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ABSTRACT

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Abstract

After the turn of the millennium, a strategy called capital structure arbitrage started to gain interest among academics and practitioners. In this relative value trading strategy, a structural credit risk model is used to identify dislocations in the pricing of a firm's capital structure. If a pricing misalignment between a company's debt and equity instruments is found, a balanced relative value position including both debt and equity instruments is established. In a scenario where the prices converge back to their fundamental values, the trade should be profitable. In this thesis, both the structural credit risk model used to generate the trading signals and the strategy execution in itself are analyzed.

First, the aim is to test how the Merton (1974) Moody's KMV credit risk model performs in a capital structure arbitrage setting when different calibration methodologies are utilized. Second, a new trading execution strategy involving variance and credit default swaps is tested. To test the model and the proposed strategy execution methodology, a sample consisting of 102 European obligors is analyzed during the post-financial crisis era spanning from 2.8.2012 to 30.7.2019. Finally, results are compared to previous studies so that conclusions regarding the viability of the tested approach can be made.

The results indicate that the use of market-implied data, e.g., implied equity volatility, in the model calibration leads to improved model accuracy and higher trading strategy profits on average. Similar results are found if Student's t-distribution is applied in default probability calculations instead of the normal distribution. Additionally, the use of variance swaps in the trading strategy can be seen as a valid alternative compared to cash equities, for example. With the best-performing model variant, Sharpe ratios calculated from monthly excess returns vary between 0.43 and 0.59.

Altogether, both the Merton (1974) Moody's KMV and the variance swap-based execution strategy can be seen to perform inline or in some instances even better than other model and strategy specifications when the results are compared to previous studies.

Key words	Capital structure arbitrage, Merton model, Moody's KMV, variance swap, CDS
Further information	

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Tiivistelmä

Vuosituhannen vaihteessa akateemikot ja edistykselliset sijoittajat alkoivat kiinnittää entistä enemmän huomiota uuteen strategiaan, joka nojautui yksittäisen yhtiön pääomarakenteessa ilmenevien hinnoitteluvirheiden hyödyntämiseen. Tässä pääomarakennearbitraasiksikin kutsutussa strategiassa sijoitetaan riskiekvivalentisti yhtiön osakkeesta ja luottoriskistä riippuvaisiin instrumentteihin, mikäli hinnoitteluvirhe onnistutaan havaitsemaan rakenteellista luottoriskimallia hyödyntämällä. Olettaen, että käytetty luottoriskimalli tuottaa luotettavia signaaleja pitäisi hankittujen instrumenttien nettotuoton olla positiivinen, kun hinnoitteluvirhe markkinoilla korjautuu. Tässä tutkielmassa tarkastellaan sekä signaaleja tuottavaa rakenteellista luottoriskimallia että strategian toteuttamista käytännössä.

Tutkimusongelma rakentuu kahden osa-alueen varaan. Ensinnäkin tavoitteena on testata millaisia tuloksia Merton (1974) Moody’s KMV -luottoriskimallilla ja sen erilaisilla kalibraatiometodeilla on mahdollista saavuttaa pääomarakennearbitraasiin keskittyvässä viitekehyksessä. Tämän lisäksi analysoidaan uutta strategian toteutusmetodia, jossa hyödynnetään varianssin (varianssiswap) ja luottoriskin vaihtosopimuksia. Tulokset lasketaan otoksesta, joka koostuu 102 eurooppalaisesta yrityksestä ja joka ulottuu elokuusta 2011 aina heinäkuuhun 2019 saakka. Jotta lähestymistavan tehokkuutta voidaan kommentoida, vertaillaan tuloksia aikaisemmissa tutkimuksissa käsiteltyihin tuloksiin.

Tulokset osoittavat, että markkinoilta johdetun informaation ja Studentin t-jakauman käyttö normaalijakauman sijaan luottoriskimarginaaleja laskettaessa johtavat keskimäärin korkeampiin strategiatuottoihin ja parantuneeseen ennustetarkkuuteen. Lisäksi huomataan, että varianssin vaihtosopimukset toimivat strategiaa toteutettaessa osakkeita vastaavalla tavalla. Soveltuvimman strategiavariantin kuukausittaisista ylituotoista laskettu Sharpen luku kustannusten jälkeen on 0,43 ja 0,59 välillä riippuen strategian toteutustavasta. Tulosten valossa voi siis todeta, että Merton (1974) Moody’s KMV -malliin nojaavilla luottoriskiennusteilla ja varianssin vaihtosopimuksiin pohjaavalla strategialla voidaan saavuttaa tuloksia, jotka ovat linjassa aikaisempien tutkimustulosten kanssa kanssa.

Asiasanat	Pääomarakennearbitraasi, Mertonin malli, Moody’s KMV, varianssiswap, CDS
Muita tietoja	

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ON CAPITAL STRUCTURE ARBITRAGE

Analyzing the Effects of Structural Credit Risk Model Calibration and Equity Variance Hedging

Master's Thesis
in Accounting and Finance

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1 INTRODUCTION

1.1 Background

Before the financial meltdown of 2008, Boaz Weinstein – a renowned chess grandmaster and the youngest-ever managing director at the global investment bank behemoth Deutsche Bank – was in charge of an internal trading group focusing on market making and proprietary trading in a variety of credit and equity instruments. His group, called Saba, had been extremely successful during an era characterized by the wild rise of proprietary trading schemes backed by major investment banks. Weinstein and his fellow trades reportedly raked in annual profits between $600 and $900 million during the years 2006 and 2007 alone. In the preceding eight-year period, returns were also significant and consistently positive. Dubbed as the world's best credit trader, Weinstein specialized in a strategy called capital structure arbitrage in which relative value positions are formed to benefit from misalignments in the pricing of firms' capital structures. In this study, this somewhat mysterious strategy and its profitability are analyzed by combining a new post-financial crisis sample consisting of 102 European obligors with a novel implementation methodology. Coming back to Mr. Weinstein, the year 2008 turned out to be catastrophic for him and for his team as losses of approximately $1.8 billion occurred. (Wall Street Journal 2009; Saba Capital 2020) Based on this anecdotal evidence, it seems that the strategy exhibits characteristics similar to tail risk insurance selling. This question, and many others, are addressed in this master's thesis.

Capital structure arbitrage, sometimes called credit arbitrage or credit-equity trading, belongs to the class of fixed income arbitrage strategies where the aim is to identify and ultimately take advantage of temporary mispricings between company's equity and debt instruments (Duarte, Longstaff & Yu 2006, 787-788; Yu 2006, 47). The development of the credit derivatives market accompanied by the belief among practitioners that cross-asset pricing misalignments can occasionally occur led to the wide-spread usage of this strategy among hedge funds and proprietary trading desks at the beginning of this millennium (Ju, Chen, Yeh & Yang 2015, 90; Wojtowicz 2014). Before the development of credit default swaps (CDS), market participants used bonds and equities to utilize these opportunities. Later, however, bonds were often replaced with credit default swaps due to their appealing characteristics when it comes to risk and liquidity (Ju et al. 2015, 90).

In this thesis, the focus will be on CDS-based capital structure arbitrage. A typical strategy of this kind relies heavily on a structural credit risk model that takes as inputs company's liabilities and the market value of its equity. The output, on the other hand, is a default measure or a credit spread. The most famous structural credit risk model is the one developed by Merton (1974), which sees a firm's equity as a European call option on its total assets. This revelation enables the use of Black & Scholes (1973) type of framework when deriving the default probability measure. To iterate the strategy implementation further, one can now utilize the Merton (1974) model default measure and calculate a synthetic CDS spread. By comparing this synthetic CDS spread to market quotes, it is possible to engage in trades that would be profitable in the case of convergence. For example, if the synthetic CDS spread is notably higher than the market quote, that would imply – assuming that the model is correct – that the equity market has a more negative view on company's credit quality compared to the CDS market. If the equity market is assumed to be correct in its view, the rational move would be to buy protection from the CDS market. If the market spread eventually converged with the synthetic quote, the mark-to-market of the position would in this case be positive. In a situation where a market participant does not want to address which market is pricing the risk correctly, a position can be taken on both markets by using a predefined hedge ratio to correctly scale the two trades. (Yu 2006, 47)

The enthusiasm that capital structure arbitrage sparked at the beginning of this millennium has encouraged academics to analyze the execution and profitability of this strategy rather thoroughly (see Yu 2006, Duarte et al. 2006, Bajlum & Larsen 2008, Imbierowicz & Cserna 2008, Wojtowicz 2014, Ju et al. 2015, Huang & Luo 2016 and Zeitsch 2017). The overall results of these studies are supportive of the strategy. Still, many of these studies highlight the risks that arise from single positions that end up diverging instead of converging. In light of this evidence, it is essential to understand that this strategy is far from being a textbook example of arbitrage since the positions are based on a model that can be calibrated and adjusted in many ways. Lastly, instrument level strategy execution naturally affects the results regarding profitability. Earlier studies focus on trading equities relative to credit default swaps, while some of the latest research looks into equity options as a possible substitute. The rationale behind the use of equity options is to hedge the CDS leg against fluctuations in option implied equity volatility instead of hedging the effects of equity price movements. In option jargon, this would translate into hedging vega instead of delta. If only the correlations between changes in equity prices or implied volatility against CDS spreads are looked at, no large differences can be observed. However, the sensitivity between the CDS spread and option-implied equity volatility is several orders of magnitude higher than the sensitivity between CDS spreads and equity prices. (Zeitsch 2017, 8;12) Given this information, smaller and less capital intensive positions are needed to hedge the CDS positions if instruments linked to equity volatility are used.

