Kraay standard errors throughout my analysis.

5. Data

Since my study is mainly based on CDS spread, return and leverage data, I rely on the database of Refinitiv Datastream. It is the most comprehensive data source for CDS related data and is widely used for various fields of research with an emphasis on equity and credit markets. I choose to rely on Refinitv Datastream data which goes back until the 14^{th} of December 2007. First, I extract European daily individual single-name corporate CDS mid-spreads of 5 year tenors of contracts that include the modified-modified restructuring clause and start reporting on the 14^{th} of December 2007. Additionally I rely on senior unsecured seniorities to have comparable contracts in my sample. My data selection is motivated by the work of Berndt et al. (2007), who show that restructuring risk has material impact on the premium, amounting on average 6% to 8% of the value of protection against non-restructuring default events. I exclude financial firms, since the financial leverage of these firms are not comparable to non-financial firms, which can be traced back to the inherent characteristics of the different business models. The remaining population is afterwards filtered for data quality purposes, such that contracts in my sample report regularly and I exclude the possibility of distorted estimates due to illiquidity reasons. Contracts that stop reporting throughout my observation period are dropped. In general, my sample period covers daily observations spanning the period from 14^{th} of December 2007 until the 14^{th} of December 2020. My final CDS dataset consists of 75 obligors and 3392 observations per obligor, resulting in 254.400 observations. I define eight economical sectors based on the sector classification from Refinitiv Eikon. These sectors consist of the following: Consumer Non-Cyclical, Consumer Cyclicals, Industrials, Utilities, Technology, Healthcare, Energy and Basicmaterials. Furthermore I define the following time periods: *Full Period* (14.12.2007 - 14.12.2020), *Financial Crisis* (14.12.2007 - 31.12.2009), *European Sovereign Debt Crisis* (01.01.2010 - 31.12.2013), *Tranquil Period* (01.01.2014 - 28.02.2020) and the *Corona Crisis* (01.03.2020 - 14.12.2020).

Data for the input variables of the CG model estimation, calibration and subsequent panel regression analysis are also retrieved from Refinitv Datastream. I obtain daily total return index values, actual closing prices, the risk-free rate, the number of common shares outstanding, total financial debt, the daily euro turnover volume, daily VSTOXX index values and minority interest for each obligor. Regarding the derivation of the counterparty credit risk index (CRI), I retrieve CDS quotes in the same fashion as described above for financial institutions, most prominent known to be major European CDS dealers (see appendix F). The sector specific recovery rates are taken from the paper by Gambetti et al. (2019) displayed in appendix G. Since my second specification of the CG model relies on option implied volatilites, I also obtain Refinitiv Datastream option-implied volatilities from constant one year at-the-money put and call options of the respective obligors. As not for all reference entities traded options exist, I define a subsample for my option implied CG model estimation to circumvent this problem. Furthermore, available Refinitv option data does not start reporting on the 14^{th} of December 2007, such that I augment the first period of the financial crisis and hence shortening the observation period to be consistent with the other defined time periods. The subsample period covers the horizon from 1^{st} of January 2010 until the 14^{th} of December 2020 and consists out of 46 obligors with 2857 daily observations totaling to 131.422 data points.

6. Results

6.1. Reference Entity Sample Composition and Summary Statistics

In this section I display my reference entity sample composition of industry sectors, geographical location and credit rating with the aim to provide an extensive overview of my sample. Table 1 gives an overview on the industry sector composition (Panel A) and the country distribution (Panel B) of my sample of CDS reference entities. Panel C depicts the rating distribution of obligors. Considering panel A, it becomes obvious that my sample is distributed across all eight sectors with pronounced weights in consumer non-cyclicals and cyclicals as well as industrials. Together these sectors make up more than half to the entire sample sector distribution. On the other hand the remaining sector weights are rather evenly distributed. Panel B shows that the majority of my sample contracts is either located in Germany, Great Britain or France by marking more than 60% of my sample country distribution. This result is largely driven by the selection process described in section 5, because the most liquid and thus frequently reporting contracts have a tendency for higher data quality and are more likely to pass the imposed data quality filters with a self-selection process tilting the data set towards the European economies. Panel C reveals that the rating distribution is rather homogeneous, because the majority of my sample reference entities belong to the investment grade rating, whereas only roughly 10% can be classified as speculative grade. This fact motivates my study design to not group the CG model estimation and subsequent panel regressions by credit ratings as done in other studies like Collin-Dufresne et al. (2001), but by economical activity and thus sectors. With this classification I am able to identify sector specific idiosyncratic model performance and empirical determinants of credit default swap spreads dynamics.

Since the CG model estimation relies strongly on its input variables, I proceed with providing summary statistics that should allow for identification of sector specific patterns which might be helpful to understand and interpret the model performance and pricing analysis in section 6.2. Furthermore, it allows for an Explorative Data Analysis (EDA) such that the relation between model input variables and the model output can be assessed. Table 2 reports summary statistics for all CG model input variables on a per sector basis. The column named "*mean*" in table 2 depicts the cross-sectional means of the model input variables over the model estimation period. When the columns *mean* and *median* are compared, it becomes obvious that nearly all model input variables exhibit right skewed distributions, except for the energy sector with cross-sectional debt-per-share and stock prices being left skewed. The number of individual variable observations naturally is constant for all sectors with 3392 observations per obligor as my empirical analysis is based on a balanced panel dataset. Only for the variable *option implied volatility*, the number of observations deviates because of the shortened observation window for the option implied volatility CG model estimation explained in chapter 5. Regarding the financial leverage of firms, the sector consumer cyclicals shows the highest leverage with DPS values ranging from 8.17 to 47.15, whereas the sector energy together with technology, utilities and healthcare show low intrasector leverage. When considering equity volatility, it is noticeable that consumer cyclicals exhibit the highest degree of volatility with a mean volatility of 35.42%, whereas in comparison the sector healthcare exhibits on average close to 10 percentage points lower equity volatility. All other sectors show medium volatility with value above 25% but lower than 30%. The comparison between option-implied and equity volatility draws a clear picture. Option-implied volatility shows lower lows and higher highs with overall both lower median and mean values in comparison to equity volatility for all sectors. This indicates that option-implied volatility exhibits a higher degree of sensitivity embedded into derivative markets rather than volatility in equity markets, by also providing a lower overall standard deviation for implied volatility for all sectors. Additionally, the kurtosis of input variables does not show a clear pattern. The values mostly remain smaller than one and alternate in signs between sectors.

This provides evidence on the fact that the data is mainly mesokurtic, except for option-implied volatility which is leptokurtic with kurtosis values above three ranging from 3.2 to 187.7, except for the sectors technology and basic materials. Taking kurtosis, skewness and long right tails into account, the cross-sectional distribution of option-implied volatility is predominantly described by a small number of positive outliers that drive the majority of their time-variation. This supports the idea of quicker absorption of information in derivative markets than in equity markets.

6.2. Correlation and Pricing Analysis

In this section I analyze the CG model performance in its two specifications. In a first step, I estimate each model and visualize its mean cross-sectional performance over all sectors. Figure 2 depicts the estimated mean cross-sectional CDS spread for all sectors using the CG model with an asset volatility estimator of 1000-day rolling window equity volatility. The coordinate axis shows spread in bps, whereas the abscissa axis depicts the time covering my sample period from December 2007 to December 2020. It can be seen that the the model spreads tend to follow the empirical spreads. The CG model is able to produce sensible spreads in the cross-section in size and magnitude. After the peak in 2009 with close to 300 bps resulting from increased credit risk due to the global financial crisis, model spreads tend to stay higher than market spreads. This overprediction is mainly due to the selected moving average window which produces so called *ghost effects* when the window is large enough such that initial shocks remain in the estimated time-series even long after the shock has died out (see e.g. Penza, Bansal, Bansal, and Bansal (2001)). This effect is especially prominent when the shock enters and leaves a system quick, which is the case for the financial crisis due to government bail-out programs and

Table 1: Overview of Industry Sector, Country and Rating Sample Composition.

This table gives an overview on the industry sector composition (Panel A) and the country distribution (Panel B) of my sample of CDS reference entities. Panel C depicts the rating distribution of obligors. Industry sector classifications and country affiliations are retrieved from Refinitiv Eikon. For the rating composition the credit rating masterscale from Standard and Poor's Global Ratings is used.

Panel A: Sector distribution of reference entities			
Sector	Count	Sector	Count
Consumer Non Cyclicals	13 (17.33%)	Healthcare	7 (9.33%)
Consumer Cyclicals	23 (30.67%)	Energy	3 (4.00%)
Industrials	10 (13.33%)	Basicmaterials	7 (9.33%)
Utilities	7 (9.33%)	Technology	5 (6.67%)
Panel B: Country distribution of reference entities			
Country	Count	Country	Count
Germany	14 (18.67%)	Netherlands	7 (9.33%)
Great Britain	20 (26.67%)	Austria	1 (1.33%)
France	17 (22.67%)	Greece	1 (1.33%)
Sweden	4 (5.33%)	Spain	2 (2.67%)
Finland	3 (4.00%)	Austria	1 (1.33%)
Switzerland	1 (1.33%)	Italy	3 (4.00%)
Portugal	1 (1.33%)	Belgium	1 (1.33%)
Panel C: Rating distribution of reference entities			
Rating	Count	Rating	Count
Investment Grade			
AAA	0 (0%)	A	8 (10.67%)
AA+	0 (0%)	A-	11 (14.67%)
AA	0 (0%)	BBB+	16 (21.33%)
AA-	1 (1.33%)	BBB	22 (29.33%)
A+	2 (2.67%)	BBB-	4 (5.33%)
Speculative Grade			
BB+	5 (6.67%)	CCC	0 (0%)
BB	0 (0%)	CC	0 (0%)
B	1 (1.33%)	C	0 (0%)
B-	1 (1.33%)	D	0 (0%)

further economical support, reducing uncertainty directly absorbed in the credit derivatives market as reflected in decreasing market spreads. This behavior of model spreads is mainly due to a mismatch between credit and equity markets, since equity volatility stays higher for longer. This finding matches the study of Bedendo et al. (2011), who show the same behavior of the CG model for the American market. In comparison to the first peak, the model can, on average, cope better with the peaks due to sovereign debt crisis in 2011 and 2012. It yields mean cross-sectional values of 230-250 bps, where in 2013 the model spreads again closely follow market spreads, declining to 80 bps thereafter in the defined tranquil period of 2015. Since credit risk increased gradually over time, the specification of the model allows for a better performance and estimation of spreads. The peak in the corona crisis is again picked up by the model with subsequent higher spreads after the initial peak in March 2020, analog to the peak in the financial crisis, again mainly due to a ghost effect of the selected window length.

Figure 3 shows the estimated mean cross-sectional CDS spread for all sectors using the CG model with an asset volatility estimator of one year at-the-money option-implied volatility. It is visible that the model is in the cross-section able to better fit to short term changes in the market spread, especially noticeable in the two peaks of the sovereign debt crisis 2011 an 2012 with a reduction in market spread between the two peaks closely followed by the model. Spreads are in the short run much more volatile than compared to model spreads in figure 2, supporting the hypothesis that information is quicker absorbed in derivatives markets and thus reflected in its price. This allows for a better fit of the model compared to market spreads. The corona crisis of March 2020 shows that model severely overpredicts market spreads in times of uncertainty and high implied volatilities, leading to a deviation of model and market spreads. In comparison to figure 2, this overprediction shows the short term sensitivity of the model, which is in case of the extreme uncertainty in March 2020 oversensitive, result in a divergence between

Table 2: CG Model Input Summary Statistics.

This table presents summary statistics for all CG model input variables on a sector basis. The variable DPS depicts the debt-per-share of each firm for the sector cross section, estimated as described in chapter 4.2. $Equity$ represents the sector cross-sectional stock price. $EquityVolatility$ denotes the 1000 trading-day moving average standard deviations scaled by $\sqrt{252}$ to obtain annualized volatilities. $Option-impliedVolatility$ depicts the Black-Scholes extracted volatilites of obligor specific at-the-money call and put options with a constant maturity of one year. $Risk-free-rate$ represents the 5 year constant maturity treasury bond middle rate. I report the time-series means of the daily mean (*Mean*), standard deviation (*SD*), skewness (*Skew*), kurtosis (*Kurt*), minimum (*Min*), fifth percentile (*5%*), 25th percentile (*25%*), median (*Median*), 75th percentile (*75%*), 95th percentile (*95%*), and maximum (*Max*) values of the cross-sectional distribution of each variable. The column labeled n indicates the number of individual variable observations within each sector.