To take this vega hedging approach a one step further, variance swaps are analyzed in this thesis instead of equity options. Briefly, variance swaps are over-the-counter derivatives that enable the investor to take views on future realized volatility against current implied volatility (Bossu 2006, 50). Compared to options, variance swaps provide a purer exposure to future volatility or, technically, to future variance.[1] Thus, variance swaps are the most fitting instrument to truly test if the vega hedging approach should be considered as a valid alternative to its more traditional delta hedging counterpart.

1.2 Research problems

The research problems aimed to be addressed in this study can be divided into two broad categories, namely into the model and strategy-specific problems. Let us start with the model-specific ones. The structural model of choice in this thesis is the Merton (1974) model mentioned above. To ultimately calculate default probabilities for the synthetic CDS spread, the methodology of Moody's KMV is applied.[2] In itself, it is interesting to analyze the Moody's KMV Merton (1974) model in a capital structure arbitrage setting since typically the CreditGrades model is selected in previous studies (see, e.g., Yu 2006, Duarte et al. 2006, Bajlum & Larsen 2008 and Wojtowicz 2014).[3] Furthermore, it has been well documented that the Merton (1974) model generally produces credit spreads that are significantly lower compared to market spreads (see, e.g., Ogden 1987, Lyden & Saraniti 2001 and Eom, Helwege & Huang 2004). In order to address this issue, among others, various model calibration methodologies are analyzed in terms of mean spread estimation errors.

It can be said that the most critical consideration in the calibration process is the choice of equity volatility. In order to solve the latent model parameters such as asset volatility, an estimate of equity volatility has to be provided. Typically, average historical volatility has been used in the calibration (see, e.g., Yu 2006,

[1] The contract is based on variance or volatility squared instead of volatility due to valuation and hedging reasons (Demeterfi, Derman, Kamal & Zou 1999, 3).

[2] Regarding Moody's KMV, see Crosbie & Bohn (2003).

[3] For a detailed description of the CreditGrades model, see Finger, Finkelstein, Lardy, Pan, Ta & Tierney (2002).

Imbierowicz & Cserna 2008 and Bajlum & Larsen 2008). This simple approach, however, produces spreads that are not sensitive to changing market conditions. To improve the accuracy and sensitivity of the synthetic spread, deep out-of-the-money put implied volatility alongside with variance swap rates are used in this thesis, and thus compared to results generated with historical volatility. Compared to deep out-of-the-money or at-the-money implied volatilities, variance swap rates reflect implied volatility given the whole range of strikes, thus incorporating all the information contained in the volatility surface. Overall, the relationship between CDS spreads and option-implied volatilities have been studied extensively by, for example, Carr & Wu (2009). When determining the unknown credit parameters, i.e., calibrating and eventually solving the structural model parameters, practitioners and academics alike argue that by utilizing the equity options market instead of just the equity market, more accurate results can be achieved (Elkhodiry, Paradi & Seco 2011, 46). Moreover, in capital arbitrage studies in which implied volatility is used to calibrate the structural model, the achieved synthetic spread accuracy seems promising (see, e.g., Zeitsch 2017).

As said, volatility calibration plays a key role in terms of model accuracy and responsiveness. However, the distribution used to determine default probabilities has an essential role as well. With the Moody's KMV model applied in this study, the simplest solution is to rely on the normal distribution, as is the case in the capital structure arbitrage study conducted by Zeitsch (2017). Nevertheless, Crosbie & Bohn (2003) already note that this simple approach does not come without its drawbacks. The fact that the total asset value representing a point of default for the obligor, also known as the default barrier, is indeed random undermines the underlying assumption regarding the deterministic relationship between default probabilities and the Merton (1974) model default measures. Further, Crosbie & Bohn (2003) highlight that the empirical default distribution exhibits fatter tails and hence higher kurtosis than the normal distribution. To avoid these above mentioned pitfalls, Crosbie & Bohn (2003) utilize a proprietary empirical distribution to map default probabilities. In this thesis, the aforementioned challenges are combated and analyzed by taking advantage of the Student's t-distribution, and then testing whether model accuracy and strategy returns are affected. Additionally, a fully risk-neutral calibration, i.e., a calibration which only relies on market-implied data instead of historical figures, is tested. In this approach, not only volatility calibration is risk-neutral, but also, the default barrier is derived in a risk-neutral manner. This is done by following the novel methodology introduced by Zeitsch (2017). By taking advantage of the risk-neutral default barrier, obligors with unusual capital structures, such as financials, can be included in the sample, and thereby it is feasible to test the methodology's effectiveness.[4]

Put more formally; the model-specific research questions are the following:

- Is the Merton (1974) Moody's KMV model comparable to other applied models in terms of model accuracy and strategy profitability?
- Does the use of implied volatility and variance swap rates improve model responsiveness compared to historical volatility?
- How the use of t-distribution instead of the normal distribution affects model accuracy?
- What is the impact experienced by applying a risk-neutrally calibrated default barrier? Does it improve results especially with financials?

Moving on to the other main focus of this thesis, i.e., to strategy-specific research problems. Consequently, strategy returns are intertwined with the tested model calibration methods because unbiased trading signals play an essential role in a successful implementation. Hence, these two focus areas should not be analyzed in isolation. Considering that in most of the previous capital structure arbitrage studies stocks are used to hedge the CDS positions, the use of equity variance as a substitute can be seen as the most exciting theme in terms of strategy execution. Even though Carr & Wu (2009) highlight that there is a clear connection between CDS spreads and implied volatility, the equity volatility component has not been thoroughly introduced as a part of the trading strategy. In previous studies, only Zeitsch (2017) uses equity options as the equity leg with promising results. For two specific reasons, it is intriguing to take advantage of variance swaps in both model calibration and strategy execution. First, the prevailing variance swap rate for a particular tenor is calculated by forming a well-defined options portfolio that contains puts and calls from all available strike prices. This way, all the information in the equity volatility surface at that tenor range is summarized by one number. By utilizing this risk-neutral option implied measure, the calibrated structural model should, in theory, better reflect the views of the equity options market as a whole when compared to at-the-money or out-of-the-money option implied volatilities. Second, with variance swaps, a profit and loss profile genuinely dependent on the difference between implied and realized variance can be achieved. The issue with delta-hedged option positions is that the volatility

[4] In many capital structure arbitrage studies, financials and utilities are excluded from the sample (see, e.g., Yu 2006, Wojtowicz 2014 and Huang & Luo 2016).

exposure is not pure, but instead, mostly path-dependent (Allen, Einchcomb & Granger 2006).

Other strategy-specific problems revolve around implementation methods and return characteristics. In the empirical part, individual holding period returns are analyzed as well as monthly aggregate returns. With all the tested models, different strategy implementation methods are considered for testing the robustness of the results. Moreover, different trading triggers that symbolize the threshold to open a trade are tested. To evaluate if the returns are dependent on the obligor's credit quality, a sample consisting of 102 European obligors is divided into two sub-samples. Finally, monthly strategy excess returns are regressed on common market risk factors to understand whether returns arise from exposures to the general market. Now, strategy-specific questions can be expressed as follows:

- Can a capital structure arbitrage strategy relying on vega hedging be considered as an alternative to the more traditional delta hedging approach?
- How model calibration methodology affects holding period and monthly return characteristics?
- Can common market risk factors explain monthly excess returns of the strategy?

1.3 Limitations of the study

Commenting on the limitations of this thesis, few mentionable themes come to the forefront. From a model perspective, only the Merton (1974) Moody's KMV model is analyzed thoroughly in this study. As with other studies such as Imbierowicz & Cserna (2008) and Ju et al. (2015), where multiple models are tested with the same sample, this is not done here. When comparing the Merton (1974) Moody's KMV model to other models, this is done by solely relying on the information provided by previous studies. With strategy implementation, only the vega hedge approach is tested. Corresponding to the practice with model comparisons, previous studies are used as a benchmark.

To simplify the empirical analysis, only a strategy utilizing six-month variance swaps is tested with all the model variants. Additionally, the maximum holding period is set to 180 days with all the tested strategies. This practice is in contradiction with previous studies where different maximum holding periods were analyzed as well. Again, this is done to simplify the analysis and to match the traded tenor with the selected maximum holding period. On a theoretical level, a closer link between the model calibration inputs and the traded instruments should lead to improved performance. Using shorter than the six-month tenor implied volatilities and variance swap rates in the model calibration leads to a mismatch between the trading signal and traded instruments. A mismatch of this sort could ultimately undermine the strategy's profitability.

Moreover, there are some challenges that arise from the use of variance swaps. Because the instrument only trades over the counter, the actual market quotes are somewhat invisible. However, relying on quotes constructed from prevailing option prices, an educated guess of the market price can be made. In this thesis, the variance swap data is sourced from Bloomberg. To implement the described strategy in practice, a broad network of broker-dealers should be utilized to get updated market quotes for the companies in the trading universe. As imaginable, this kind of arrangement is only attainable for large and sophisticated institutional investors.

Finally, partly due to the selected strategy implementation methodology and long trading window, the sample size is small compared to previous studies. To cover the sample starting from August of 2010 and ending in July 2019, many otherwise suitable obligors are excluded from the company universe. The second factor narrowing down the sample size is the availability of variance swap data. Nevertheless, these filters lead to a sample consisting of large European companies with both liquid CDS and options market, thus promoting the economic significance of this study.

1.4 Structure of the thesis

The thesis is structured as follows. The three following chapters focus on the relevant theoretical background. More specifically, the Merton (1974) model is discussed in detail. Concepts regarding its risk-neutral calibration, default probability, and hedge ratio determination are covered. Then, the focus shifts to capital structure arbitrage strategies and preceding studies from that field. Lastly on the theoretical front, credit default and variance swaps are discussed since these instruments are used in the execution of the strategy later in this study. The fifth chapter covers data and methodology. Empirical results are then presented in chapter six, and finally, conclusions are presented thereafter.

2 MERTON MODEL AND RISK-NEUTRAL CALIBRATION

2.1 Overview of the model

Credit risk can be defined as the risk that an obligor loses some or all of the funds that were borrowed to the creditor. If contractual payments cannot be made on time, this constitutes a default on the creditor's side. A default can also occur similarly in a credit derivative contract when the counterparty is unable to deliver the payment specified in the terms of the contract. (Hull 2012, 521) If one desires to calculate the credit risk of the creditor or the counterparty, one must determine the probability of default for that entity. To calculate the probability of default (PDF), either reduced-form or structural credit risk models can be used. Reduced-form models are formulated around the assumption that credit events occur randomly, and that the main driver behind default is an exogenous factor. The randomness in these models is commonly built around a Poisson process.[5] (Chatterjee et al. 2015, 13) Unlike reduced-form models, structural credit risk models consider the balance sheet of the company in question, and see the default arising from endogenous factors instead. The pioneering model in this class of credit risk models is the Merton (1974) model. (Elkhodiry et al. 2011)

The focus of this study is on the Merton (1974) model partly due to its simplicity, but also due to its theoretical implications given the capital structure arbitrage setting at hand. Here, the purpose is to utilize the model to calculate default probabilities for different entities. To emphasize, the model is not used to calculate credit spreads but rather to produce probability estimates that can be later used as an input when calculating the synthetic credit default swap spreads. Since financial derivatives such as CDS contracts and options are priced under the risk-neutral measure, the Merton (1974) model is later calibrated so that risk-neutrality will not be violated. This is achieved by following the methodology discussed mainly by Zeitsch (2017), where the asset drift μ is assumed to equal the risk-free rate r. Additionally, asset volatility, i.e., volatility of the asset value, and the default barrier – an asset value level signifying a point of default – are calibrated without the use of historical or real-world probabilities. Nevertheless, a model calibrated with historical volatility is also tested to see whether the risk-neutral model calibration methodology is genuinely preferable. Next, the Merton (1974) model, its assumptions, and derivation are covered in detail. Then, as-

[5]For more about reduced-form models, see, e.g., Jarrow & Turnbull (1995).

set volatility and default barrier are defined so that default probabilities can be discussed, and eventually calculated.

To get a more thorough understanding of the Merton (1974) model, let us consider a scenario where a firm consists only of a single zero-coupon bond that matures at time T, and of an equity security that is the residual claim on the firm's total assets V. In this specification, the firm can only default at time T. If the company is not able to return the principal of the bond at time T, all the remaining assets will be owned by the bondholder. In the case of default, the equity holder will receive nothing. If the firm can make the principal payment at time T, the equity holder is entitled to the assets that remain after the payment. Additionally, it must be assumed that the company will not issue new debt that outranks the outstanding claim and will not pay dividends or engage itself in stock buybacks before time T. Now, let us additionally assume that the firm's asset dynamics follow geometric Brownian motion and can be written

$$dV_t = rV_t + \sigma_V V_t dW_{t,\mathbb{Q}}, \tag{1}$$

where V_t is the value of the firm's total assets at time t, r is the risk-free rate, σ_V is the asset volatility and dW_t is the Wiener process under risk-neutral probability measure $\mathbb{Q}$.[6] (Merton 1974, 450-453) Both r and σ_V are regarded as constants. Suppose that the value of the zero-coupon bond B is dependent only on the value of the firm and time. The price of the bond is now given by $B = F(V, t)$ and the following stochastic differential equation represents the dynamics of its return process

$$dB_t = \alpha_B B_t + \sigma_B B_t W_t, \tag{2}$$

where α_B is expected return of the bond during a specified period, e.g., during a year, B_t is the value of the bond at time t, σ_B is the volatility of the bond and W_t is the standard Wiener process under real-world probability measure $\mathbb{P}$.

By using the Itô–Döblin theorem, Equation (2) can be written

$$dB_t = \left[\frac{1}{2}\sigma^2 V^2 F_{VV} + \alpha V F_V + F_t\right] dt + \sigma V F_V dW_t, \tag{3}$$

where F_V, F_{VV} and F_t stand for partial derivatives with respect to V and t. (Merton 1974, 451) To simplify notation, subscript t is omitted from the total asset value V. Following the replication argument[7] of Merton (1973) which can be used to prove the Black & Scholes (1973) model, and by simplifying, Equation (3)

[6]The dynamics of the asset value process are presented under the assumption of risk-neutrality.
[7]For the full derivation, see Merton (1973, 165) or Merton (1974, 452–453).

can be formulated as follows

$$\frac{1}{2}\sigma^2 V^2 F_{VV} + rVF_V - rF - F_\tau = 0, \tag{4}$$

where $\tau = T - t$ is the time to maturity and $F_t = -F_\tau$. (Merton 1974, 453) To solve this equation, one must first define an initial condition and two boundary conditions. In this specification, $V \equiv F(V,\tau) + f(V,\tau)$, where $f(V,\tau)$ is the value of equity and thus can expressed $f(V,\tau) = S_\tau$. Since neither the value of debt or equity can be negative, the first boundary condition takes the following form

$$F(0,\tau) = f(0,\tau) = 0. \tag{5}$$

Due to the fact that $F(V,\tau) \leq V$, the second boundary condition is (Merton 1974, 453)

$$\frac{F(V,\tau)}{V} \leq 1. \tag{6}$$

The initial condition arises from the assumptions that were laid out earlier. If $V > F(V,0)$, the firm will pay back the zero-coupon bond and due to the residual claim of the equity holder, the value of equity is $f(V,0) = V - F(V,0) = V - B$. In a scenario where $V < F(V,0)$, the debt holder would take control of all remaining assets of the firm and the equity value would simply be zero. Based on this logic, at time $\tau = 0$ the initial condition for the value of debt is simply (Merton 1974, 453)

$$F(V,0) = \min[V,B].$$

Given these conditions, it would be possible to solve the value of debt, and eventually, the unknown asset value, but instead of doing that, a more common approach can be utilized. Let us focus on the value of equity more closely. To formalize the residual claim and limited liability that the equity holder possesses, we write $f(V,\tau) = \min[0, V - F(V,\tau)]$. By rewriting the Equation (4) so that $F(0,\tau) = f(0,\tau)$, the partial differential equation for equity is naturally

$$\frac{1}{2}\sigma^2 V^2 f_{VV} + rVf_V - rf - f_\tau = 0, \tag{7}$$

and correspondingly, the initial condition is given by

$$f(V,0) = \max[0, V - B].$$

To get the boundary conditions for this partial differential equation, we replace $F(0,\tau)$ with $f(0,\tau)$ and rewrite the boundary conditions (5) and (6). (Merton 1974, 453)

By manipulating the initial representation of the value of debt, we have now ended up with an equation and boundary conditions that match the ones presented by Black & Scholes (1973).[8] The European call valuation methodology in Black & Scholes (1973) is now extended into the valuation of the firm's total assets. The nominal debt amount B takes the place of the strike price, and asset value V is naturally the underlying asset of the contract. Equity value $f(V, \tau)$ can be written in the following well-known form when σ_V is assumed to be a constant (Merton 1974, 453–454)

$$f(V, \tau) = V\Phi(d_1) - Be^{-r\tau}\Phi(d_2), \tag{8}$$

where

$$\Phi(d) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{d} e^{-\frac{1}{2}z^2} dz,$$

and

$$d_1 = \frac{\ln\left(\frac{V}{B}\right) + \left(r + \frac{1}{2}\sigma_V^2\right)\tau}{\sigma_V\sqrt{\tau}} \tag{9}$$

$$d_2 = d_1 - \sigma_V\sqrt{\tau}. \tag{10}$$

In order for the model to hold, certain assumptions need to be made. These include the so-called perfect market assumptions, and the possibility to trade continuously, the idea proposed by Modigliani & Miller (1958) that firm's value does not depend on its capital structure, flat term structure of interest rates, and that the asset value follows the dynamics presented in Equation (1). Most of these assumptions can be relaxed. However, assumptions regarding continuous trading and asset value process are essential. (Merton 1974, 450)

The primary critique of the model has been circulating around the low credit spreads, i.e., corporate bond prices, it produces. In the class of high yield bonds, the pricing errors are even more pronounced compared to investment-grade bonds. (Eom et al. 2004, 499) Research has focused on the relatively unrealistic assumptions of the model, and after the publication of Merton's (1974) seminal paper, many papers that introduce alternations to the original model have been published. Among the most notable pieces of research are Black & Cox (1976), Geske (1977), Longstaff & Schwartz (1995), Leland & Toft (1996) and Collin-Dufresne & Goldstein (2001).

Black & Cox (1976) introduce the idea that restructuring might take place before the maturity of the bond. Geske (1977), on the other hand, incorporated coupon paying bonds into the analysis. Longstaff & Schwartz (1995) use stochastic interest rates and assume a constant recovery rate[9] while Leland & Toft (1996)

[8] Equation (7) and the boundary conditions presented here match the Equations (7) and (8) in Black & Scholes (1973, 643).

[9] Recovery rate is the value of the liability given default. They are typically quoted as a fraction of the principal of the liability in question.

create a model in which the firm issues regularly new debt with a fixed maturity. In the Leland & Toft (1996) model, the equity holders can issue new equity to cover the debt payments or simply default on their obligations. Furthermore, Collin-Dufresne & Goldstein (2001) base their model on the findings of Longstaff & Schwartz (1995) and restrict the amount of leverage by using a stationary leverage ratio. Now one might ask whether these alternative representations perform better than the original model. Eom et al. (2004) analyze the aforementioned alternative models in detail, and find that all of the models produce on average significant prediction errors compared to credit spreads of non-callable corporate bonds.