	n	*Min*	*5%*	*25%*	*Mean*	*Median*	*75%*	*95%*	*Max*	*SD*	*Skew*	*Kurt*
Sector Consumer Non Cyclical:												
Cross-Sectional Distribution												
DPS	3392	12.5509	12.6867	14.3745	18.6058	16.5850	21.7585	30.9187	32.4455	5.8206	0.8447	0.0381
$Equity$	3392	13.0485	17.3355	24.0894	32.3930	31.7985	39.6753	49.1130	55.6892	9.8735	0.2423	-0.5877
$EquityVolatility$	3392	0.2039	0.2151	0.2389	0.2748	0.2655	0.3218	0.3437	0.3509	0.0442	0.2125	-1.1042
$Option-impliedVolatility$	2857	0.1272	0.1805	0.1999	0.2261	0.2190	0.2465	0.2919	0.4712	0.0362	1.6403	18.8232
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Consumer Cyclicals:												
Cross-Sectional Distribution												
DPS	3392	30.4068	30.7789	36.8354	53.4215	49.9450	66.5672	85.9017	86.3647	18.5970	0.5780	-0.0082
$Equity$	3392	11.6734	16.9983	28.8271	43.6177	40.4305	57.4919	78.2983	119.2181	19.8188	0.2901	0.3456
$EquityVolatility$	3392	0.2345	0.2517	0.2820	0.3542	0.3272	0.4511	0.4937	0.5067	0.0867	0.3507	-1.1581
$Option-impliedVolatility$	2857	0.1448	0.2101	0.2379	0.2790	0.2639	0.3061	0.4043	0.6673	0.0612	1.7125	11.9964
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Industrials:												
Cross-Sectional Distribution												
DPS	3392	9.4076	9.4695	11.1595	13.4879	12.9934	15.2042	19.5853	19.7391	3.0362	0.7547	0.0725
$Equity$	3392	7.1427	9.1722	12.4001	20.0576	18.1908	26.0221	36.9305	43.8587	8.9835	0.3339	-0.4849
$EquityVolatility$	3392	0.2198	0.2372	0.2736	0.3252	0.3101	0.3930	0.4216	0.4422	0.0634	0.2618	-0.9924
$Option-impliedVolatility$	2857	0.1354	0.2071	0.2291	0.2608	0.2483	0.2813	0.3651	0.6444	0.0493	2.1614	14.9150
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Utilities:												
Cross-Sectional Distribution												
DPS	3392	7.0131	7.0563	8.6182	10.4272	9.9958	11.5565	14.9362	23.4762	2.9656	1.4362	4.1502
$Equity$	3392	6.0838	7.2960	9.3095	12.3694	11.7405	14.68715	20.7756	25.1797	3.9910	0.7698	0.4068
$EquityVolatility$	3392	0.1786	0.1911	0.2296	0.2726	0.2705	0.3225	0.3565	0.3707	0.0518	0.0000	-0.6144
$Option-impliedVolatility$	2857	0.1303	0.1743	0.2021	0.2319	0.2260	0.2570	0.3053	0.9261	0.0460	5.9045	187.7552
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Technology:												
Cross-Sectional Distribution												
DPS	3392	5.5528	5.5655	6.3523	7.9656	7.6323	9.1944	12.6402	12.6412	2.1152	0.8544	0.3368
$Equity$	3392	4.2458	5.2343	7.2683	9.1282	9.0310	10.7312	13.2526	18.1690	2.5503	0.5372	0.6853
$EquityVolatility$	3392	0.1938	0.2089	0.2473	0.2885	0.2802	0.3479	0.3742	0.3815	0.0557	0.1007	-0.8781
$Option-impliedVolatility$	2857	0.1495	0.1691	0.2010	0.2339	0.2322	0.2619	0.3111	0.4370	0.0442	0.7318	1.5499
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Healthcare:												
Cross-Sectional Distribution												
DPS	3392	8.1712	8.2207	14.7124	24.1644	22.6190	28.3547	45.5704	47.1587	11.9837	0.5914	-0.4910
$Equity$	3392	19.3480	23.4768	30.9402	46.7214	45.0141	60.9503	76.5182	89.3498	17.5787	0.2853	-0.8863
$EquityVolatility$	3392	0.1948	0.2033	0.2243	0.2627	0.2447	0.3025	0.3820	0.3870	0.0547	0.5686	-0.5580
$Option-impliedVolatility$	2857	0.1797	0.1970	0.2156	0.2405	0.2348	0.2578	0.3080	0.4669	0.0350	1.2786	3.2485
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Energy:												
Cross-Sectional Distribution												
DPS	3392	4.9677	4.9989	6.7676	8.0392	8.1252	9.6188	11.3735	11.5489	1.8575	0.1022	-0.9705
$Equity$	3392	9.9433	15.3620	19.4333	21.4967	21.5000	23.5862	26.9941	31.4800	3.2282	-0.2396	1.4324
$EquityVolatility$	3392	0.1800	0.1927	0.2305	0.2632	0.2522	0.3087	0.3395	0.3440	0.0462	0.2782	-0.9757
$Option-impliedVolatility$	2857	0.1526	0.1695	0.1885	0.2193	0.2100	0.2433	0.2943	0.5135	0.0408	1.3767	3.9044
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580
Sector Basicmaterials:												
Cross-Sectional Distribution												
DPS	3392	12.2274	12.4535	15.7890	19.7934	19.2557	23.2284	33.5750	34.6251	5.9002	0.4108	-0.0740
$Equity$	3392	20.7291	29.2467	40.7976	52.4727	51.4565	64.3536	77.4551	86.2350	14.7322	0.2641	-0.6138
$EquityVolatility$	3392	0.1932	0.2203	0.2438	0.2872	0.2766	0.3433	0.3789	0.3864	0.0536	0.4270	-1.0931
$Option-impliedVolatility$	2857	0.1854	0.2047	0.2255	0.2542	0.2491	0.2761	0.3235	0.4375	0.0372	0.8139	0.9872
$Risk-free-rate$	3392	0.0019	0.0041	0.0124	0.0170	0.0166	0.0223	0.0295	0.0373	0.0073	0.1386	-0.4580

equity and credit derivative markets.

In a second step, I consider the sector specific conditional correlation between market and model spreads for each specification as a preliminary step in the performance analysis. In

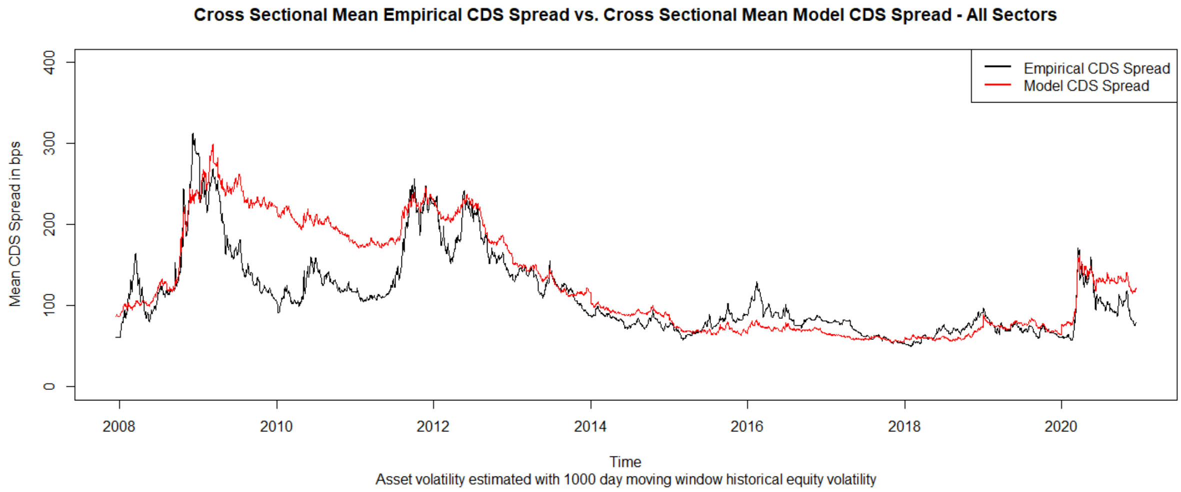

Figure 2: Estimated mean cross-sectional CDS spread for all sectors using the CG model with an asset volatility estimator of 1000-day rolling window equity volatility.

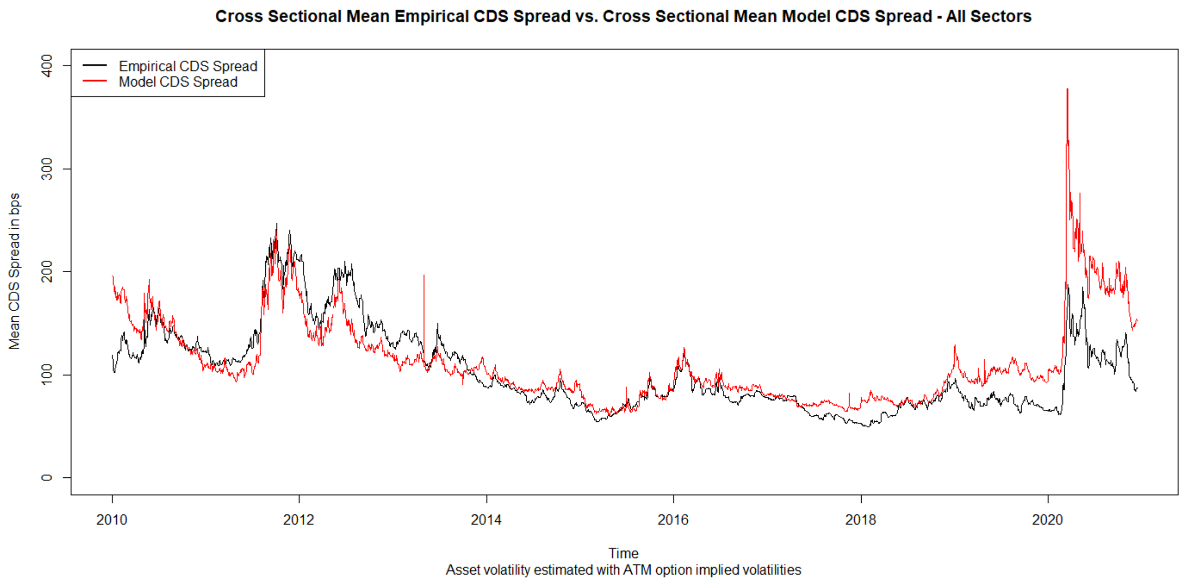

Figure 3: Estimated mean cross-sectional CDS spread for all sectors using the CG model with an asset volatility estimator of one year at-the-money option implied volatility.

table 3 panel A depicts each intrasector correlation estimated with Person product-moment coefficients and panel B depicts the Spearman rank coefficients. For all sectors, except for Energy in its both specifications and technology in its implied volatility specification, the full period exhibits strong correlation between market and model spreads.Values range from 0.546 for the option-implied CG model spreads for the sector consumer non-cyclicals, to 0.814 for the option-implied CG model spreads for the sector utilities.

Regarding the correlation for the historical volatility specifications only, panel A shows that the corona crisis period exhibits the lowest correlations, except for the consumer cyclicals sector, with low to medium correlation of 0.064 for consumer non-cyclical to 0.309 for the sector healthcare. I estimate negative correlations of −0.135 and −0.372 for the sector technology in the financial crisis period and the sector energy for the corona crisis period, indicating that the model is not able to follow market spreads in times of financial turmoil for the respective sectors. If only the implied volatility specification is considered, it is noticeable that model spreads exhibit higher correlation with market spread in times of crisis when volatility is high and spreads shoot up. The tranquil period, on the other hand, shows the lowest correlation for this specification, indicating that the implied vol model is able to follow market spreads best. This can be seen by the significant changes in both credit and equity markets at the same time. Furthermore, the implied volatility estimated spreads have significantly higher correlation with markets spreads in the corona crisis period than the historical volatility specification for all sectors. This aspect further supports the visual analysis when comparing figures 2 and 3. Regarding the historical volatility specification, the corona crisis exhibits the lowest correlation, both leading to the conclusion that the model is not able to cope with short term increased dynamics in CDS market spreads. Regarding the full sample period, there is no clear pattern which model specification has higher correlation with market spreads. The comparable continuous low correlation for the historical volatility corona crisis period is thereby compensated by changing medium to high correlations in the European sovereign debt crisis period and tranquil period. In correspondence to that, it has to be noted that the full period correlations are not directly comparable, since the financial crisis is not part of the full period for the implied vol specification.

The estimated Spearman rank coefficients in panel B draw the same picture as the Pearson product-moment correlations in panel A with slight different estimates in magnitude. Still they are similar enough to exclude the possibility of biased and distorted results in the subsequent pricing and regression analysis due to non-linearity. All in all, the conditional pricing analysis shows that there exists a strong enough relation between model and market spreads. My results allow for the detailed pricing and regression analysis in order to assess the ability of the CG model to price credit risk in the the cross-section. The previous results are similar in size and magnitude to the correlations measured by Bedendo et al. (2011).

Table 17 in the appendix depicts the assessment of possible autocorrelation in the spirit of Byström (2006). I report Ljung-Box test statistics for each obligor in the sample of empirical and CG model spreads both estimated with historical volatility and option implied volatility. LB(5) indicates the Ljung-Box statistic with 5 lags and LB(10) with 10 lags respectively. For each specification I report the total number of significant variables defined to equal the 5% significance level or higher. Regarding empirical spreads, 54 CDS time series exhibit significant autocorrelation when 5 lags are estimated, resulting in 72% of the sample. When 10 lags are included, 65 CDS time series show significant autocorrelation accounting for 87% of the sample. This result is in line with Byström (2006) who also finds that the vast majority of CDS index market spreads are autocorrelated. Thus I can support his findings also for individual CDS contracts in the European market. Furthermore, I test estimated model spreads and find that the degree of autocorrelation is smaller than for market spreads, however a significant share of the sample shows significant autocorrelation amounting to 63% for 5 lags and 76% for 10 lags in the historical volatility specification and 70% for 5 lags and 78% for 10 lags in the implied volatility specification. This finding deviates from Byström (2006), who concludes that CDS index model spreads do not show high degrees of autocorrelation. Hence, CDS markets could be subject to inefficiencies. Based on these findings, I cannot support this hypothesis as even different model specifications and number of lags do not change the picture dramatically. It is to note that, although the degree of autocorrelation in model spreads is still high, the historical volatility specification yields a lower share of autocorrelation than the market or implied volatility model spreads, indicating that equity markets are less subject to possible inefficiencies if the narrative of Byström (2006) is applied.

Finally, I assess the actual pricing performance of the CG model in its respective specifications by means of forecasting metrics. To do so, I calculate the bias, the mean absolute error and the root mean squared error as defined in chapter 4.3. Table 4 presents the results of the CG model pricing analysis, whereas Panel A depicts key metrics for the 1000-day historical volatility specification and panel B depicts key metrics for the option implied volatility specification. Considering panel A, over all time periods the highest bias, MAE and RMSE are measured in the consumer non-cyclical sector with values of 77.33, 222.09 and 237.80 bps respectively. The model therefore shows the highest degree of mispricing in absolute terms for this sector. Table 15 in the appendix show that this result is not due to high overall spreads which would relativize the mispricing since median sector spreads amount to 74.118 bps. Table 1 depicts low leverage by low debt-per-share median values of 16.586 and comparable low equity volatility of 0.2665, indicating the model shortcomings of reliably estimating spreads if input variables do not exhibit enough variation to drive model inherent credit risk. The consumer cyclicals sector shows the second worst performance with a bias of 77.91 bps, an MAE of 193.3 bps and a RMSE of 235.86 bps. However, when the overall level of market spreads are considered, the picture changes in favor of this sector since it shows the highest median sector spread amounting to 110.999. Thus, a 50% higher market spread level shows good relative model performance compared to the overall market spread level of other sectors. Table 1 again provides insights on how the distribution of model input variables determine model performance, since obligors for the sector consumer cyclicals show the highest median DPS value of 49.9450, median equity value with 40.4305 and highest equity volatility value with 0.3272. This further underlines the initial indication that model performance is highly dependent on input parameter distribution. In contrast to that, the sectors utilities, technology, healthcare, energy and basic materials all exhibit a negative bias showing that the model tends to underestimate market spreads for these sectors. The comparison between the bias and the mean absolute error further indicates a continuous underperformance of the model relative to market spreads, since negative bias values turn by construction to positive MAE values with same magnitude. When again model input parameter distributions are compared in table 1, the drawn picture above remains since DPS, equity and equity volatility exhibit a too small variation to drive model inherent credit risk.

Comparing different time periods, table 4 shows high MAE and RMSE values for the financial crisis and European sovereign debt crisis and corresponding increased variability

Table 3: Conditional Correlation Analysis.

This table reports the conditional sector specific correlation between daily market and model spreads, whereas model spreads are estimated with the CreditGrades model using 1000-trading-day equity volatility (MA Vol) and option implied volatility (Implied Vol). The sector classification is retrieved from Refinitiv Eikon and consists out of Consumer Non-Cyclical, Consumer Cyclicals, Industrials, Utilities, Technology, Healthcare, Energy and Basicmaterials. Furthermore, I report intrasector time dependent correlations for the following time periods: *Full Period* (14.12.2007 - 14.12.2020), *Financial Crisis* (14.12.2007 - 31.12.2009), *European Sovereign Debt Crisis* (01.01.2010 - 31.12.2013), *Tranquil Period* (01.01.2014 - 28.02.2020) and the *Corona Crisis* (01.03.2020 - 14.12.2020). I augment the time period *Financial Crisis* (14.12.2007 - 31.12.2009) for the option-implied volatility CG model specification, due to a smaller subsample and shortened observation window. Panel A presents Pearson product-moment correlations, whereas Panel B reports Spearman rank correlations. To obtain average sector specific correlations, I follow Corey et al. (1998) and transform individual correlations r to the Fisher z-transform via $Z = \frac{1}{2}ln\left(\frac{1+r}{1-r}\right)$. Then the average of all sector specific z-transformed is derived $\bar{Z} = \frac{1}{n}\sum_{i=1}^{n} Z_i$. Afterwards the average z-transformed variable is then back-converted using $\bar{r} = \frac{e^{2\bar{Z}}-1}{e^{2\bar{Z}}+1}$ to obtain an average sector specific correlation coefficient.

Panel A: Pearson Product-Moment Correlation

	Consumer Non-Cyclical		Consumer Cylclicals		Industrials		Utilities	
	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol
Full Period	0.596	0.546	0.636	0.586	0.732	0.700	0.702	0.814
Financial Crisis	0.379		0.598		0.383		0.576	
European Sovereign Debt Crisis	0.466	0.516	0.576	0.573	0.555	0.658	0.664	0.831
Tranquil period	0.447	0.488	0.378	0.327	0.583	0.618	0.503	0.675
Corona Crisis	0.064	0.560	0.572	0.709	0.125	0.622	0.308	0.582

	Technology		Healthcare		Energy		Basicmaterials	
	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol
Full Period	0.571	0.317	0.551	0.634	0.319	0.282	0.685	0.736
Financial Crisis	-0.135		0.315		0.216		0.431	
European Sovereign Debt Crisis	0.611	0.558	0.442	0.484	0.589	0.470	0.660	0.709
Tranquil period	0.594	0.449	0.224	0.383	0.518	0.836	0.660	0.689
Corona Crisis	0.124	0.264	0.309	0.644	-0.372	0.716	0.249	0.765

Panel B: Spearman Rank Correlation

	Consumer Non-Cyclical		Consumer Cylclicals		Industrials		Utilities	
	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol
Full Period	0.613	0.475	0.745	0.698	0.751	0.764	0.708	0.842
Financial Crisis	0.472		0.637		0.406		0.646	
European Sovereign Debt Crisis	0.528	0.540	0.642	0.629	0.580	0.624	0.665	0.817
Tranquil period	0.479	0.579	0.542	0.562	0.602	0.711	0.562	0.631
Corona Crisis	0.048	0.552	0.553	0.755	0.043	0.625	0.224	0.722

	Technology		Healthcare		Energy		Basicmaterials	
	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol	MA Vol	Implied Vol
Full Period	0.611	0.339	0.625	0.721	0.559	0.429	0.768	0.853
Financial Crisis	-0.087		0.373		0.502		0.472	
European Sovereign Debt Crisis	0.624	0.574	0.466	0.584	0.754	0.497	0.602	0.669
Tranquil period	0.632	0.572	0.189	0.433	0.441	0.706	0.707	0.734
Corona Crisis	0.210	0.110	0.281	0.542	-0.501	0.678	0.157	0.756

of intrasector pricing measures in crisis times depicted by the standard deviation of MAE and RMSE. This finding shows that model spreads from backward-looking equity volatility are subject to the inability to adjust to new information quick enough, such that pricing gaps converge over defined time periods. This implies that the consumer non-cyclicals, consumer cyclicals, healthcare and basicmaterials sectors exhibit the highest forecasting metrics in the financial crisis, whereas the sectors energy, technology, utilities and industrials show highest mispricing in the European sovereign debt crisis. Considering time periods with lowest mispricing, the RMSE seems lowest for the sector consumer cyclicals, industrials and energy, as expected for the tranquil period. Counter intuitively for all remaining sectors, the model performs best in the corona crisis compared to all other time periods, indicating a higher degree of adaptation to dynamical changes in market environments than anticipated.

Turning to panel B, I test the hypothesis that the CG model calibrated using implied volatility overall performs better than the model in panel A. Furthermore, I test the hypothesis whether the model in panel B outperforms in times of increased volatility, i.e. in crisis periods as indicated by Wagner (2008) and Cao et al. (2011). Panel B illustrates that the consumer non-cyclical sector shows the worst model performance with the highest bias, MAE and RMSE for all time periods considered. If the performance between historical and option implied volatility is regarded, the latter performs worse for the full period in the magnitude of 30 to 40 bps between forecasting measures with corresponding increased variability in pricing measures. This result provides a first conflicting result, in contrast to the findings of Wagner (2008) and Cao et al. (2011). Further assessment shows that my initial findings seem to be highly sector dependent as the consumer cyclicals, industrials, technology and healthcare sectors exhibit a better model performance when forward-looking option-implied volatility is used. This type of volatility reduces the pricing metrics between 20 bps for technology to about 50 bps in the cross-section for the consumer cyclicals sector. Besides that, also the variability of pricing metrics seem to be highly reduced. On the other hand, sectors energy and basicmaterials show worse implied-volatility based model performance besides the already mentioned consumer non-cyclicals sector. Although showing slight worse implied volatility model performance, the utilities sector exhibits decreased variability in the Bias, MAE and RMSE.

When the performance clustered by time periods is assessed between panel A and B, it turns out that for the majority of sectors, the European sovereign debt crisis yields the highest pricing error, consistent with findings of panel A. The corona crisis in panel A exhibits much higher pricing errors than in panel B for the consumer cyclicals and technology sectors with a magnitude of up to 50 bps. If table 1 is considered, the distribution of model specific parameters again explain the pricing performance, since for consumer cyclical the median option implied volatility is the highest among all sectors with 0.2639, closely followed by 0.2322 for technologies. Thus, again the narrative of my pricing analysis continuous in which parameter distributions determine the model performance contingent on model calibration procedures, implying that model performance is by definition inherently sector specific due to unique sector specific model input parameter distributions.

6.3. Model Gap Analysis

In this sub-section, I analyze the model pricing error defined as the gap between model and market spreads in correspondence to section 4.3. For that I implement sector specific panel regressions on obligor specific and individual factors as described in chapter 4.4. In appendix E, I report regression diagnostic statistics valid for all regression setups as staionarity and multicollinearity are analyzed for all regression variables used. The results of the unit root test based on Levin et al. (2002) in table 18 show that all regression variables have p-values of 0, rejecting the null of non-stationarity. The only exception is the weekly change in the slope of the yield curve. However, as Bedendo et al. (2011) employ this variable in their regression procedure and all other variables are stationary, I proceed with the analysis of VIF values to a set threshold of 3. The results are presented in table 19. Panel A shows VIF values for regression variables using historical volatility information, ranging from 1.01 to 2.06 at maximum, hence indicating no multicollinearity concerns for these regressions. Panel B depicts the same range for VIF values, also indicating no evidence of multicollinearity.

The corresponding results for the gap estimated between the CG model calibrated with equity volatility can be found in table 5. Table 5 shows that the adjusted R^2 ranges from 0.066 for the consumer non-cyclicals sector to 0.687 for the technology sector, indicating vast sector specific explanatory power of selected independent variables.

The first finding to discuss is that the weekly change in the counterparty risk index (CRI) exhibits highly significant factor loadings for all sectors with negative signs, such that the weekly change in the gap reduces if the weekly change in CRI is positive. This result is in line with intuition since model and market spreads should converge if counterparty credit risk increases, thus driving the aggregated level of credit risk higher and therefore increasing model as well as market spreads. Furthermore, counterparty credit risk seems to be a highly important determinant of the gap, that is not controlled for in the regression scope of other empirical studies. The factor loadings for the weekly change in the VSTOXX index also reflect this aspect. It captures the overall level of risk and risk aversion and shows that estimated coefficients are comparable in size and magnitude, even though they are only statistically significant for sector regressions (1), (2), (3), (7) and (8). The weekly change in the slope of the CRI also has comparable significant coefficients in magnitude and size. An increase in the change of the slope will reduce the weekly change in the gap, implying that market sentiment will increase since the difference in long tenor minus short tenor spreads increase. Hence default probabilities in the short run are reduced and default probabilities in the long run are higher due to a technical reduction in long term survival probabilities. The results of the company returns are intuitive and statistically significant at 1% for the majority of sectors, since a negative sign states that an increase in returns has a larger reducing effect on market spreads than on model spreads, supporting the findings of Bedendo et al. (2011). Equity volatility estimates yield mixed results with alternating signs for the sectors and only three sectors show significant coefficient estimates. This results contradicts the study of Bedendo et al. (2011) who control for option implied volatility and find that volatility is a crucial determinant of the gap and CDS market and model spreads. Contributing to this result, I find that changes in the credit curve also yield mixed results with significant estimates for half of all sectors. Hence, the credit curve does seem to contribute to the dynamics of the gap, but it does not correspond with the effect described in chapter 4. This result is in line with Bedendo et al. (2011) who confirm this ambiguity for the North Ameri-

Table 4: Model Pricing Analysis.

This table presents the results of the CG model pricing analysis. Panel A depicts key metrics for the 1000-day historical volatility specification and panel B for the option-implied volatility specification. I divide my sample into 8 sectors and 5 time periods. The sector classification is retrieved from Refinitiv Eikon and consists of: Consumer Non-Cyclical, Consumer Cyclicals, Industrials, Utilities, Technology, Healthcare, Energy and Basicmaterials. I further divde my sample according to the following time periods: *Full Period* (14.12.2007 - 14.12.2020), *Financial Crisis* (14.12.2007 - 31.12.2009), *European Sovereign Debt Crisis* (01.01.2010 - 31.12.2013), *Tranquil Period* (01.01.2014 - 28.02.2020) and the *Corona Crisis* (01.03.2020 - 14.12.2020). Since my option implied CG model specifications consists out of a smaller sub-sample with shortened observation window, I augment the time period of the financial crisis to ensure comparability within each time period as described in chapter 5. I report the following three pricing metrics and their corresponding standard deviations: the bias (*Bias*), the mean absolute error (*MAE*) and the root mean squared error (*RMSE*). Their estimation procedure is described in chapter 4.3.