In this thesis, the model of choice is the original Merton (1974) model even though some of its assumptions are indeed relatively unrealistic. As was highlighted by Eom et al. (2004), the spread prediction accuracy of the more sophisticated models was weak as well. Hence, the use of some alternative structural model in this study cannot be seen to be the most relevant choice available. The aim here is not to use the Merton (1974) model in spread prediction but instead in default probability determination, and thus the focus will be on model calibration and parameter selection. Next, these aspects are discussed in detail.

2.2 Asset volatility and the default barrier

Continuing with Equation (8), it can be observed that the value of the call $f(V, \tau)$ is already known since it represents the market capitalization of the firm. Conversely, the face value of debt B, in Merton's specification, is not as straight forward to characterize because it can be defined in two ways when dealing with real-world applications. First, it can be seen as the firm's total liabilities, and thus a simple balance sheet value can be used. Alternatively, though, the parameter can be said to represent an asset value level that signifies default. If the firm's asset value drops significantly and hits this so-called default barrier, the firm is in default. To calculate an estimate for the firm value V at time t, parameter B must first be determined. Another latent and also the most important parameter in the model is asset volatility σ_V which appears in Equations (9) and (10) (Zeitsch 2017, 8). In this section, these parameters are discussed, starting with asset volatility, and then moving on to a more granular presentation of the default barrier.

In asset volatility determination, multiple different methodologies can be used. However, only the three most fundamental methods are covered here; those being the proxy method, maximum likelihood method, and the volatility restriction method (see, e.g., Li & Wong 2008). The proxy method, first introduced by Jones, Mason & Rosenfeld (1984), relies on an asset value approximation calculated from market values and book values alike. After asset value estimates have been calculated covering a certain period, a time series can be constructed, and then the volatility of assets calculated. The maximum likelihood methodology, initially proposed by Duan (1994), builds on the assumption that the firm value follows a log-normal distribution. Hence, asset volatility can be determined by maximizing the suggested likelihood function. Finally, the volatility-restriction method, which, according to Li & Wong (2008), is the most popular method used in structural models, is implemented by simultaneously solving two equations that originate from the Merton (1974) model. Following the methodology pioneered by Ronn & Verma (1986), the two equations are

$$S_t = C_{\text{Black–Scholes}}[V_t, \sigma_V, \tau, B_t, r] \tag{11}$$

and

$$\sigma_S = \left(\frac{V_t}{S_t}\right)\frac{\partial S_t}{\partial V_t}\sigma_V \tag{12}$$

where S is the equity market capitalization. Equation (11) corresponds with the definition of equity value given by the Merton (1974) model, and Equation (12), on the other hand, can be derived by applying the Itô–Döblin theorem and following the assumption that the value of the firm's equity is dependent only on the firm value V and time to maturity τ. Now, asset volatility and ultimately the asset value can be solved by first estimating equity volatility σ_S and then finding a solution that satisfies these equations. This iterative procedure is repeated at each time point when asset volatility and asset value must be calculated. Given the popularity of the volatility restriction method, it is crucial to understand its challenges. Firstly, it violates the assumption of constant volatility in the Merton (1974) model (Li & Wong 2008, 754). Additionally, as Duan (1994) notes, the major issue with this methodology is the underlying proposition that Itô–Döblin theorem and related assumptions must hold at every time point. This proposition, however, is hardly true since equity prices might exhibit sudden and relatively large jumps.

In this thesis, a somewhat similar methodology introduced by Zeitsch (2017) is followed. Starting with Equation (12) as an initial representation, let us define essential boundary conditions for the asset value V_t at time t. Firstly, the following must hold

$$V_{t|S_t=0} = B'(t,T), \tag{13}$$

where $B'(t,T)$ denotes the default barrier, which depends on current time t and certain maturity T. To express Equation (13) more intuitively, one can think that if the market capitalization of the firm at time t is zero, then all that is left is the value indicated by the default barrier. Further, Equation (13) represents the behavior of firm value near default.

The second boundary condition reflects the dynamics of V_t when the firm's capital consists mostly of equity. Put mathematically, if S is significantly larger than $B'(t,T)$ and assuming that

$$\lim_{B'(t,T)\to 0} \frac{S_t}{V_t} = 1,$$

and by extending this so that

$$\lim_{B'(t,T)\to 0} \frac{\partial S_t}{\partial V_t} = 1$$

we have the second boundary condition. In the expressions above, lim denotes limit. By taking the first-order approximation of Equation (13) at $B'(t,T)$, we get

$$V_t \approx B'(t,T) + \frac{\partial V_t}{\partial S_t} S_t.$$

As noted by Zeitsch (2017), a simple representation that respects these boundary conditions is given by

$$V_t \approx B'(t,T) + S_t. \tag{14}$$

Now, by combining Equation (12) with the representation in Equation (14), asset volatility σ_V takes the following form

$$\sigma_V = \sigma_S \frac{S_t}{S_t + B'(t,T)}. \tag{15}$$

This expression is used to calculate asset volatility later in this study. The formula derived by Zeitsch (2017) is equivalent to the one by Finger et al. (2002), which is used as a part of the CreditGrades methodology.[10] To eventually calculate the asset volatility, estimates for the default barrier $B'(t,T)$ and equity volatility σ_S must be given.

Now, let us focus on the equity volatility parameter a little more thoroughly. In the original Merton (1974) paper, the use of historical equity volatility is suggested for the calibration. Similarly, in the CreditGrades methodology, equity volatility is calibrated with historical volatility based on an estimation window of 1000 days

[10] CreditGrades is a quantitative credit assessment model developed together with Deutsche Bank, Goldman Sachs, JPMorgan, and RiskMetrics Group. It can be seen as a contender for the Moody's KMV methodology.

(Finger et al. 2002, 19). As noted by Zeitsch (2017), the use of historical equity volatility dampens the model's responsiveness to recent equity volatility and hence leads to an underestimation of the CDS spread. Since the goal of this thesis is to construct a model that swiftly identifies trading opportunities, the role of model responsiveness cannot be undermined.

To address this issue, implied volatility from equity options can be utilized. Given the aim to risk-neutrally calibrate the Merton (1974) model, the use of option-implied volatility is essential since it can be seen as a risk-neutral value which importantly incorporates the volatility risk premium as well (see Figlewski 2016 and Carr & Wu 2008). Moreover, it is well established in prior literature that if information from equity options is used when estimating credit-related information, results undergo a significant improvement (Elkhodiry et al. 2011, 69). For example, Bharath & Shumway (2008) find that the use of option-implied volatility instead of historical equity volatility substantially improves the out-of-sample default forecasting accuracy of the Merton (1974) model. Furthermore, studies have shown that there exists a clear link between credit spreads and option-implied volatility (see, e.g., Carr & Wu 2009 and Elkhodiry et al. 2011). This link translates into reliable results when implied volatility is used to estimate CDS spreads (Cao, Yu & Zhong 2010 and Cao, Yu & Zhong 2011). Due to this strong empirical backing, option implied volatility is primarily used to calibrate the equity volatility σ_S parameter later in this thesis.

Moving on to the derivation of the default barrier, it can be seen that the default barrier plays a role in the asset volatility calculations. However, the importance of this parameter is not comparable to the one of asset volatility (Afik, Arad & Galil 2012, 4). In many of the previous studies, the default barrier is assumed to be a constant that consists of short term and half of the company's long term debt (see, e.g., Crosbie & Bohn 2003 and Vassalou & Xing 2004).[11] Random default barrier methodologies have also been used in order to generate spreads that could closely match the market spreads (see, e.g., Finger et al. 2002). For example, Elkhodiry et al. (2011) find supportive evidence towards using a random default barrier in credit spread determination. Here, the novel approach of Zeitsch (2017) is followed. This default barrier model can be said to belong to the group of random default barrier models.

Starting with Equation (13), and assuming that it holds when S approaches

[11] For more about the constant default barrier, see Longstaff & Schwartz (1995) and Leland & Toft (1996).

zero we get

$$\lim_{S_t \to 0} V_t = B'(t,T).$$

The aim is to find an asset value level that signifies a point of default given the asset value dynamics defined in Equation (1), a predefined maturity T, total liabilities B_t, risk-free rate r and asset volatility σ_V. Once again, it is possible to use Black & Scholes (1973) methodology to solve this problem.

The first step in this iterative procedure is to set an initial value for the default barrier $B'(t,T)$. Assuming that loss given default (LGD) is 60% of total assets, one could use the following estimate

$$B'_1(t,T) = B_t \times 0.6,$$

where the subscript 1 represents the iteration step. Next, this estimate must be used to calculate asset volatility σ_V with Equation (15). Then, by continuing this iteration procedure, a solution for $B'(t,T)$ must be found that satisfies

$$\lim_{B'(t,T) \to 0} C_{\text{Black–Scholes}}[B'_i(t,T), \sigma_V, \tau, B_t] \approx 0, \tag{16}$$

where $C_{\text{Black–Scholes}}$ refers to the formula of a long European call by Black & Scholes (1973), and in this instance is defined by

$$f(B'_i, \tau) = B'_i(t,T)\Phi(d_1) - B_t e^{-r\tau}\Phi(d_2),$$

where $\tau = T - t$ and

$$\Phi(d) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{d} e^{-\frac{1}{2}z^2} dz,$$

and

$$d_1 = \frac{\ln\left(\frac{B'_i}{B_t}\right) + \left(r + \frac{1}{2}\sigma_V^2\right)\tau}{\sigma_V \sqrt{\tau}}$$

$$d_2 = d_1 - \sigma_V \sqrt{\tau}.$$

Moreover, i in the subscript denotes iterative step i.