	Bias	*Std(Bias)*	*MAE*	*Std(MAE)*	*RMSE*	*Std(RMSE)*
Panel A: Historical Volatility Specification						
Sector Consumer Non Cyclical						
Full Period	77.33	156.10	222.09	144.06	237.50	145.90
Financial Crisis	107.79	211.70	297.97	195.93	309.47	195.87
European Sovereign Debt Crisis	74.73	151.34	215.89	139.59	218.87	140.18
Tranquil Period	72.65	145.38	205.68	134.35	212.84	134.89
Corona Crisis	47.92	126.21	184.57	115.26	188.58	115.80
Sector Consumer Cyclicals						
Full Period	77.91	53.34	193.30	42.93	235.86	49.92
Financial Crisis	87.28	92.49	291.31	73.86	327.87	77.34
European Sovereign Debt Crisis	174.24	71.50	255.84	60.25	272.86	62.78
Tranquil Period	12.62	38.49	119.48	29.69	126.90	30.65
Corona Crisis	75.60	60.07	198.40	46.29	210.39	48.05
Sector Industrials						
Full Period	6.59	35.18	86.91	25.71	100.77	27.43
Financial Crisis	17.35	49.26	112.99	36.24	130.50	35.38
European Sovereign Debt Crisis	23.35	47.49	105.01	35.77	114.16	36.44
Tranquil Period	-8.09	25.48	67.82	16.34	74.65	17.45
Corona Crisis	8.44	35.13	76.52	26.68	81.61	26.82
Sector Utilities						
Full Period	-86.60	17.90	86.99	17.73	109.30	26.25
Financial Crisis	-76.70	13.77	76.70	13.77	92.90	20.17
European Sovereign Debt Crisis	-143.57	39.99	143.59	39.99	160.19	47.13
Tranquil Period	-59.61	9.86	59.70	9.8	63.50	10.48
Corona Crisis	-34.60	10.93	40.17	7.07	41.26	7.18
Sector Technology						
Full Period	-61.68	34.25	77.33	33.48	129.55	77.21
Financial Crisis	-51.43	14.29	65.31	5.93	75.14	6.85
European Sovereign Debt Crisis	-115.19	95.76	140.67	89.52	200.02	143.96
Tranquil Period	-38.19	10.47	44.59	13.58	50.01	15.96
Corona Crisis	-0.73	28.18	43.41	18.19	49.25	20.16
Sector Healthcare						
Full Period	-14.61	21.18	69.13	22.56	97.00	40.72
Financial Crisis	74.33	115.97	170.39	98.06	183.91	99.87
European Sovereign Debt Crisis	-23.74	19.83	75.49	17.70	88.41	26.71
Tranquil Period	-37.33	5.87	37.33	5.87	39.03	6.03
Corona Crisis	-22.04	2.45	22.26	2.36	24.55	3.03
Sector Energy						
Full Period	-63.53	8.59	63.55	8.59	73.63	11.40
Financial Crisis	-51.74	2.61	51.74	2.61	56.62	3.38
European Sovereign Debt Crisis	-85.23	16.32	85.23	16.32	97.51	21.37
Tranquil Period	-55.84	7.85	55.84	7.85	59.44	7.98
Corona Crisis	-44.41	4.87	44.71	5.16	60.73	8.05

(Continued)

Table 4—continued

Sector Basicmaterials						
Full Period	-75.69	15.49	76.44	15.75	88.63	20.32
Financial Crisis	-130.32	42.46	130.32	42.46	139.22	44.34
European Sovereign Debt Crisis	-81.05	19.56	83.43	18.97	90.07	19.02
Tranquil Period	-58.65	9.59	58.70	9.59	62.67	10.89
Corona Crisis	-39.56	4.34	39.56	4.34	43.08	4.35
Panel B: Option-Implied Volatility Specification						
Sector Consumer Non-Cyclical						
Full Period	132.01	207.65	266.27	190.90	274.90	191.47
European Sovereign Debt Crisis	129.18	216.18	283.44	196.92	286.88	197.86
Tranquil Period	136.05	205.31	258.34	190.06	265.01	190.73
Corona Crisis	114.74	185.76	241.21	169.95	245.81	170.57
Sector Consumer Cyclicals						
Full Period	27.69	61.34	158.70	44.03	184.50	46.67
European Sovereign Debt Crisis	10.20	69.40	179.47	48.64	193.28	50.02
Tranquil Period	22.92	56.15	134.69	42.41	144.59	44.10
Corona Crisis	153.57	90.42	240.96	77.35	264.73	78.61
Sector Industrials						
Full Period	-19.35	38.99	86.75	24.14	96.86	27.14
European Sovereign Debt Crisis	-24.16	52.84	110.79	33.69	117.36	36.00
Tranquil Period	-25.81	30.07	70.71	16.92	74.78	18.00
Corona Crisis	55.49	45.38	90.17	40.47	106.98	43.36
Sector Utilities						
Full Period	-107.26	7.04	107.67	7.33	129.05	9.16
European Sovereign Debt Crisis	-177.08	12.11	177.08	12.11	190.33	12.62
Tranquil Period	-70.12	4.44	70.12	4.44	72.19	4.18
Corona Crisis	-43.65	3.53	49.34	9.19	72.60	31.98
Sector Technology						
Full Period	-30.74	13.00	54.26	11.83	62.85	11.02
European Sovereign Debt Crisis	-50.19	15.81	65.84	7.23	70.50	5.87
Tranquil Period	-33.45	16.97	42.04	13.24	47.15	12.95
Corona Crisis	88.87	30.37	91.00	28.78	104.29	29.90
Sector Healthcare						
Full Period	-31.57	15.69	63.64	21.74	81.34	30.88
European Sovereign Debt Crisis	-23.12	27.92	106.89	40.99	121.47	49.88
Tranquil Period	-39.76	13.64	40.75	12.76	43.29	12.56
Corona Crisis	-10.45	4.85	23.36	2.70	33.46	7.37
Sector Energy						
Full Period	-63.38	18.28	64.49	18.44	71.29	21.18
European Sovereign Debt Crisis	-87.99	28.68	87.99	28.68	93.24	31.32
Tranquil Period	-53.32	13.69	53.32	13.69	55.84	13.80
Corona Crisis	-17.29	1.54	32.69	3.69	43.47	3.24
Sector Basicmaterials						
Full Period	-97.5	26.02	97.52	26.03	109.59	31.27
European Sovereign Debt Crisis	-148.51	46.29	148.51	46.29	151.84	46.93
Tranquil Period	-71.37	16.45	71.37	16.45	77.17	18.92
Corona Crisis	-43.21	6.96	43.53	7.12	45.10	7.38

can credit derivatives market. As the risk-free rate is also a model input parameter, the interpretation of its contribution in explaining the changes in the gap is not straight forward. As in Bedendo et al. (2011), it does not seem to be a determinant of the gap dynamics. The same result holds for the slope of the yield curve. This slope is statistically significant at the 10% level in model (1) and thus provides no contribution to explaining the dynamics of the gap. Illiquidity does not seem to have any significant factor loadings and thus also does not contribute to the explanatory power of the gap. This result is also in line with Bedendo et al. (2011) who discover mixed results and mostly insignificant regression estimates. However the finding contradicts studies like the one of Tang and Yan (2007) who find significant liquidity risk premia in credit derivatives markets. I conclude that for European CDS gaps, liquidity spillover from equity markets do not seem to affect the difference in market and model spreads. As Bedendo et al. (2011) point out, illiquidity spillover might affect market and model spreads at the same time and hence does not affect the gap. In order to test if illiquidity affects market or model spreads individually, I run subsequent panel regressions on model and market spreads separately in subsection 6.4 and 6.5. The results related to lagged changes in the gap are inconclusive. Most of the coefficients are not significant and vary in sign. Thus, I cannot say some type of mean reverting behavior exists and therefore large changes in the gap are reabsorbed in the following gap spreads. In consequence "convergence is more likely to occur when model spreads move back towards market spreads"[8]. As I estimate regression coefficients with Driscoll-Kraay standard errors correcting for spatial and intertemporal dependence, it is to note that this could also affect the significance of lagged regressions variables.

To analyse the panel regression specification and the completeness of the model, table 5 depicts the number of principal components extracted from the error term that explain 80% or more of the explained variation. It becomes apparent that common factors are largely sector specific since the number of extracted variables is heterogeneous. Common factors explaining 80% of the variation range from 2 in case of regressions (4) and (6), to 9 factors for regression (3). In case of regression (2), (7) and (8) 4 factors are extracted and regression (5) finds 5 principal components that explain at least 80% in the left over variation of the error term. The principal component analysis for the gap error term points out that the regression specification is highly sector specific with sector common variables missing for model (4) and (6), when defining up to two components as model misspecifications. My results are comparable to those of Collin-Dufresne et al. (2001) who also concludes that common factors are still missing from regression specifications. Nevertheless, they do not analyse the gap between some model and market spreads, but address principal components extracted from regressions with the market spread as dependent variable.

Table 6 shows regression estimates for the same setting as table 5, where now the gap is estimated using option-implied CG model spreads. All in all, table 6 allows for similar conclusions as table 5. Counterparty credit risk and equity returns are still a highly significant determinant of the gap, whereas the CRI slope has much weaker explanatory power in the cross-section of sectors. Since forward-looking information backed out of option markets are already embedded in model spreads, further variables controlling for market sentiment might not exhibit the same importance as compared to using historical information for derivation of the model spreads in table 5. The same holds for the slope of the credit curve, which is also less significant in the cross-section as compared to table 5. When considering the model completeness via PCA, I discover that the model error terms are driven by fewer principal components when imposing the restriction to account for at least 80% of its explained variance. This suggests that the model lacks more common factors than the model specifications in table 5. A feasible explanation could be the lack of variables from option markets such as volatility skew or the weekly change in implied volatility. This aspect is also represented in comparably low adjusted R^2 values ranging from 0.045 to 0.333.

6.4. Model Spread Analysis

To better understand the determinants of the European credit default swap spread dynamics, I run sector panel regressions similar to those of the previous section. Table 7 reports the estimates for the equity volatility calibrated model spreads. The difference between the gap regressions of table 5 and the model regressions of table 7 is that now independent variables are also directly used as input variables to derive the dependent variable.

The estimated regression coefficients for company returns are again highly statistical significant and posses the expected sign. In consequence, the model spreads react inverse to company returns. This is not surprising since the model is build on the assumption that credit risk emerges from the relation between the amount of equity and liabilities (financial leverage). Hence, positive equity returns reduce the risk of experiencing a credit event by construction, since leverage would decrease and ceteris paribus the price for credit protection should fall. The same holds true for equity volatility. Since the model is calibrated using 1000-day equity volatility, volatility increases when the risk of hitting the default barrier increases and thus also the model spreads should increase. This is largely the case for model (1), (3), (4) and (5) as they posses positive estimates that are statistically significant at the 5% level. Another model input parameter is the risk-free rate. Because the asset drift of the company is modeled as described in chapter 4.2, I expect that the asset drift increases when the risk-free rate increases and hence the asset value deviates from the default barrier if all other parameters are held equal. In consequence, negative estimates are expected, because credit risk would subsequently decrease as the distance to default increases. This is also observed in table 7, as I obtain negative coefficients for the majority of sectors. Nevertheless these estimates are not always statistically significant. Only models (5), (7) and (8) exhibit estimates that are also statistically significance at the 5% and 1% level respectively. The weekly change in the slope of the yield curve is only significant for the sector healthcare, indicating that it does not explain the variation in cross-sectional model spreads as claimed by Bedendo et al. (2011). Similar to table 5, the illiquidity factor is not significant except for model (1) but with a high coefficient estimates and a large standard error. Therefore I omit this estimate from my study

[8] Bedendo et al. (2011), p. 667.

Table 5: Determinants of the Gap between Market and Model CDS Spreads - Equity Volatility Calibration.

This table reports the estimates from a panel regressions of weekly changes in the difference between market and CG model 5-year CDS mid spreads calibrated with 1000-day equity volatility of equation (39). (1) reports estimates for the sector Basicmaterials, (2) for the sector Consumer Non-Cyclicals, (3) Consumer Cyclicals, (4) Energy, (5) Industrials, (6) Technology, (7) Utilities and (8) Healthcare. Using equation (39), I regress the weekly gap for each obligor (in basis points) on a sector-specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) estimated by means of equation (38) and using a rolling one week window. I report Driscoll and Kraay (1998) standard errors that are adjusted for heteroskedaticity and spatial correlation in parentheses below the respective estimate. The adj. R^2 is corrected for the fixed-effect and thus includes the full model. It estimates how much of the variation is explained, since idiosyncratic fixed effects contribute to the explanatory power in the variation of the depended variable. The number of principal components is determined such that the explained variance amounts to 80% or more. The sample period covers December 2007 to December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Risk free rate	1.359	0.404	−0.277	−0.266	0.393	−0.925	0.984	−0.156
	(1.139)	(1.261)	(1.878)	(0.996)	(2.156)	(1.106)	(1.519)	(0.601)
Δ Slope yield curve	−0.180*	−0.079	−0.127	0.007	−0.116	−0.061	0.014	0.059
	(0.093)	(0.088)	(0.127)	(0.101)	(0.084)	(0.215)	(0.131)	(0.061)
Δ VSTOXX	−0.214***	−0.219**	−0.323*	−0.019	−0.048	−0.158	−0.263**	−0.170*
	(0.075)	(0.097)	(0.193)	(0.170)	(0.072)	(0.200)	(0.121)	(0.094)
Δ CRI	−0.342***	−0.313***	−0.478***	−0.298***	−0.273***	−0.497***	−0.483***	−0.173***
	(0.059)	(0.050)	(0.097)	(0.060)	(0.037)	(0.082)	(0.064)	(0.034)
Δ Slope CRI	−0.223	−0.390***	−0.562***	−0.375***	−0.259***	−0.423**	−0.459***	−0.162***
	(0.165)	(0.108)	(0.165)	(0.079)	(0.100)	(0.184)	(0.131)	(0.055)
Δ Slope CDS	−0.106	0.110	0.446***	0.186	−0.067	0.561***	0.319**	−0.223*
	(0.185)	(0.076)	(0.059)	(0.240)	(0.061)	(0.042)	(0.130)	(0.116)
Company returns	−0.026	−1.119***	−1.377***	0.445**	−0.815***	−0.533*	0.172	−0.776***
	(0.121)	(0.108)	(0.208)	(0.214)	(0.095)	(0.301)	(0.131)	(0.122)
Equity volatility	−0.042	−0.211***	0.268**	−0.117**	0.001	−0.261	−0.055	−0.003
	(0.043)	(0.071)	(0.109)	(0.048)	(0.041)	(0.214)	(0.063)	(0.073)
ILLIQ	1,745.408	0.035	0.113	11.445	−0.081	15.091	−0.265	−2.497
	(10,798.990)	(0.045)	(0.320)	(58.040)	(0.153)	(12.552)	(0.240)	(2.938)
Δ Gap(-1)	−0.052	−0.062**	0.021	0.180**	0.055**	0.089	0.020	0.007
	(0.049)	(0.030)	(0.021)	(0.074)	(0.025)	(0.075)	(0.046)	(0.060)
Δ Gap(-2)	0.042	−0.034	−0.042*	0.001	0.006	−0.118	−0.050	0.001
	(0.052)	(0.028)	(0.022)	(0.063)	(0.029)	(0.082)	(0.055)	(0.053)
Observations	4,056	8,788	15,548	2,028	7,436	3,380	4,732	4,732
Adjusted R^2	0.153	0.066	0.283	0.272	0.096	0.687	0.209	0.074
No. of Principal Components	3	4	9	2	5	2	4	4

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

as it is most likely driven by data issues for this sector. Upon closer inspection it turns out that the basicmaterials sector possesses rather low illiquidity estimates. Hence the regression estimates for the entire sector are likely distorted by extremely large coefficients that compensate the low values of the independent variable. Since the illiquidity measure is calculated uniformly for all obligors as well as sectors and does appear to provide explanatory power in the remaining models, I leave estimated values in table 7 as they are with the note that the regression coefficient should not be subject to interpretation. I conclude that illiquidity does not explain the variation in the weekly change of the model spread. The results related to the VSTOXX variable are counter-intuitive as their estimates are negative, wherefore the model spreads de-

Table 6: Determinants of the Gap between Market and Model CDS Spreads - Option-Implied Volatility Calibration.

This table reports the estimates from a panel regressions of weekly changes in the difference between market and CG model 5-year CDS mid spreads calibrated with option-implied volatility extracted out of at-the-money put and call options with constant maturity of one year in correspondence to equation 39. (1) reports estimates for the sector Basicmaterials, (2) for the sector Consumer Non-Cyclicals, (3) Consumer Cyclicals, (4) Energy, (5) Industrials, (6) Technology, (7) Utilities and (8) Healthcare. Using equation 39, I regress the weekly gap for each obligor (in basis points) on a sector-specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I use the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) estimated by means of equation (38) and using a one week window. I report Driscoll and Kraay (1998) standard errors that are adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. It estimates how much of the variation is explained, since idiosyncratic fixed effects contribute to the explanatory power in the variation of the depended variable. The number of principal components is determined such that the explained variance amounts to 80% or more. The sample period covers January 2010 to December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Risk free rate	−0.548	−1.370	0.384	1.984	−1.710	0.422	−3.007	−0.546
	(1.677)	(2.694)	(4.531)	(3.269)	(4.041)	(3.559)	(4.606)	(1.985)
Δ Slope yield curve	0.061	−0.004	0.202	0.117	0.009	−0.091	0.192	0.284**
	(0.142)	(0.116)	(0.152)	(0.121)	(0.131)	(0.198)	(0.233)	(0.115)
Δ VSTOXX	−0.061	0.079	0.906***	0.553*	0.335	0.263	−0.016	0.537***
	(0.176)	(0.181)	(0.316)	(0.332)	(0.267)	(0.185)	(0.167)	(0.145)
Δ CRI	−0.329***	−0.373***	−0.037	−0.507***	0.079	0.079	−0.745***	−0.039
	(0.117)	(0.065)	(0.113)	(0.080)	(0.157)	(0.083)	(0.125)	(0.062)
Δ Slope CRI	−0.210	−0.179*	−0.053	0.138*	−0.164	−0.041	−0.083	−0.228*
	(0.194)	(0.106)	(0.148)	(0.082)	(0.131)	(0.144)	(0.230)	(0.116)
Δ Slope CDS	−0.065	−0.127	0.010	−0.027	0.002	−0.061	−0.034	−0.040*
	(0.081)	(0.110)	(0.096)	(0.082)	(0.062)	(0.121)	(0.079)	(0.022)
Company returns	−0.101	−1.671***	−0.980***	−0.237	−0.331**	−0.141	−0.072	−0.166**
	(0.083)	(0.178)	(0.151)	(0.165)	(0.155)	(0.330)	(0.090)	(0.084)
Equity volatility	0.052**	−0.043	0.164	0.511***	0.137	0.415	0.060*	0.057
	(0.026)	(0.127)	(0.121)	(0.111)	(0.126)	(0.262)	(0.035)	(0.066)
ILLIQ	3,941.809	−1.158	0.087	−136,224.900	−0.039	−0.122	1.093	608.030
	(15,059.270)	(1.059)	(0.338)	(100,019.500)	(0.049)	(0.806)	(0.937)	(6,935.499)
Δ Gap(-1)	−0.071	−0.035	−0.029	−0.194**	−0.172**	−0.247*	−0.082	0.136***
	(0.044)	(0.036)	(0.085)	(0.081)	(0.068)	(0.148)	(0.052)	(0.052)
Δ Gap(-2)	0.026	−0.036	−0.108**	−0.159**	−0.066	−0.149**	−0.040	−0.084
	(0.050)	(0.031)	(0.055)	(0.075)	(0.071)	(0.067)	(0.057)	(0.086)
Observations	2,276	5,121	7,966	1,138	4,552	1,707	1,707	1,707
Adjusted R^2	0.08	0.067	0.045	0.333	0.057	0.096	0.287	0.114
No. of Principal Components	2	3	5	1	3	2	2	2

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

crease when the weekly change in VSTOXX is positive. This would indicate a decoupling of credit derivatives and equity derivatives markets, such that the aggregated level of risk implied in option prices would not translate into the credit risk indicated by the CG model. It could be the case that the calibration method of the model influences this finding. As a consequence I control for this aspect in my panel regressions with CG model option-implied estimated spreads. The corresponding results can be found in table 8. Considering aggregated risk in more detail, I obtain positive factor loadings for the weekly change in the counterparty credit risk index. These findings are in line with prior expectations, indicating that model spreads increase when counterparty credit risk also increases. The weekly change in the slope of the CRI yields mixed results with mostly insignificant estimates and alternating signs. The regression estimates of the slope from the credit curve however indicates that a steeper slope is related to the model spreads tending to decrease because the aggregated level of risk in short term tenors reduces in comparison to long term tenors. The CG model is thus able to account for the term structure of credit risk. Lagged variables are statistically significant at the 1% level for the consumer non-cyclicals sector. They carry negative coefficients implying that a mean-reverting behavior indeed exists. However, this effect is not found in other sectors such that its existence should be considered with caution. On the other hand, the principal component analysis of model (1) to (8) shows that the pattern from table 5 remains, although the degree of misspecification is slightly lower because for each model, except for model (4), at least one principal component more is needed to attain 80% explained variance in the error term. As I do not account for further granularity in the PCA by e.g. only considering the first two components, the results could arise from statistical noise or randomness. Hence, there are still common sector specific factors missing. This is also found by Collin-Dufresne et al. (2001) who consider local demand and supply shocks on credit derivative markets as a feasible explanation as this story would fit the sector specific variation in components.

Table 8 reports regression coefficients from fixed-effects panel regressions of weekly deltas in model 5-year CDS mid-spreads estimated by the CG model that is calibrated with option-implied volatility that is extracted from at-the-money put and call options with constant maturity of one year based on equation (40). The most important change in coefficient estimates can be seen for the weekly change in VSTOXX, because now increases in the index are positively related to model spreads. These estimates are statistically significant at the 1% level for model (3), (7) and (8). Model (6) exhibits statistical significance at the 5% level, whereas model (4) is only significant at the 10% level. This shows a fundamental aspect in model spread sensitivities contingent on the model calibration procedure with dependencies on what type of markets information are extracted from, subsequently used to estimate the model. My result are thus in line with prior expectations, supporting the hypothesis that determinants of model spreads are highly dependent on model input variables used. Furthermore, counterparty credit risk seems much more important in the sector cross-section using implied volatility as compared to historical volatility. Now model (1), (3), (5), (6), (7) and (8) show factor loadings that are statically significant at the 1% level. This fact indicates that the model calibrated with forward-looking information is much better in picking up counterparty credit risk than the model that relies on past information by using historical volatility. This result hints at a close alignment between credit derivatives and equity markets since the CRI is measured via market spreads in a way such that increased counterparty risk is anticipated by equity derivatives markets before the risk materializes, increasing model spreads. Related to this, the slope of the CRI is also highly important, since the basicmaterials, utilities and healthcare sectors exhibit statistcally significant loadings at the 1% level with negative estimates. Model spreads decrease when short term spreads for counterparties decrease and the slope therefore increases thus providing lower anticipated counterparty risk in the short term. Furthermore, model spreads lagged by one and two weeks accordingly exhibit statistically significant negative coefficients, indicating a higher degree of mean-reverting behavior, which is consistent with the findings of Bedendo et al. (2011). A possible explanation could be that the reactive nature of option-implied volatilties allows the model to faster absorb higher spreads in the cross-section than it is the case with long run volatility windows.

All in all, the comparison between table 7 and table 8 shows that the calibration method has a substantial impact on the identification of determinants of model spreads. Thus, model calibration procedures and following regression interpretations should be assessed accordingly. They should always be tested for different model specifications in order to determine common factors that drive spreads independent from the model calibration.

6.5. Market Spread Analysis

In the third and last model specification I consider market spreads in order to identify drivers of the variation in spreads independent from selected model specifications and calibration methods. To have consistent regression specifications, I stick with the already employed firm-specific as well as common macro-factors. Table 9 shows estimates from the panel regressions of weekly changes in market 5-year CDS mid spreads using equation (41).

As with the two previous regression model specifications (equation (39) and (40), both the weekly change in the counterparty credit risk index as well as obligor equity returns are strongly statistically significant for all sectors at the 1% level and carrying the expected signs. This result indicates that the CRI as well as equity returns are important determinants in the cross-section of European credit default swap spread dynamics. Changes in market spreads, on the other hand, are not sensitive to changes in the risk-free rate. Here higher risk-neutral asset drifts due to an increase in the risk-free rate with corresponding lower default probabilities do not exist in my sample and sample period. This contradicts the results found by Collin-Dufresne et al. (2001), Longstaff and Schwartz (1995) and Duffee (1998) who focus on corporate bond markets. For the term structure of counterparty credit risk, I estimate positive factor loadings that are statistically significant at the 1% and 5% level for all sectors except basicmaterials and healthcare. This result contrasts previously estimated coefficient, that have been usually negative with comparable significance levels. Market spreads tend to increase when the slope of CRI increases, indicating that the market anticipates future higher counterparty credit risk in long tenor contracts (here 10 years) increasing spreads for long tenors which would again increase the slope, by pricing this in to current market spreads. This result is somewhat surprising, since market tenors are always constant at 5 years, such that future increased counterparty

Table 7: Determinants of CG Model CDS Spreads - Equity Volatility Calibration.

This table reports the estimates from the panel regressions of weekly changes in 5-year CDS mid model spreads estimated by the CG model calibrated with 1000-day rolling window equity volatility. The regression specification is performed based on equation (40). (1) reports estimates for the Basicmaterials sector, (2) for the Consumer Non-Cyclicals sector and (3), (4), (5), (6), (7) and (8) for the sectors Consumer Cyclicals, Energy, Industrials, Technology, Utilities and Healthcare respectively. Using equation (40), I regress the weekly change in model spreads for each obligor (in basis points) on a sector specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) calculated based on equation (38) over a one week window. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. It estimates how much of the variation is explained, since idiosyncratic fixed effects contribute to the explanatory power in the variation of the depended variable. The number of principal components is determined such that the explained variance amounts to 80% or more. The sample period starts in December 2007 and end is December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Risk free rate	−0.278	0.118	−0.968	0.182	−0.776***	−0.265	−0.485***	−1.287**
	(0.232)	(0.381)	(0.784)	(0.128)	(0.274)	(0.323)	(0.155)	(0.512)
Δ Slope yield curve	0.012	0.056	0.063	0.019	−0.009	−0.046	0.020	0.095**
	(0.028)	(0.044)	(0.071)	(0.016)	(0.039)	(0.046)	(0.014)	(0.045)
Δ VSTOXX	−0.171***	−0.031	−0.290***	−0.066*	−0.157**	−0.319***	−0.020	−0.060
	(0.036)	(0.066)	(0.093)	(0.035)	(0.068)	(0.071)	(0.015)	(0.086)
Δ CRI	0.036***	−0.034*	0.124***	0.011	0.036	0.032*	0.011*	−0.004
	(0.010)	(0.018)	(0.031)	(0.008)	(0.022)	(0.016)	(0.006)	(0.023)
Δ Slope CRI	0.002	−0.036	0.061	0.037**	0.003	0.062	−0.008	−0.113***
	(0.026)	(0.029)	(0.093)	(0.017)	(0.036)	(0.053)	(0.013)	(0.038)
Δ Slope CDS	−0.003	−0.024	−0.039***	0.012	−0.040**	−0.023***	−0.003	−0.068
	(0.018)	(0.017)	(0.010)	(0.011)	(0.017)	(0.007)	(0.014)	(0.075)
Company returns	−0.674***	−1.459***	−2.519***	−0.250***	−1.464***	−1.577***	−0.394***	−0.886***
	(0.054)	(0.096)	(0.164)	(0.045)	(0.069)	(0.145)	(0.037)	(0.126)
Equity volatility	0.066**	−0.085*	0.277***	0.039**	0.091**	0.072	0.001	0.057
	(0.031)	(0.051)	(0.093)	(0.017)	(0.045)	(0.062)	(0.021)	(0.069)
ILLIQ	5,875.112**	0.022	0.251	0.286	0.037	4.496	0.110*	−3.219
	(2,776.769)	(0.040)	(0.301)	(5.319)	(0.159)	(7.294)	(0.057)	(3.321)
Δ CG(-1)	−0.005	−0.106***	0.018	0.058	−0.011	0.134**	0.058*	−0.002
	(0.036)	(0.035)	(0.024)	(0.052)	(0.031)	(0.054)	(0.033)	(0.054)
Δ CG(-2)	0.057*	−0.071***	0.003	0.004	0.016	0.00005	0.058***	0.028
	(0.034)	(0.027)	(0.026)	(0.046)	(0.027)	(0.041)	(0.017)	(0.060)
Observations	4,056	8,788	15,548	2,028	7,436	3,380	4,732	4,732
Adjusted R^2	0.434	0.122	0.351	0.465	0.441	0.560	0.377	0.102
No. of Principal Components	4	3	10	2	6	3	5	5