This novel methodology, introduced by Zeitsch (2017), allows us to define the risk-neutral default barrier. By defining the default barrier in this manner, it is allowed more accurately to reflect changing market dynamics and thus change daily. Market responsiveness is further amplified by the use of implied volatility measures when the asset volatility is calibrated. It is important note however, that because the Black & Scholes (1973) formula is a set of non-linear non-negative equations, the root of Equation (16) must be approximated. This is accomplished by utilizing the Broyden method and assuming an over 99% drop in the market capitalization of the firm. For more about the Broyden method, see Dennis Jr & Schnabel (1996).

2.3 Default probabilities in the Merton model

To price credit default swap contracts (CDS), one has to provide probabilities of default for different maturities so that the CDS spread at time t can be calculated. In this section, the default probability calculation methodology based on Moody's KMV methodology is covered (see, Crosbie & Bohn 2003). As said, the methodology relies on the Merton (1974) model and was initially developed by the KMV company founded by Stephen Kealhofer, John McQuown, and Oldřich Vašíček. In 2002, the company was acquired by Moody's, hence the name Moody's KMV. (Moody's 2019) The parameters derived earlier are linked to the presentation shown here. Additionally, relevant studies regarding the model's robustness and forecasting capabilities are discussed.

Starting with the definition of probability of default, we can write

$$p_t = \mathbb{P}[V_t \leq B'(t,T) \mid V_{t=0} = V_t] = \mathbb{P}[\ln V_t \leq \ln B'(t,T) \mid V_{t=0} = V_t], \tag{17}$$

where p_t denotes the probability of default by time t, V_t follows dynamics presented in Equation (1) and is given by Equation (14) and $B'(t,T)$, on the other hand, is defined in Equation (16). (Crosbie & Bohn 2003, 17; Zeitsch 2017, 5) Given the dynamics in Equation (1), the value of assets at time t is

$$\ln V_t = \ln V_{t=0} + \left(r - \frac{\sigma_V^2}{2}\right)t + \sigma_V \sqrt{t}\epsilon,$$

where r is the risk-free rate, σ_V is the asset volatility in Equation (15), and $\epsilon \sim N(0,1)$. Taking $\ln V_t$ and substituting it in Equation (17) yields

$$p_t = \mathbb{P}\left[\ln V_t + \left(r - \frac{\sigma_V^2}{2}\right)t + \sigma_V \sqrt{t}\epsilon \leq \ln B'(t,T)\right].$$

By rearranging we get

$$p_t = \mathbb{P}\left[-\frac{\ln \frac{V_t}{B'(t,T)} + \left(r - \frac{\sigma_V^2}{2}\right)t}{\sigma_V \sqrt{t}} \geq \epsilon\right].$$

Since $\epsilon \sim N(0,1)$, we can see that

$$p_t = N\left[-\frac{\ln\frac{V_t}{B'(t,T)} + \left(r - \frac{\sigma_V^2}{2}\right)t}{\sigma_V\sqrt{t}}\right], \tag{18}$$

where N denotes the cumulative normal distribution. (Crosbie & Bohn 2003, 17–18; Zeitsch 2017, 5) From this expression, the so called distance-to-default (DD) is given by

$$DD = \frac{\ln\frac{V_t}{B'(t,T)} + \left(r - \frac{\sigma_V^2}{2}\right)t}{\sigma_V\sqrt{t}},$$

which is the number of standard deviations that asset value must decrease before hitting the default barrier.

Looking back at Equation (18), it is important to address the implicit assumption about the existence of a deterministic relationship between the default probability and the DD measure (Campbell, Hilscher & Szilagyi 2008, 2914). Empirically, however, this does not seem to hold because the point of default in terms of asset value is in itself random. To handle this somewhat unrealistic assumption, a specific distance to default value is mapped to a default probability based on historical data in the original Moody's KMV model. (Crosbie & Bohn 2003, 18) Moreover, as noted by Crosbie & Bohn (2003), when the empirical distribution is compared to the normal distribution, the tails of the empirical distribution are significantly fatter.

When analyzing the performance of the Merton (1974) DD model, one can either evaluate the default ranking or default probability estimation performance of the model. When Merton (1974) model is used to rank firm by their default risk, the results are promising. With default probability estimations, the performance has been slightly poorer. (Jessen & Lando, 2015, 493) In Vassalou & Xing (2004), they analyze how default risk affects equity returns by using the Merton (1974) model to calculate a default likelihood indicator (DLI) for individual firms in their sample. They follow Moody's KMV methodology with the exception of utilizing the normal distribution and find that the calculated DLI captures information regarding future defaults when the effects of firm size and asset volatility are controlled. Similarly, Bharath & Shumway (2008) find that the distance to default measure in the Moody's KMV methodology can be utilized when forecasting defaults. However, according to their study, this is mostly due to the functional form of the distance-to-default measure. Moreover, they conclude that default probabilities calculated with the Merton (1974) model cannot be accepted to be a sufficient statistic for the probability of default.

In light of this evidence, Merton (1974) model seems not to be the most optimal method when calculating default probabilities if one has to rely on the normal distribution. To still benefit from the functional form of the model while averting these challenges, Student's t-distribution is tested alongside the normal distribution in this study. To to further improve the responsiveness of the synthetic model spread, these distributions are implemented together with the risk-neutral calibration methodologies discussed earlier. By testing both the normal and the t-distribution, it is conceivable to analyze the effects arising from distribution selection precisely.

3 CAPITAL STRUCTURE ARBITRAGE

3.1 Strategy description

Capital structure arbitrage, a rather prominent strategy among hedge funds before the financial crisis, can be described as a relative value trading strategy that involves an equity and a debt instrument of a specific firm (Duarte et al. 2006, 787–788). To successfully find these relative value trading opportunities, it is essential to use a model that links the firm's equity and debt instruments pricing-wise. The link can be established by taking advantage of a structural credit risk model, such as the Merton (1974) model. (Yu 2006, 47) The selected model is used to identify whether the pricing of these two instruments is consistent. If large misalignments can be found, the arbitrageur will construct a position that includes the equity and debt instruments of a specific firm. The weights and exact positioning depends on the hedge ratio and on the signal given by the structural model. For example, if the pricing of the debt instrument given the price indicated by the model seems to be too low, the trader will establish a long debt position and a complementary short equity position. The trader benefits if the price of the debt instrument eventually rises and thus converges with the model price. If the misalignment between the model and market price is regarded to be fundamental, the equity price should not move markedly during the trade. Moreover, on a trade level the strategy is based on an idea of utilizing a temporary mispricing between firm's equity and debt instruments.

Since the development of the global CDS market, the main debt instruments used in capital structure arbitrage strategies have been credit default swaps instead of corporate bonds. Higher liquidity and purer credit risk reflection of credit default swaps have been among the main contributors behind this trend. (Ju et al. 2015, 90) The equity leg has been typically constructed by simply trading the stocks of the company in question. However, the strong linkage between firm's CDS and implied equity volatility as documented by, e.g., Carr & Wu (2009) has motivated the use of equity options as well.[12] To give a specific example of the implementation with these instruments, one must first understand the role of the structural model used. To judge whether an "arbitrage" opportunity exists, the structural model is applied in the default probability determination process. Next, this probability is used to calculate a synthetic CDS spread that serves as the strategy's trading signal. To demonstrate the typical strategy implementation

[12]For the use of equity options in a capital arbitrage setting, see Zeitsch (2017).

used in, e.g., Yu (2006), let us denote the synthetic model spread at time t as $CDS_{model,t}$ and the market CDS spread as $CDS_{market,t}$. Additionally, let us call α as the trading trigger, which is expressed in percentage terms. Now, a long CDS position is opened if

$$CDS_{model,t} > (1+\alpha) \times CDS_{market,t},$$

and hedged with a long equity position, which is sized based on the calculated hedge ratio. If options are traded instead of equities, a short volatility position should be opened. For example, this translates into selling put options. If, on the other hand,

$$CDS_{market,t} > (1+\alpha) \times CDS_{model,t},$$

a short CDS position combined with a short equity position is opened. In options terms, a long volatility position should be opened by, for example, buying put options. Typically, the trading trigger α is either 50%, 100% or 200% while the maximum holding period for a single trade varies between 30 days to 180 days (see, e.g., Yu 2006, Duarte et al. 2006 or Ju et al. 2015) A position is closed if it the model spread converges with the market spread, i.e. $CDS_{model,t} \approx CDS_{market,t}$, the maximum holding period is reached or a preset maximum drawdown limit is crossed. The position is profitable if the CDS position converges while the equity market acts as indicated by the hedge ratio. However, as is evident in the literature, individual positions might be extremely risky due to further divergence of both the CDS and equity positions. If the maximum drawdown or holding period limit is hit often, the strategy's aggregate performance might suffer significantly.

As can be seen, the model used to generate the trading signals, i.e., calculate the synthetic CDS spread, plays a central role in the strategy execution. In the academic literature, the CreditGrades model[13] and the previously discussed Merton-based Moody's KMV model[14] are the most used ones. The CreditGrades model, initially developed by a consortium of investment banks and research firms to standardize and improve credit risk management methodologies, is a structural model with a different functional form than the Moody's KMV model (Finger et al. 2002, 1;9). Additionally, there are some differences regarding parameter estimation in the original representations of the models. To focus more on the parameter estimation, one should set sights on the most important input parameter in a structural model: volatility (Zeitsch 2017, 8). Since the aim is to benefit from misalignments in markets that should price new information relatively effectively,

[13]Finger et al. (2002).

[14]Crosbie & Bohn (2003).

responsiveness is a central model characteristic.[15] Search for responsiveness and the encouraging results of many academic studies (see, e.g., Cao et al. 2010 and Cao et al. 2011) have motivated the use of implied equity volatility instead of historical volatility when calibrating the model. Responsiveness can be likewise improved by applying a random default barrier methodology (see, e.g., Finger et al. 2002). Next, studies regarding capital structure arbitrage are discussed in detail. Additionally, time is spent to discuss why it seems to be possible to earn excess returns by following the strategy.