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

credit risk seems to have market wide spillover effects affecting all tenors and are not picked up by estimated model spreads in table 7 and 8. For the slope of the credit curve I obtain estimates in accordance to table 7 and 8, providing cross-validation that not only model spreads are driven by the term structure of credit risk, but also market spreads. Considering equity volatility, factor loadings for basicmaterials and healthcare are positive and statistically significant at the 10% level, whereas for the energy and industrials sector they are significant at the 1% and 5% level respectively. Hence market spreads react to increased equity volatility, supporting the finidngs of Collin-Dufresne et al. (2001) who state

Table 8: Determinants of CG Model CDS Spreads - Option-Implied Volatility Calibration.

This table reports the estimates from the panel regressions of weekly changes in 5-year CDS mid model spreads estimated by the CG model calibrated with option-implied volatility extracted from at-the-money put and call options with constant maturity of one year based on equation (40). The regression specification is performed according to equation (40). (1) reports estimates for the Basicmaterials sector, (2) for the Consumer Non-Cyclicals sector and (3), (4), (5), (6), (7) and (8) for the sectors Consumer Cyclicals, Energy, Industrials, Technology, Utilities and Healthcare respectively. Using equation (40), I regress the weekly change in model spreads for each obligor (in basis points) on a sector specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) calculated from equation (38) over a one week rollig window. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed-effect and thus includes the full model. It estimates how much of the variation is explained, since idiosyncratic fixed effects contribute to the explanatory power in the variation of the depended variable. The number of principal components is determined such that the explained variance amounts to 80% or more. The sample period covers January 2010 to December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Risk free rate	0.615	−2.095	7.399*	4.964	1.877	2.033	−1.201	−0.276
	(1.192)	(1.795)	(4.471)	(3.187)	(4.396)	(3.419)	(1.338)	(1.861)
Δ Slope yield curve	0.002	0.059	0.243	0.107	−0.051	−0.141	−0.076	0.253**
	(0.082)	(0.083)	(0.169)	(0.106)	(0.124)	(0.190)	(0.060)	(0.103)
Δ VSTOXX	0.212	0.260	0.956***	0.629*	0.262	0.446**	0.356***	0.723***
	(0.142)	(0.163)	(0.280)	(0.326)	(0.302)	(0.189)	(0.098)	(0.151)
Δ CRI	0.279***	−0.023	0.890***	−0.020	0.536***	0.397***	0.186***	0.286***
	(0.054)	(0.034)	(0.124)	(0.054)	(0.188)	(0.088)	(0.028)	(0.066)
Δ Slope CRI	−0.245***	−0.115	−0.151	0.188*	−0.143	−0.147	−0.122**	−0.391***
	(0.084)	(0.086)	(0.166)	(0.108)	(0.136)	(0.160)	(0.056)	(0.115)
Δ Slope CDS	−0.015	0.028	0.056	0.109*	0.051	0.059	−0.008	−0.040*
	(0.065)	(0.069)	(0.124)	(0.066)	(0.074)	(0.137)	(0.033)	(0.021)
Company returns	−0.216**	−1.892***	−1.334***	−0.367**	−0.580***	−0.132	−0.100**	−0.102
	(0.098)	(0.187)	(0.187)	(0.145)	(0.175)	(0.317)	(0.051)	(0.074)
Equity volatility	0.054*	0.007	0.205	0.661***	0.227	0.426	−0.059***	0.065
	(0.027)	(0.124)	(0.129)	(0.134)	(0.155)	(0.264)	(0.022)	(0.064)
ILLIQ	−8,510.414	−1.041	−0.133	−115,783.700*	−0.085	−0.164	1.297	−2,155.885
	(13,081.930)	(1.065)	(0.267)	(68,406.250)	(0.066)	(0.769)	(0.933)	(6,388.933)
Δ CG(-1)	−0.167***	−0.040	−0.106	−0.119**	−0.160**	−0.234	−0.110	0.085
	(0.056)	(0.034)	(0.067)	(0.053)	(0.064)	(0.147)	(0.080)	(0.066)
Δ CG(-2)	0.035	−0.054**	−0.002	−0.201***	−0.020	−0.134**	0.011	−0.064
	(0.074)	(0.027)	(0.039)	(0.055)	(0.060)	(0.064)	(0.059)	(0.093)
Observations	2,276	5,121	7,966	1,138	4,552	1,707	1,707	1,707
Adjusted R^2	0.211	0.119	0.195	0.468	0.121	0.135	0.345	0.259
No. of Principal Components	2	3	5	1	3	2	2	2

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

that "the contingent-claims approach implies that the debt claim has features similar to a short position in a put option. Since option values increase with volatility, it follows that this model predicts credit spreads should increase with volatility. This prediction is intuitive: Increased volatility increases the probability of default."[9] Illiquidity does only seem to drive spreads for consumer cyclicals for which I estimate a strongly statistically significant factor loading at the 1% level with expected positive sign and plausible magnitude, such that illiquidity equity spillover effects seem to be sector dependent and also for the CG model not detectable. Lagged market spreads show significant factor loadings primarily in one week lagged spreads with positive coefficient, indicating

[9] Collin-Dufresne et al. (2001), p. 2181

that mean-reverting behavior does not seem to exist in market spreads and thus contrasting the findings from option-implied derived CG model spreads. This indicates a disconnection between equity and credit derivatives markets when assessing the inter-dependencies and persistence of spreads. Section 6.6 investigates this relation in more detail. The adjusted R^2 values are overall significantly higher for market regressions than for model regressions, ranging from 0.154 for the sector consumer non-cyclicals to 0.702 for technologies. The PCA reflects this by 3 or more principal components needed to explain at least 80% in error term variance, except for model (4) and (6).

6.6. Predictive Power of CreditGrades

In the last step of my main analysis I test the predictive ability of the CG model to forecast market spreads. As assessed in section 4.4 and pointed out by Bedendo et al. (2011), empirical evidence exists that new information is typically priced in faster in equity markets than in credit markets. To test this hypothesis for the European market I regress weekly deltas in market spreads on weekly deltas in model spreads with one and two lags as well as weekly deltas of market spreads with a lag of one week accordingly. Since the selection of the number of lags is arbitrary, I stick to the study design of Bedendo et al. (2011) to have comparable estimates. Furthermore, I distinguish the predictive ability of the model in its both specifications to provide additional insights on the source of the possible lead-lag relationship between equity and credit derivatives markets. Panel A of table 10 shows the predictive abilities of the CG model, because the variation in empirical market spreads are significantly driven by current model spreads as well as the first weekly lag in change of model spreads. Especially the sector basicmaterials and industrials exhibit significant predictive patterns up to the second lag in model spreads, providing evidence for sector specific predictive abilities of the model. On the other hand, also market lagged variables are significant for both sectors, such that some degree of market inherent inefficiency could influence the predictive ability of the CG model. This aspect underlines the findings in market regressions of section 6.5, such that inefficiencies relate to autocorrelation assessed in section 6.2. When panel A is compared to panel B, it becomes clear that the CG model calibrated with option-implied volatility is also subject to predictive abilities, although now significant for the first lag in changes of the model spread for basicmaterials and energy. My results are comparable to the study of Bedendo et al. (2011) in the way that coefficient estimates are comparable in size and magnitude as well as the overall adjusted R^2. This supports the study of Bedendo et al. (2011) who conclude that significant noise in the estimation procedure or model misspecifications could result in low R^2 values. Additionally, it is interesting to note that when comparing the adjusted R^2 between panel A and panel B, the sector technology, utilities and healthcare show material differences in explanatory power of predictive regressions as the coefficient of determination increases for sector technology and healthcare by more than 10 percentage points when option-implied volatilities are used in the model estimation procedure, whereas utilities decreases by that amount. This aspect provides further evidence on the fact that the predictive ability of the model is both contingent on sectors as well as on the estimation procedure of the model itself, leaving the conclusion by Byström (2006) and Bedendo et al. (2011) who only assess the predictive ability of the model in one specification with a grain of salt.

7. Robustness

7.1. Analysis for CDS Tenors of one and 10 years

In this section I control my previous results for robustness by accounting for the length of which the credit protection will last, namely the tenor of the credit default swap testing results for 1 and 10 year tenors respectively. For this I retrieve one-year and 10-year CDS mid spreads in the same fashion as outlined in section 5 using Refinitiv Datastream. I then proceed with the estimation of determinants of the gap, market and model spreads as in section 6. Appendix H shows panel regression outputs for one year tenors (H.1) and 10-year tenors (H.2). All in all, results are highly similar for CRI, the risk-free rate and the slope of the yield curve since the latter two are still statistically insignificant and do not contribute to the dynamics of gap, model and market spreads in line with my results using 5-year tenors. The factor CRI matches the significance and estimated regression coefficient in size and magnitude, since I calculate 1 and 10 year CRI index values (see appendix F), matching the duration of dependent variable spreads in the robustness analysis. For company returns, I find significantly larger coefficients, especially for 1 year tenors, for gap, model and market spreads, indicating that 1-year credit protection horizons have substantial impact on the likelihood of experiencing a default event by deviating from the default barrier when equity returns are higher. This fact provides further evidence on the fact that model and market spreads are highly sensitive to equity development, especially when the credit protection entails short horizons. In the same fashion I find increased regression coefficients for the term structure of counterparty credit risk and the credit curve, pronounced for 1 year tenors. This underlines that not only obligor equity returns, but also the aggregated credit risk profile on both the credit protection seller and buyer side is highly important when considering the drivers of the cross-sectional cost of credit risk. On the other hand, long tenors of 10 years do not show increased coefficients, showing that only short horizons are sensitive to pivots and changes in the term structure. The 10-year tenor regression outputs in appendix H.2 show that especially in option-implied CG-model and market spread specifications, the factor loadings for the weekly change in VSTOXX are much higher and most often statistically significant as compared to results in section 6. Thus leading to the conclusion that long credit protection tenors are driven by aggregated market wide implied volatility. Consequently, the horizon of

Table 9: Determinants of Market CDS Spreads.

This table reports the estimates from the panel regressions of weekly changes in market 5-year CDS mid spreads using equation (41). (1) reports estimates for the Basicmaterials sector, (2) for the Consumer Non-Cyclicals sector and (3), (4), (5), (6), (7) and (8) for the sectors Consumer Cyclicals, Energy, Industrials, Technology, Utilities and Healthcare respectively. Using equation (39), I regress the weekly change in market spreads for each obligor (in basis points) on a sector specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) calculated from equation (38) over a one week rolling window. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. It estimates how much of the variation is explained, since idiosyncratic fixed effects contribute to the explanatory power in the variation of the depended variable. The number of principal components is determined such that the explained variance amounts to 80% or more. The sample period starts in December 2007 and ends in December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Risk free rate	−1.654	−0.409	−0.839	0.431	−1.133	0.622	−1.567	−1.071
	(1.117)	(1.117)	(1.747)	(0.978)	(1.724)	(1.113)	(1.480)	(0.654)
Δ Slope yield curve	0.184**	0.106*	0.183	0.011	0.099	0.002	0.008	0.037
	(0.092)	(0.059)	(0.120)	(0.104)	(0.065)	(0.205)	(0.135)	(0.041)
Δ VSTOXX	0.054	0.249**	0.046	−0.036	−0.042	−0.165	0.240*	0.113***
	(0.068)	(0.106)	(0.220)	(0.185)	(0.098)	(0.228)	(0.123)	(0.042)
Δ CRI	0.377***	0.272***	0.602***	0.308***	0.311***	0.531***	0.494***	0.168***
	(0.055)	(0.045)	(0.091)	(0.060)	(0.038)	(0.082)	(0.066)	(0.025)
Δ Slope CRI	0.226	0.333***	0.621***	0.415***	0.271**	0.489**	0.450***	0.049
	(0.177)	(0.100)	(0.215)	(0.086)	(0.107)	(0.220)	(0.139)	(0.056)
Δ Slope CDS	0.106	−0.101	−0.483***	−0.174	0.038	−0.586***	−0.322**	0.151*
	(0.190)	(0.080)	(0.066)	(0.246)	(0.060)	(0.041)	(0.129)	(0.084)
Company returns	−0.648***	−0.355***	−1.149***	−0.690***	−0.630***	−0.988***	−0.566***	−0.108***
	(0.120)	(0.075)	(0.129)	(0.231)	(0.103)	(0.347)	(0.129)	(0.034)
Equity volatility	0.105*	0.071	0.006	0.155***	0.071**	0.356	0.058	0.057*
	(0.055)	(0.054)	(0.036)	(0.051)	(0.033)	(0.251)	(0.061)	(0.030)
ILLIQ	4,116.700	−0.016	0.138***	−13.209	0.087	−10.320	0.380	−0.594
	(10,010.510)	(0.024)	(0.048)	(58.866)	(0.100)	(9.816)	(0.251)	(1.062)
Δ CDS(-1)	−0.026	0.085*	0.060*	0.188***	0.164***	0.086	0.022	0.022
	(0.038)	(0.045)	(0.033)	(0.068)	(0.029)	(0.073)	(0.044)	(0.033)
Δ CDS(-2)	0.080*	0.050	−0.029	−0.010	0.059**	−0.086	−0.032	0.082*
	(0.044)	(0.044)	(0.039)	(0.059)	(0.030)	(0.074)	(0.054)	(0.044)
Observations	4,056	8,788	15,548	2,028	7,436	3,380	4,732	4,732
Adjusted R^2	0.268	0.154	0.494	0.332	0.263	0.702	0.250	0.196
No. of Principal Components	3	6	11	2	6	2	4	4

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

priced in forward-looking information is much longer than typically anticipated by studies that assess 5-year tenors only. On the other hand, VSTOXX factor loadings for 1 year do not significantly deviate from estimated coefficients in section 6, underlining the presumption of pricing in forward-looking information with long time horizons for gap, model and market spreads.

7.2. Time Period Regressions

Besides the assessment of different tenors, I control my results for different time periods. With this approach I test the hypothesis if factor loadings of determinants in gap, model and market spreads are time dependent, reflecting different drivers of spreads contingent on the economical state like crisis and tranquil periods. Since my sample period covers three crisis times (the financial, sovereign debt and

Table 10: Predictive Regressions.

This table reports the estimates from the predictive panel regressions of weekly changes in market spreads on weekly changes in model spreads with one and two lags and weekly deltas of market spreads with a lag of one week accordingly. Panel A reports predictive regressions using equation (42) according to the CG model calibrated with 1000-day rolling window equity volatility. Panel B reports predictive regressions using equation (42) according to the CG model calibrated with option-implied volatility using constant one year at-the-money put and call options. (1) reports estimates for the Basicmaterials sector, (2) for the Consumer Non-Cyclicals sector and (3), (4), (5), (6), (7) and (8) for the sectors Consumer Cyclicals, Energy, Industrials, Technology, Utilities and Healthcare respectively. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. It estimates how much of the variation is explained, since idiosyncratic fixed effects contribute to the explanatory power in the variation of the depended variable. The sample period covers the time span form December 2007 to December 2020 for panel A and January 2010 to December 2020 for panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Historical Volatility Specification								
Δ model spread	1.064***	0.061***	0.337***	2.543***	0.353***	1.738***	2.292***	0.065**
	(0.118)	(0.014)	(0.050)	(0.363)	(0.045)	(0.462)	(0.494)	(0.027)
Δ model spread (-1)	0.452***	0.020	0.068**	−0.114	0.057**	−0.128	−0.867*	0.022
	(0.130)	(0.013)	(0.027)	(0.356)	(0.025)	(0.163)	(0.456)	(0.028)
Δ model spread (-2)	0.420**	0.014	0.011	−0.376	0.078***	0.309	0.132	0.025
	(0.165)	(0.011)	(0.033)	(0.260)	(0.027)	(0.208)	(0.277)	(0.018)
Δ market spread (-1)	−0.117**	0.087*	0.066	0.205*	0.124***	0.020	0.034	−0.017
	(0.060)	(0.049)	(0.073)	(0.114)	(0.035)	(0.045)	(0.112)	(0.038)
Observations	4,056	8,788	15,548	2,028	7,436	4,732	3,380	4,732
Adjusted R^2	0.198	0.015	0.102	0.211	0.140	0.088	0.157	0.015
Panel B: Option-Implied Volatility Specification								
Δ model spread	0.533***	0.117***	0.305***	0.308***	0.142***	1.183***	0.049**	0.162***
	(0.075)	(0.024)	(0.046)	(0.032)	(0.033)	(0.247)	(0.020)	(0.041)
Δ model spread (-1)	0.149**	0.001	0.033	0.172***	0.016	−0.057	0.010	−0.016
	(0.060)	(0.015)	(0.041)	(0.043)	(0.016)	(0.204)	(0.008)	(0.026)
Δ model spread (-2)	0.016	0.027	0.019	0.003	0.040*	−0.074	0.009	0.026*
	(0.074)	(0.024)	(0.041)	(0.030)	(0.023)	(0.127)	(0.007)	(0.016)
Δ market spread (-1)	−0.012	0.064	0.058	−0.047	0.132***	−0.062	−0.019	0.009
	(0.057)	(0.058)	(0.125)	(0.071)	(0.050)	(0.060)	(0.084)	(0.064)
Observations	2,276	5,121	7,966	1,138	4,552	1,707	1,707	1,707
Adjusted R^2	0.187	0.046	0.122	0.240	0.155	0.201	0.058	0.304

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

corona crisis) and one tranquil period between 2014 to early 2020, I provide various market conditions in which I test the hypothesis that regression estimates are time dependent and measure the degree of explanatory power contingent on market environment and economical conditions. For this I perform panel regressions analog to section 6 grouped by time periods.

Analog to table 5 and 6, table 11 reports estimates from the panel regressions of weekly changes in the difference between market and CG 5-year model CDS mid spreads calibrated using the 1000-day equity volatility for model (1) to (4). In contrast, model (5) to (7) are calibrated with option-implied volatilities. Model (1) covers the financial crisis, model (2) the European sovereign debt crisis, model (3) the tranquil period between 2014 and early 2020 and model (4) the corona crisis. The same holds true for model (5) to (7), although the financial crisis time period is augmented due to limited option data availability. In the first step, only factor loadings between model (1) and (4) are compared. When considering the weekly change in risk-free rate and the weekly change in the slope of the yield curve, time period results confirm sector results since no regression estimates are statistically significant at the 5% level or higher. The change in VSTOXX index values are strongly statistically significant for the financial crisis and European sovereign debt crisis with negative signs such that gap spreads converge when aggregate option-implied volatility is high. Nevertheless this finding is different for the crisis times as the coronas crisis exhibits no significant loading. The weekly change in CRI is always statistically significant for all time periods with negative signs and hence provides evidence on the fact that counterparty credit risk is a important determinant of CDS spread gaps. The slope of the CRI is only significant for the financial crisis and corona crisis time period such that in times of highly increased short term uncertainty, unique to those time periods, an increase in the slope will reduce gap spreads. This result shows that when the term structure of counterparty credit risk changes, uncertainty and thus also uncertainty in the counterparties financial health will increase long term spreads and thus increase the slope. Hence, an increase in the slope will move model and market spreads upwards and therefore narrowing the gap. Turning to the credit curve, only crisis periods exhibit positive and statistically significant factor loadings implying that an increase in the slope also increases the gap, resulting in time periods where there is a fundamental shift in credit risk term structure for which the CG model derived spreads deviate from market spreads. Company returns are statistically significant for all time periods and carry negative signs, underlining that the gap reduces if returns increase and the asset value of firms deviates from the default barrier. Equity volatility remains with alternating signs, implying it is unlikely driving the gap. Illiquidity is never significant at the 5% level or higher, supporting my findings from section 5.

For the models (5) to (7) that use option-implied CG model calibration to calculate the gaps, I obtain factor loadings for VSTOXX comparable in significance to models (1) to (4), but now with positive signs. This implies that gaps increase when the aggregated implied volatility increases. The risk-free rate is only significant for the tranquil period, supporting the finding in section 6.3 that it does not seem to systematically drive gap spreads. The same holds true for the slope of the yield curve since only model (5) yields a significant factor loading. Company returns, illiquidity and equity volatility are mostly in line with the main results, providing no additional time dependent idiosyncraticies. The lagged gap variable estimates show that time and calibration specific mean-reverting tendencies exist, supporting the result in 6.3 that high option-implied estimated gap spreads seem to be absorbed in following gap spreads which is indicated by negative coefficients of the lagged change in the gap that is statistically significant at the 1% level in model (5) and (6).

Considering table 12 and model (1) to (4), the risk-free rate, the slope of it and the illiquidity measure are not statistically significant in any time period, indicating that model spreads are not driven by these factors. This supports the empirical evidence of my main analysis. Factor loadings are strongly statistically significant at the 1% level for changes in VSTOXX in crisis periods (model (1), (2) and (4)), and at the 5% level for the tranquil period for which the coefficient estimates are reduced by more than half. Consistent with my sector specific regressions, I estimate negative coefficients implying that model spreads decrease when implied volatility increases. Factor loadings for CRI are statistically significant only for the financial crisis and the corona crisis, indicating that model spreads are mainly driven by counterparty credit risk in times of increased aggregated uncertainty with possible spillover and contagion effects in dealer CDS markets. Furthermore, the slope of the CRI index also reflects this finding. The term structure of credit risk is consistent with prior expectations, such that factor loadings are statistically significant when credit risk materializes in crisis times and not significant for the tranquil period. Signs are negative, indicating that model spreads decrease when the term structure becomes steeper, which in line with the chapter 6.4. Company returns are statistically significant for all periods carrying negative signs and thus supporting the evidence that the CG model is able to capture the decrease in PD's when asset values deviate from the default barrier due to increased equity returns. This finding is valid for every economical condition and environment. Corresponding to that, factor loadings for equity volatility show support for the prior expectations of Collin-Dufresne and Goldstein (2001) by displaying positive and statistically significant estimates for the variation in equity volatility in crisis periods only. This fact highlights that the model captures increased default risk when assets are more likely to hit the barrier due to greater variability in equity. The estimates related to the lagged variables are consistent with the gap time period regressions. Interdependencies do not seem to exist when assessing the model estimated with historical volatility. When considering model (5) to (7), the findings change. Analog to table 8, lagged model spreads seem to cause current model spreads to revert, such that mean reverting behavior is present in all time periods affecting one and two week lagged variables. Model calibration also seems to have impact on CRI, since every time period shows statistically significant factor loadings, indicating that counterparty credit risk seems to be important as also depicted in table 13. Regarding VSTOXX factor loadings, the CG model is now able to react in the assumed direction. Hence, model spreads increase when aggregated implied volatility increases.

In the last step of my robustness analysis I consider time period regressions on market spreads in the same way as for gap and model spreads. Since market regressions are independent from model estimation procedures, the results from models (1) to (4) cover all four time periods. For the risk-free rate and the slope of the yield curve coefficients are for no time period significant at the 5% level or higher. Hence, estimated model spreads capture the driver of the variation well. Regarding autocorrelation contingent on market environment, I estimate a positive regression coefficient at 1% for the financial crisis, such that market spreads tend to increase if prior spreads increased. Market spreads have a higher ten-

Table 11: Determinants of the Gap between Market and Model CDS Spreads - Time Period Regressions.

This table reports the estimates from the panel regressions of weekly changes in the difference between market and CG 5-year model CDS mid spreads calibrated with 1000-day equity volatility in models (1) to (4). In models (5) to (7) the model is calibrated using option-implied volatilities extractedfrom at-the-money put and call options with constant maturity of one year. (1) reports estimates for the financial crisis time period using historical volatility calibration, (2) for the European sovereign debt crisis time period using historical volatility calibration, (3) for the tranquil time period using historical volatility calibration, (4) for the Corona crisis time period using historical volatility calibration. Model (5) reports estimates for the European sovereign debt crisis time period using option-implied volatility calibration, (6) for the tranquil time period using option-implied volatility calibration and model (7) for the Corona crisis time period using option-implied volatility calibration. I regress the weekly gap for each obligor (in basis points) on a time period specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) calculated from equation (38) over a one week horizons. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. For model (1) to (4) the sample period covers the time span starting in December 2007 up to December 2020, whereas for model (5) to (7) the sample periods covers January 2010 to December 2020. Hence I expand the financial crisis time period for the option-implied regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Risk free rate	0.738	−2.121	−1.423	−1.802	−2.064	−3.602**	−7.306
	(1.698)	(1.294)	(1.496)	(3.330)	(1.554)	(1.692)	(10.910)
Δ Slope yield curve	−0.856*	0.178	0.093	−0.382	0.375**	0.240	0.601
	(0.450)	(0.181)	(0.150)	(0.576)	(0.180)	(0.230)	(1.611)
Δ VSTOXX	−0.698***	−0.339**	−0.111	0.361	0.462***	0.210***	1.161**
	(0.262)	(0.137)	(0.075)	(0.243)	(0.178)	(0.069)	(0.455)
Δ CRI	−0.310***	−0.422***	−0.568***	−0.808***	−0.185***	−0.352***	−0.011
	(0.080)	(0.056)	(0.105)	(0.056)	(0.072)	(0.120)	(0.208)
Δ Slope CRI	−0.445***	0.098	0.080	−1.000***	0.008	0.125	−2.027**
	(0.136)	(0.089)	(0.120)	(0.364)	(0.087)	(0.156)	(0.925)
Δ Slope CDS	0.260***	0.547***	−0.032	0.503***	−0.049	−0.073***	−0.002
	(0.095)	(0.039)	(0.167)	(0.060)	(0.036)	(0.022)	(0.053)
Company returns	−1.104***	−1.366***	−0.599***	−0.944***	−0.633***	−0.419***	−1.069***
	(0.270)	(0.100)	(0.049)	(0.191)	(0.077)	(0.047)	(0.165)
Equity volatility	0.266**	−0.091	−0.120***	0.085	−0.006	−0.013	0.089*
	(0.119)	(0.114)	(0.042)	(0.063)	(0.064)	(0.040)	(0.049)
ILLIQ	0.156	0.012	0.085*	0.004	0.010	−0.018	−0.303*
	(0.410)	(0.041)	(0.049)	(0.171)	(0.030)	(0.038)	(0.155)
Δ Gap(-1)	0.026	0.062	0.001	0.0001	−0.129***	−0.120	−0.026
	(0.026)	(0.053)	(0.027)	(0.045)	(0.030)	(0.084)	(0.103)
Δ Gap(-2)	−0.038	−0.077	−0.018	−0.066*	−0.030	−0.092***	−0.150*
	(0.039)	(0.055)	(0.023)	(0.040)	(0.024)	(0.033)	(0.081)
Observations	7,800	15,525	24,000	2,925	9,476	14,720	1,794
Adjusted R^2	0.115	0.489	0.223	0.660	0.052	0.059	0.146

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

dency to be more persistent in times of high volatility in line with findings of Bedendo et al. (2011), although not entirely consistent with other crisis times as only the financial crisis exhibits significant estimates. Independent regression vari-

Table 12: Determinants of CG Model CDS Spreads - Time Period Regressions.