3.2 Empirical evidence: Results, implementation and market efficiency

After the turn of the millennium, capital structure arbitrage started to catch the practitioners' and academics' attention. As one of the first extensive studies in the field, Yu (2006) analyses the returns and risks associated with a capital structure arbitrage strategy by using credit default swaps and equities in the implementation. A sample ranging from the year 2001 to 2004 consisting of 261 North American firms is analyzed. Using a CreditGrades model calibrated with 1000-day historical equity volatility, Yu (2006) finds that with a maximum position holding period of 180 days, the strategy offers positive mean holding period returns from 0.13% to 1.01% depending on obligor's credit quality and the strategy setup. Applying a trading trigger of 50%, the mean aggregate monthly return for obligors with speculative credit ratings is 2.78%. To consider transaction costs, Yu (2006) uses a 5% bid-ask spread for CDS trades. The costs of equity trades are neglected. However, the profitability of the strategy is highly dependent on the strategy setup. In the implementation, a position is closed if the model spread converges with the market spread. Given a 30-day maximum holding period, almost none of the trades converged, resulting in a situation where the mean holding period return is negative or marginally positive. Due to the model's weak responsiveness and low correlation between CDS spreads and equities, the losses on individual positions are occasionally significant, Yu (2006) concludes.

Using the same sample period and size as Yu (2006), Duarte et al. (2006) utilize the CreditGrades model calibrated with 1000-day historical volatility and find that the strategy on an aggregate level leads to positive mean returns and high Sharpe ratios thus matching the findings of Yu (2006). They find that the

[15] This is so also from the perspective of model and market spread convergence.

strategy returns have positive skewness; hence the strategy cannot be identified to rely on selling tail risk insurance.[16] Moreover, four out of the six strategies tested in the study show positive alphas at a 10% significance level when regressed with Fama & French (1993) three-factor model and other asset class excess returns. Regardless of the positive alphas, Duarte et al. (2006) report that the strategy is somewhat driven by market risk and is likewise cyclical.

Following Yu (2006) and partly Duarte et al. (2006), Bajlum & Larsen (2008) aim to solve the issues regarding responsiveness of the structural model when calibrated with historical volatility. Since the fundamental idea behind the strategy is to find a mispricing between company's equity and debt instruments, one can see that a calibration methodology that helps to find trading opportunities more swiftly is preferable compared to a methodology that leads to unresponsive model output. To test this, Bajlum & Larsen (2008) calibrate the CreditGrades model with implied equity volatility and historical volatility. Following Yu (2006) with the strategy implementation by using a maximum holding period of 180 days and a trading trigger of 200%, Bajlum & Larsen (2008) find that for speculative-grade obligors the mean holding period return is 2.64% if the calibration is done with historical volatility. By using implied equity volatility in the calibration, a mean holding period return of 4.61% is achieved for these obligors. For investment-grade obligors, the difference in returns is less significant. Furthermore, Bajlum & Larsen (2008) report that the use of implied volatility resulted in a higher rate of convergence, thus addressing the issues with model unresponsiveness.

Continuing with studies aiming to improve model accuracy and responsiveness, Ju et al. (2015) use the multi-period Geske & Johnson (1984) model modified by Chen & Yeh (2006) (from now on the extended Geske & Johnson (1984) model) to test whether the model performs better than the CreditGrades methodology in a capital structure arbitrage setting. With the Geske & Johnson (1984) model, it is possible to consider a debt structure that consists of obligations with different maturity dates, whereas the CreditGrades model sees liabilities only as one obligation with a single maturity date (Ju et al. 2015, 99). They use a sample of 369 North American obligors starting from 2005 and ending in 2008 and follow Yu (2006) with the strategy implementation. By calibrating the model with 1000-day historical volatility and using similar transaction cost methodology as Yu (2006), Ju et al. (2015) report monthly median returns ranging from 0.61% to 4.28% with the extended Geske & Johnson (1984) model and median returns from 0.57% to

[16] A strategy that most of the time offers steady positive returns with low volatility but might experience significant drawdowns that undermine the overall profitability of the strategy.

3.97% with the CreditGrades model.[17] Hence, according to the results above and based on the observation that the extended Geske & Johnson (1984) model produces lower pricing errors, the authors see the extended Geske & Johnson (1984) as a more preferable model compared to the vanilla CreditGrades model. Other results regarding the profitability of capital structure arbitrage strategy in their sample are somewhat contradictory to the academic consensus. For example, they find that the mean holding period returns for companies with high credit quality are higher than for companies with speculative-grade ratings. In fact, the mean holding period returns for companies with high yield ratings are clearly negative at -5.60%. Additionally, they report that the strategy returns are negatively skewed, and large losses occur, especially during the financial crisis.

With the goal of improving the implementation of the CreditGrades model and demonstrating positive excess returns offered by capital structure arbitrage, Huang & Luo (2016) calibrate the CreditGrades model with implied volatility and analyze a sample of over 200 obligors from January 2001 to June 2004. General results are in line with previous research. First of all, Huang & Luo (2016) are able to replicate the results of Bajlum & Larsen (2008) regarding volatility calibration. More precisely, they conclude that a model calibrated with implied volatility outperforms the model employed by, e.g., Yu (2006), which is calibrated with historical volatility. Second, they find that the strategy returns cannot be explained by common factors such as the Fama & French (1993) factors or the momentum factor. Furthermore, the results of regressions made against the excess returns of the S&P 500 Industry Index, Lehman Brothers Baa Intermediate Index or Tremont Fixed Income Arbitrage Index do not support the notion that the returns are driven by systematic factors. These results are somewhat similar than the ones of Yu (2006) and Duarte et al. (2006). Thirdly, Huang & Luo (2016) observe that the strategy returns are positively skewed thus complementing the results of, once again, Yu (2006) and Duarte et al. (2006), and also the results of Bajlum & Larsen (2008).

As one of the most recent studies discussing the strategy, its implementation and overall results, Zeitsch (2017) tests a new calibration and modeling methodology focusing mainly on improving the responsiveness of the model spread by using a risk-neutral calibration, i.e., employing implied market information instead of historical data. Since the methodologies and ideas presented in Zeitsch (2017) are essential from the perspective of this thesis, the paper is analyzed thoroughly. Two distinct themes separate the study conducted by Zeitsch (2017) from previous research. First, the model of choice is not the most often used CreditGrades model

[17]Median returns vary based on the strategy configuration.

but the original Merton (1974) model combined with the Moody's KMV model. Second, the equity leg of the strategy is not executed with equities but instead with options. With this approach, the role of equity volatility as a suitable and more stable hedge for the opposite CDS trade is highlighted.

When implementing the Merton (1974) model, Zeitsch (2017) uses deep out-of-the-money (OTM) put implied volatility in the calibration process. In contrast, previous studies have focused on using at-the-money implied volatility at best.[18] As is identified in the paper, volatility can be seen as the most important input parameter in a structural model. Model's ability to reflect sudden changes in market sentiment and improved signal detection can be mentioned as the main rationales supporting the use of implied volatility. To further improve the responsiveness, deep OTM puts can be utilized. Following the argumentation of Zeitsch (2017), a long CDS position can be viewed as a long put option on the firm's total asset value. To specify, asset value can be thought of as the price of the underlying and value of debt as the strike price. If the market capitalization of the firm declines, ceteris paribus, the value of the long put increases, i.e., the CDS spread increases. If market participants expect the market capitalization to decline significantly, the demand for deep OTM equity puts will result in a rise of implied volatilities for these options. Hence, according to this logic, the volatilities of these deep OTM equity options can be seen to contain relevant information about the changing capital structure dynamics from the perspective of structural modeling. On top of the typical asset volatility calibration, Zeitsch (2017) takes advantage of deep OTM implied volatilities in the default barrier derivation. The aim here is to respect risk-neutrality as outlined earlier. The novel derivation allows the default barrier to reflect changes in market sentiment dynamically. Moreover, the barrier is no longer backward-looking like the default barrier parameters employed in the CreditGrades framework.

The execution of the capital arbitrage strategy of Zeitsch (2017) differs significantly from previous studies. As has been the standard in the field, stocks have been used as the equity leg in the execution. Zeitsch (2017), however, argues that this is not necessarily the optimal way. He analyses the correlations between CDS spreads, market capitalization and implied volatility, and finds that the correlation with the CDS spread is almost identical for both variables. Additionally, anecdotal evidence points to the conclusion that the relationship between the CDS spread and implied volatility is more linear than the one with market capitalization. Moreover, the volatility sensitivity of the market capitalization favors the

[18]More specifically, Zeitsch (2017) uses one month 10-delta puts in the volatility calibration.

use of volatility instead of equities. To hedge, for example, a ten basis point move in the CDS spread with equities, a large position would be needed due to low sensitivity. Since a change in the CDS spread results in a relatively large move in implied volatility, a position size for the hedge is more manageable than in the aforementioned case. In the implementation, Zeitsch (2017) uses liquid options to construct the hedges. The hedge ratio is calculated empirically by first regressing the CDS spread against deep OTM implied volatility, and then by determining the option position size so that the profit and loss sensitivity of the option matches with the CDS position. To identify trading signals, Zeitsch (2017) relies not on the commonly used trading trigger approach but instead on a Euclidean distance (L^2 distance) to determine the historical difference between the model and the market spread. If the distance during the last month increased significantly compared to the historical L^2 distance, it strengthened. Ultimately, L^2 distances are sorted from smallest to largest and then sorted again by signal strength starting from the strongest. The top 10 signals lead to trades with equal weights. As can be seen, the strategy is very selective.