This table reports the estimates from the panel regressions of weekly changes in 5-year model CDS mid spreads estimated by the CG model calibrated with 1000-day equity volatility in models (1) to (4). Models (5) to (7) are then calibrated with option-implied volatilities extracted from at-the-money put and call options with constant maturity of one year. (1) reports estimates for the financial crisis time period using historical volatility calibration, (2) for the European sovereign debt crisis time period using historical volatility calibration, (3) for the tranquil time period using historical volatility calibration, (4) for the Corona crisis time period using historical volatility calibration. Model (5) reports estimates for the European sovereign debt crisis time period using option-implied volatility calibration, (6) for the tranquil time period using option-implied volatility calibration and model (7) for the Corona crisis time period using option-implied volatility calibration. I regress the change in weekly model spread of each obligor (in basis points) on a time period specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) calculated using equation (38) over a one week horizons. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. For model (1) to (4) the sample period spans the time period from December 2007 to December 2020, whereas for model (5) to (7) the sample period covers January 2010 to December 2020. Hence I expand the financial crisis time period for the option-implied regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Risk free rate	0.096	0.149	−0.449	−0.067	0.490	−3.584**	−0.173
	(0.557)	(0.674)	(0.806)	(0.922)	(1.307)	(1.594)	(6.637)
Δ Slope yield curve	−0.117	−0.012	0.099	0.123	0.180	0.347*	−0.736
	(0.158)	(0.070)	(0.082)	(0.212)	(0.115)	(0.183)	(0.986)
Δ VSTOXX	−0.325***	−0.241***	−0.120**	−0.218***	0.604***	0.345***	1.029**
	(0.120)	(0.048)	(0.053)	(0.047)	(0.134)	(0.112)	(0.379)
Δ CRI	0.064**	0.015	0.039	0.077**	0.306***	0.224***	1.545***
	(0.032)	(0.017)	(0.037)	(0.039)	(0.042)	(0.077)	(0.162)
Δ Slope CRI	0.155***	−0.011	0.043	−0.670***	−0.206***	0.138	−1.672**
	(0.058)	(0.031)	(0.052)	(0.173)	(0.066)	(0.119)	(0.666)
Δ Slope CDS	−0.024	−0.017***	0.008	−0.044***	−0.066**	−0.004	−0.079
	(0.022)	(0.005)	(0.012)	(0.011)	(0.026)	(0.012)	(0.049)
Company returns	−2.013***	−2.226***	−0.975***	−2.104***	−0.845***	−0.479***	−0.946***
	(0.213)	(0.074)	(0.039)	(0.087)	(0.085)	(0.051)	(0.149)
Equity volatility	0.286***	0.131**	0.060	0.106**	0.063	0.0002	0.104**
	(0.096)	(0.057)	(0.049)	(0.044)	(0.062)	(0.043)	(0.047)
ILLIQ	0.367	0.039	0.049	−0.226	−0.037	−0.038	−0.663**
	(0.389)	(0.034)	(0.037)	(0.177)	(0.037)	(0.040)	(0.303)
Δ CG(-1)	−0.005	0.012	0.004	−0.083	−0.119***	−0.109	−0.193***
	(0.040)	(0.026)	(0.027)	(0.095)	(0.035)	(0.085)	(0.073)
Δ CG(-2)	0.015	−0.015	−0.025	−0.070	0.014	−0.094***	−0.063
	(0.046)	(0.026)	(0.026)	(0.053)	(0.029)	(0.031)	(0.044)
Observations	7,800	15,525	24,000	2,925	9,476	14,720	1,794
Adjusted R^2	0.302	0.358	0.346	0.593	0.160	0.090	0.360

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

ables like the risk-free rate, the slope of the yield curve, counterparty credit risk, the slope of it and company returns remain consistent with the sector market regressions in terms of statistical significance and the magnitued of the estimates.

Table 13: Determinants of Market CDS Spreads - Time Period Regressions.

This table reports the estimates from the panel regressions of weekly changes in market 5-year CDS mid spreads. (1) reports estimates for the financial crisis time period, (2) for the European sovereign debt crisis time period, (3) for the tranquil time period and (4) for the Corona crisis time period. I regress the change in weekly market spread for each obligor (in basis points) on a time period specific constant, the weekly change in the risk-free rate defined as the 3-month EURIBOR, the weekly change in the slope of the yield curve defined as the 12 month EURIBOR minus the one-month EURIBOR and the weekly change of the VSTOXX index, the weekly change in the CRI and the weekly delta of the CRI slope defined as the mid-spread of a 10-year tenor CRI index value minus the mid-spread of a one-year tenor CRI index value. As firm specific variables, I consider the weekly obligor (company) return, weekly equity volatility, the weekly delta of the credit curve expressed as the CDS slope defined as the mid-spread of a 10-year tenor CDS minus the mid-spread of a one-year tenor CDS of the same reference entity and the illiquidity factor derived by Amihud (2002) calculated with equation (38) over a one week time horizons. I report Driscoll and Kraay (1998) standard errors adjusted for heteroskedaticity and spatial correlation. The adj. R^2 is corrected for the fixed effect and thus includes the full model. The sample period covers December 2007 to December 2020.

	(1)	(2)	(3)	(4)
Δ Risk free rate	−0.709	2.105*	0.848	1.648
	(1.605)	(1.210)	(1.098)	(2.980)
Δ Slope yield curve	0.616*	−0.180	−0.008	0.479
	(0.374)	(0.153)	(0.132)	(0.457)
Δ VSTOXX	0.444**	0.126	0.001	−0.545**
	(0.179)	(0.135)	(0.058)	(0.259)
Δ CRI	0.375***	0.436***	0.603***	0.866***
	(0.064)	(0.061)	(0.118)	(0.055)
Δ Slope CRI	0.601***	−0.103	−0.032	0.514
	(0.144)	(0.095)	(0.115)	(0.368)
Δ Slope CDS	−0.265***	−0.565***	0.038	−0.549***
	(0.087)	(0.039)	(0.175)	(0.066)
Company returns	−0.926***	−0.843***	−0.378***	−1.148***
	(0.138)	(0.093)	(0.052)	(0.177)
Equity volatility	0.003	0.217**	0.176***	0.008
	(0.037)	(0.099)	(0.068)	(0.059)
ILLIQ	0.191***	0.041	−0.037	−0.213*
	(0.041)	(0.041)	(0.024)	(0.117)
Δ CDS(-1)	0.128***	0.075	0.037	0.006
	(0.042)	(0.061)	(0.040)	(0.046)
Δ CDS(-2)	−0.028	−0.054	0.010	−0.026
	(0.064)	(0.061)	(0.038)	(0.052)
Observations	7,800	15,525	24,000	2,925
Adjusted R^2	0.235	0.603	0.221	0.746

Significance Levels: *p<0.1; **p<0.05; ***p<0.01

From that I conclude that these factors drive spreads regardless of the environment in which obligors operate. The slope of the CDS exhibits negative and strongly statistcally significant coefficient estimates in crisis times, whereas it does not in the tranquil period, thus showing that the term structure of credit risk has impact on market spreads when credit risk is more likely to materialize. In contrast to all other previous regressions, I estimate a positive factor loading for equity illiquidity in the financial crisis time period, showing time varying illiquidity spillover effects from equity to credit markets. This result illustrates the importance of distinguishing time periods and provides feasible arguments that drivers of credit risk are not time invariant, but to a certain extent highly time dependent.

8. Conclusion

With this thesis I tried to shed light onto the dynamics of the European credit derivatives market by assessing the performance of the CreditGrades model used to quantify credit risk in the cross-section of my sample of reference entities. The conditional correlations show that strong relationships between estimated model and market spreads exist but they seem to be highly sector dependent. This points out that model performance has be be addressed on a per sector level. The historical volatility calibrated model cannot follow market spreads in times of financial turmoil mainly due to the ghost effect of constant sliding equity volatility window that prevent the model to incorporate new information quickly. On the other hand, the implied-volatility calibration can better adjust to new information, thus supporting the hypothesis of quicker incorporation of information in equity derivatives markets formulated by Cao et al. (2011), Bedendo et al. (2011) and Wagner (2008). Correlations are higher in times of increased volatility both in equity and credit derivatives markets, together with the pricing analysis of forecasting metrics leading to the conclusion that the model parameter distribution has major impact on the model performance. This fact underlines the model related downside that credit risk is driven by the distance between asset value and default barrier. Thus, sectors which do not exhibit high financial leverage and low equity volatility (implied volatility) show severe model under-performance. Practical model implementation always needs to be assessed together with a model back-testing to analyse the relation between parameter distribution and the ability of the model to derive credit risk in the cross-section. When assessing autocorrelations in model and market spreads, I confirm the findings of Byström (2006) that market inefficiencies do exist. This is because market spreads are highly autocorrelated, resulting in effects on pricing and model performance thereafter. However my findings deviate from Byström (2006) in the regard that also model spreads show high degrees of autocorrelation which is later also addressed in performed panel regressions. Turning to the determinants of the gap between model and market spreads, I discover that structural variables explain variations well since the risk-free rate and the slope of it are mostly statistically insignificant. On the other hand, equity returns and counterparty credit risk are almost always useful to explain the weekly variation in gap, model and market spreads. Factors like aggregated implied volatility, the term structure of counterparty credit risk and the credit curve are highly sector specific in the explanatory value of spreads. The illiquidity factor of Amihud (2002) does not seem to drive CDS spreads, thus I can reject the hypothesis that equity illiquidity spillover effects are reflected in gap, model and market spreads. Determinants of model spreads depend, as expected, on model calibration procedures resulting in the ability of the option-implied volatility to pick up market aggregated implied volatility depicted by positive VSTOXX loadings. Mean-reverting behavior of gap and model spreads found by Bedendo et al. (2011) also depends on model calibration procedures, as option-implied derived model spreads exhibit stronger mean-reversion and historical volatility estimated spreads show higher persistence. With my sample of reference entities I can confirm the predictive ability of the CG model also in the European market as also discovered by Byström (2006) and Bedendo et al. (2011). However, upon closer inspection the predictive ability depends on sector and model calibration procedures such that capital structure arbitrage strategies, exploiting this market inefficiency, have to be chosen carefully. My robustness analysis shows that determinants of gap, model and market spreads are related to CDS tenors and time periods. Short term CDS tenors of one year exhibit higher sensitivities to equity returns, the term structure of counterparty credit risk and the credit curve. For long tenors, VSTOXX appears more important, especially for option-implied gap and model spreads, showing that the horizon of priced in forward-looking information is much longer than anticipated when using 5-year tenors. Panel regression grouped by time periods show that determinants of gap, model and market spreads are, to some extent, time variant, whereas CRI and equity returns are always statistically significant with comparable signs. Especially the slope of CRI and the credit curve contribute over-proportional to the explanatory value in times of financial turmoil, indicating the importance of market sentiment on the credit protection of the buyer and seller side. I can show that illiquidity spillover effects from equity to credit markets exist for market spreads in the financial crisis, highlighting the importance of detecting time variation in determinants. My analysis can be expanded in future research based on two main aspects. A first extension might be related to the model calibration itself. Better data availability with access to proprietary databases such as Markit, Moodys or S&P could yield more accurate recovery rates of underlying bonds, thus most likely improving model performance. Additionally, different asset volatility approximations could be used such as EWMA-, GARCH models or different historical volatility windows to derive a more granular view on the calibration contingent model performance outlined by my results. A second extension might focus on my regression approach. The frequency of weekly observations could be adjusted to match observation frequencies for which more macroeconomic variables are reported, e.g. monthly, quarterly or bi-annually. This would allow factors like GDP or unemployment rates to enter the regression specification and could provide additional insights. To compensate the number of reduced data points, a longer observation period can be defined. This is, however, only possible if other datasources with long back reaching historical data are available. Furthermore, different econometric techniques can be used and compared, such as panel quantile regressions or Markov regime switching models in style of Alexander and Kaeck (2008). With these methods it would be possible to correct results for path dependencies induced by selected econometric methods, identifying regression model inherent tendencies. In addition, further liquidity measures, such as the bid-ask spread, could be used to further assess the role of possible illiquidity in credit derivatives markets. Finally, future research could test the above mentioned aspects in performing capital structure arbitrage strategies where different model specifications and subsequent risk-return profiles are compared.

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