Based on a large sample starting from 2004 to 2011 and consisting of 830 companies, Zeitsch (2017) backtests the strategy outlined here. The first two years of the sample are used to calibrate the model, i.e., to calculate hedge ratios and trading signals. Then, an out-of-sample study is conducted with real market bid-ask prices. Using a maximum holding period of 6 months, Zeitsch (2017) finds that 70% of the trades are profitable with a high convergence rate of 80% and a mean holding period of 30 days. The approximately same number of short and long trades supports the claim regarding market neutrality of the strategy. Furthermore, the highest returns occur during the volatile periods of 2008 and 2009, contradicting the results of Ju et al. (2015). The most striking result with the implementation is that only 12% of the universe is traded. The total amount of trades is only 284, which is extremely low given the sample size. Perhaps the selectivity of the approach is one key factor behind the high rate of positive returns. Overall, the model spreads are, in most cases, close to the market spread resulting in the small number of trades. In light of this evidence, the approach of Zeitsch (2017) requires more analysis. In this thesis, selected parts of the methodology are tested and analyzed further with new, post-financial crisis data.

Now one might wonder why this strategy overall seems to offer relatively high excess returns. Are credit and equity markets fully integrated and efficient? Imbierowicz & Cserna (2008) focus on these questions and especially on the efficiency of the CDS market. Applying the CreditGrades, Leland & Toft (1996) and Zhou (2001) models to a global sample of 808 obligors from the year 2002 to 2006, they find that a capital arbitrage strategy with a trading trigger of 20% and no holding period restrictions generate Sharpe ratios from 0.60 to 1.47 depending on the credit quality of the obligor.[19] They argue that the promising results of Yu (2006) and Duarte et al. (2006) support the notion of market inefficiency. However, by analyzing the sample returns, Imbierowicz & Cserna (2008) find that the market efficiency improved from the beginning of the sample period. According to their analysis, the CDS market reached efficiency during the years 2004 and 2005. Later evidence of high excess returns associated with capital structure arbitrage contradict with this piece of evidence (See, e.g., Wojtowicz 2014 and Zeitsch 2017).

Another comprehensive study focusing on testing and explaining the performance of the strategy is conducted by Wojtowicz (2014). Focusing on a post-financial crisis sample covering a period from July of 2010 to November of 2012 and utilizing a novel volatility calibration methodology – namely implied CDS volatility – with the CreditGrades model, the authors report a mean holding period return of 7.47%.[20] They find that approximately 65% of the trades make a profit and argue that the strategy cannot be identified as a strategy relying on shorting tail risk. Furthermore, companies with lower credit quality seem to generate higher holding period returns than obligors with investment-grade ratings. Wojtowicz (2014) analyze and discuss the factors that might be behind high mean holding period returns. Unlike previous studies, the authors find that strategy returns are somewhat explained by common risk factors such as bond indices and the S&P 500 Index. Focusing more on return attribution, the different price discovery speeds of the equity and CDS markets cannot be accredited due to an average holding period of 80 days.[21] Moreover, by incorporating a liquidity score calculated by Markit, the authors discover that companies with the highest liquidity scores generate the highest returns. Hence, according to Wojtowicz (2014), liquidity cannot be the main culprit behind the excess returns. However, the profits exhibit clustering, i.e., most of the profits occur during a short period. For the arbitrageur, this might cause issues and constraints regarding optimal capital allocation. Ul-

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[19]Returns are calculated after transaction costs. Like Yu (2006), 5% bid-ask spread is used. For equities, a ten bps transaction cost is assumed.

[20]Implied CDS volatility is the volatility level that makes the model spread equal to the market spread. Wojtowicz (2014) used a one-year moving average of the implied CDS volatility in the model calibration.

[21]There exist no academic consensus regarding the lead-lag relationship between equity and the CDS markets. For example Byström (2005), Norden & Weber (2009) and Kiesel, Kolaric & Schiereck (2016) find that equity markets lead the CDS markets whereas Zhu (2006), Acharya & Johnson (2007) and Amadori, Bekkour & Lehnert (2014) find the CDS markets to lead the equity markets.

timately, profit clustering can be an impediment to arbitrage. (Wojtowicz 2014, 29–30)

Continuing with the limits to arbitrage theme, Kapadia & Pu (2012) find that short-term pricing discrepancies are common between equities and credit default swaps. Additionally, the authors report that approximately 29% of these discrepancies can be explained with factors constituting limits to arbitrage. These factors include equity volatility, liquidity, and idiosyncratic risk. Still, most of the discrepancies disappear when the estimation horizon is 50 days, which is closer to a typical holding period in capital arbitrage strategies than the 5-day period in which approximately 41% of the equity and CDS pricing relative pricing changes can be considered to be as discrepancies. Overall, the explanations behind the strategy's profitability remain to be mixed. As can be seen, the area requires further research whether the strategy is still profitable today, and if so, why that might be the case. In this thesis, the strategy's profitability is examined with a new and never before tested sample ranging from August 2010 to the end of July 2019.

Table 1: Summary table describing sample details and applied methodologies in previous capital structure arbitrage studies

Table reports the sample and methodology details of the previous capital structure arbitrage studies. NA in Sample details column refers to North America. In the third column, CG is the abbreviation used for the CreditGrades model. The last column offers a description of the instruments utilized in the strategy implementation of the respective study.

Author(s)	Sample details	Model	Volatility calibration	Instruments
Yu (2006)	2001–2004, 261 obligors & NA	CG	1000-day historical volatility	CDS & equities
Duarte et al. (2006)	2001–2004, 261 obligors & NA	CG	1000-day historical volatility	CDS & equities
Bajlum & Larsen (2007)	2002–2004, 221 obligors & NA	CG	Implied ATM volatility	CDS & equities
Cserna & Imbierowicz (2008)	2002–2006, 808 obligors & Global	CG, Leland & Toft (1996) and Zhou (2001)	Historical volatility	CDS & equities
Wojtowicz (2014)	07/2010–11/2012, 183 obligors & NA	CG	CDS implied volatility	CDS & equities
Ju et al. (2015)	2004–2008, 369 obligors & NA	CG & extended Geske-Johnson model (2006)	1000-day historical volatility	CDS & equities
Huang & Luo (2016)	01/2001–06/2004, 213 obligors & NA	CG	Implied ATM volatility	CDS & equities
Zeitsch (2017)	2004–2011, 830 obligors & Global	Merton (1974) model & Moody's KMV	Implied OTM volatility	CDS & equity options

4 STRATEGY EXECUTION WITH CREDIT DEFAULT AND VARIANCE SWAPS

4.1 CDS pricing and valuation

As highlighted before, the strategy execution in this thesis relies on credit default swaps (CDS) and variance swaps. To construct and calculate the trading signals, hedge ratios, and mark-to-market values of both instruments, it is of essence to thoroughly understand how both credit default and variance swaps are priced. In this chapter, these themes are covered comprehensively.

Starting with the pricing mechanics of the traded debt instrument, a credit default swap is defined as a derivative contract in which the protection buyer receives the invested principal in a case of default. On the other hand, the protection seller is willing to facilitate this sort of insurance policy due to the regular premium payments that the buyer has agreed to make. (White 2013, 1) The reference entity of the contract is typically a bond issued by a corporate, agency, or a sovereign. Credit default swaps were invented by Blythe Masters in 1994, who at the time worked for J.P. Morgan & Co. After their invention, the market has increased significantly, and even though credit default swaps were at the heart of the financial crisis, their popularity has not abated. (Schmidt 2016, 9) More generally, credit default swaps are used to take credit risk or to hedge against it. Via CDS positions, one can get exposure to a single company or a diversified basket consisting of multiple obligors. Credit default swaps are commonly used as a building block in structured products in which retail or institutional clients typically take the short exposure. On the other side, asset managers and financial institutions, for example, are willing to facilitate these short positions due to hedging or credit risk transfer purposes. Credit default swaps can be utilized in many ways given the limits and targets of one's investment operations. Capital structure arbitrage is just one example of how CDS contracts can be used in a relative value strategy setting.[22]

Compared to bonds, credit default swaps have many benefits. First of all, CDS contracts are standardized and thus can be traded effectively without the need to analyze the details and unique characteristics linked generally to corporate bonds, for example. Secondly, CDS contracts are more liquid than bonds. Moreover, CDS contracts reflect the pure credit risk of the reference entity and are not corrupted by the assumed risk-free term structure like bonds are. (Hull, Nelken & White

[22] For more about practical applications of credit default swaps, see Hull (2012).

2004, 4) These reasons, among others, make CDS contracts useful in the context of capital structure arbitrage. To comment about the conventions in the CDS market place, one can say that the 5-year tenor is the most liquid one. Contracts with 1-, 3-, 7- and 10-year tenors trade, but are not as liquid as their 5-year counterpart. For an investment-grade CDS contract, the typical notional amount ranges from USD 5 to 10 million. In high yield, the amount is commonly USD 2–5 million. (Arakelyan & Serrano 2016, 141)

The technical aspects of CDS contracts are mainly governed by the International Swaps and Derivatives Association (ISDA). Before the so-called 'Big Bang' protocol introduced by ISDA in 2009, CDS contracts were settled so that the net present value of the contract was zero at the time of initiation, and hence the protection buyer agreed to pay the par spread – a coupon that sets the value of the contract to zero – in order to hedge against default. In the post-Big Bang era, however, the protection buyer pays an up-front payment to the seller and pays a standard coupon during the contract period. (White, 2013, 3) To calculate the market quote of a CDS contract, more precisely the par spread, the model and conventions outlined by ISDA are used here.[23] Next, the fundamental concepts of the valuation methodology and contract details are covered. For a more detailed presentation regarding the post-Big Bang pricing methodology, see White (2013).

In order to calculate the present value of the two legs, namely the protection and the premium leg, it is necessary to define two curves: the zero-coupon and the credit curve. According to ISDA specifications, the zero-coupon curve consists of interbank and swap rates.[24] Let us denote the zero rate from time t to time T as $R(t,T)$ and the natural logarithm as ln. By using continuous compounding, the zero rate can be expressed as

$$R(t,T) = -\frac{1}{T-t}\ln[P(t,T)], \tag{19}$$

where $P(t,T)$ is the discount factor and can be equivalently written (White 2013, 3–5)

$$P(t,T) = e^{-(T-t)R(t,T)}. \tag{20}$$

Similarly, the credit curve can now be constructed. In the case of this thesis, the credit curve, or the survival curve, is constructed by taking advantage of the default probabilities calculated with the Merton (1974) model and Moody's KMV methodology. To express the credit curve mathematically, the concept of hazard rate must first be introduced.

[23] ISDA-compliant interbank and swap rates are used later in the empirical section.

[24] A list of the specific interest rates is shown in the Appendix.

In CDS pricing, the hazard rate $\lambda(t)$ is the intensity of the Poisson process, which is used to model the probability of default in reduced-form models (White 2013, 6). Let us write the time of default as τ. Now, the probability of default during an infinitesimal time period dt, assuming that the default has not occurred before time t, is

$$\mathbb{P}(t < \tau \leq t + dt \mid \tau > t) = \lambda(t)dt,$$

where $\mathbb{P}(A \mid B)$ is simply the conditional probability of A given B. (White 2013, 6) Let $Q(t, T)$ be the survival probability from time t to time T ($t < T$). By assuming no default prior or at time t, we can write

$$Q(t, T) = \mathbb{P}(\tau > T \mid \tau > t) = \mathbb{E}^{\mathbb{Q}}(\mathbb{I}_{\tau > T} \mid \mathcal{F}_t) = e^{-\int_t^T \lambda(s)ds},$$

where $\mathbb{I}_{\tau > T}$ represents the indicator function which returns 1 if $\tau > T$ and 0 otherwise. I.e. if there is a default prior to time T implying that $\tau < T$, the survival probability would be zero. Additionally, $\mathbb{E}^{\mathbb{Q}}$ denotes the risk-neutral probability measure. (White 2013, 6)

The hazard rate defined here can be transformed into a zero hazard rate $\Lambda(t, T)$ and defined similarly than the zero rate in Equation (19). Hence,

$$\Lambda(t, T) = -\frac{1}{T - t} \ln[Q(t, T)],$$

and

$$Q(t, T) = e^{-(T-t)\Lambda(t,T)}. \tag{21}$$

Now it is observable that the survival probability curve can be seen as a similar type of a discount curve than the one that corresponds with zero rates. (White 2013, 6)

To move on with the valuation process, we assume a certain term structure of interest rates and survival probabilities. In our representation, the number of contractual payment dates is defined by $n = 1, ..., N$, and the dates are denoted $t_1, ..., t_N$ where t_N represents the maturity date of the contract. The market or par spread of the CDS that matures at time t_N is $S(t_v, t_N)$, where t_v is the valuation date. To determine the market spread at time $S(t_v, t_N)$, the present value of the premium leg must equal the present value of the protection leg. Let us now focus on the premium leg.

The present value of the premium leg can be divided into two separate components and can be written (White 2013, 8)

$$PV_{\text{Premium leg}} = PV_{\text{Premiums only}} + PV_{\text{Accrued premium}}.$$

The first term, $PV_{\text{Premiums only}}$, captures the probability-weighted present value of the future premium payments. The second term also quantifies the probability-weighted present value premiums that the protection buyer has to make when a default occurs between premium payment dates. The effect of accrued premium in the market spread is relatively small. Hence we can omit the accrued premium from our calculations for the sake of simplicity (O'Kane & Turnbull 2003, 8).

Now, the present value of the premium leg can be expressed as follows

$$PV_{\text{Premium leg}} = S(t_v, t_N) \sum_{n=1}^{N} \Delta(t_{n-1}, t_n, DCC) P(t_v, t_n) Q(t_v, t_n), \tag{22}$$

where $\Delta(t_{n-1}, t_n, DCC)$ is the time between premium payment dates as a fraction of a year calculated with a specific day count convention DCC. $P(t_v, t_n)$ is the discount factor defined in Equation (20) and $Q(t_v, t_n)$ is the cumulative survival probability defined correspondingly in Equation (21). (O'Kane & Turnbull 2003, 6–7)

To simplify notation, the concept of the risky present value of basis point ($RPV01$) can be introduced. $RPV01$ is simply the present value of one basis point of the premium leg and can be considered "risky" since the cash flows are uncertain due to the possibility of default. Equation (22) can now be simplified and expressed (O'Kane & Turnbull 2003, 3–7)

$$PV_{\text{Premium leg}} = S(t_v, t_N) \times RPV01.$$

Next, let us find an expression for the protection leg. Before the "Big Bang" protocol, the protection buyer was typically obligated to deliver a bond of the reference entity to the protection seller in a case of default. The protection seller would then settle the contract by paying the nominal to the protection payer against the bond of the reference entity. Nowadays, cash settlement is the market standard. (Colozza et al. 2014, 7) The so-called recovery rate is determined by an auction organized by ISDA. If we denote the recovery rate as RR, the loss given default is $1 - RR$. Furthermore, let us assume that a credit event can take place M times in one year. These times are fixed, hence the credit event can materialize only on times $m = 1, ..., M \times t_N$.[25] The present value of the protection leg now

[25]Naturally, the credit event can take place at any given time. To model this, one needs to use integrals and numerical integration. To simplify the calculations, discrete credit events are assumed.

takes the following form (O'Kane & Turnbull 2003, 9-10)

$$PV_{\text{Protection leg}} = (1 - RR) \sum_{m=1}^{M \times t_N} P(t_v, t_m)((Q(t_v, t_{m-1}) - Q(t_v, t_m)).$$

Finally, after deriving representations for both the premium and protection leg, we can solve the par spread. Since at time t_v, by definition

$$PV_{\text{Premium leg}} = PV_{\text{Protection leg}},$$

the par spread, or equivalently the market quote, can be written

$$S(t_v, t_N) = \frac{(1 - RR) \sum_{m=1}^{M \times t_N} P(t_v, t_m)((Q(t_v, t_{m-1}) - Q(t_v, t_m))}{RPV01}, \tag{23}$$

where (O'Kane & Turnbull 2003, 8-11)

$$RPV01 = \sum_{n=1}^{N} \Delta(t_{n-1}, t_n, DCC) P(t_v, t_n) Q(t_v, t_n). \tag{24}$$

Later in the empirical part of this thesis Equation (23) is used to calculate the synthetic CDS spread that forms the backbone of the proposed capital structure arbitrage strategy. To determine if the positions are profitable, a mark-to-market methodology must be established. By using Equations (24) and (23), mark-to-market is given by

$$MTM_L(t_v, t_N) = [S(t_v, t_N) - S(t_0, t_N)] \times RPV01(t_v, t_N), \tag{25}$$

where the subscript L refers to a long CDS contract and t_0 to the date when the position was opened (O'Kane & Turnbull 2003, 15). The mark-to-market of a short CDS position is correspondingly

$$MTM_S(t_v, t_N) = [S(t_0, t_N) - S(t_v, t_N)] \times RPV01(t_v, t_N). \tag{26}$$

where the subscript S points to a short CDS position. However, for simplicity, the current five-year CDS quote is used as an estimator of $S(t_v, t_N)$. This is standard practice in capital arbitrage studies since the CDS curve is typically relatively flat between the five-year and four and a half year mark (See, Wojtowicz 2014).

4.2 Variance swaps as an equity leg

4.2.1 Pricing and characteristics

In the capital structure arbitrage strategy analyzed closer in this thesis, variance swaps are used as the equity leg. In other words, CDS positions are hedged with implied variance (volatility squared) instead of vanilla equities. Before discussing why the former approach should be favored over the latter, it is first essential to understand the core mechanics and pricing principles behind variance swaps. In the following pages, these exact themes are covered. Additionally, other key characteristics, such as, mark-to-market conventions, market dynamics, and liquidity issues concerning variance swaps are discussed.

If an investor is willing to gain exposure to equity volatility, the instrument with which this can be accomplished most effectively is called a variance swap. This over-the-counter derivative instrument enables the investor to take views on realized volatility against current implied volatility (Bossu 2006, 50). Compared to a delta-hedged straddle, for example, variance swaps enable the investor to form a position that truly reflects the differences between realized and implied volatility. In delta-hedged straddle positions, exposure to volatility, or vega, is not constant but merely dependent on the path of the underlier's price. (Allen et al. 2006, 77) With variance swaps, constant volatility exposure can be achieved.

As volatility trading vehicles have become more sophisticated, it is possible to view volatility as an asset class of its own. In the context of variance swaps, volatility is typically defined as the root-mean-square volatility. Mathematically this can be expressed as

$$\sigma_R = \sqrt{\frac{252}{T}\sum_{i=0}^{T}\left[\ln\left(\frac{S_i}{S_{i-1}}\right)\right]^2},$$

where σ_R is the annualized realized volatility, T denotes the number of days, ln is the natural logarithm, and S_i is the price of the underlying asset at time i. (Allen et al. 2006, 9–10) If one expects that the current implied volatility levels of a stock or an index are not as high as the future realized volatility would be, one should take a long volatility position. If, on the other hand, one sees that current implied volatility levels are higher than the realized volatility will be during a specified time window, it is possible to make a trade based on this view by entering a short volatility position. By entering into a long variance swap contract, the investor will make a profit if the annualized realized variance is higher than the annualized fair value of variance. The profit and loss of the positions at maturity can be expressed as

$$P/L = (\sigma_R^2 - K_{Var}) \times N_{Variance},$$

where σ_R^2 is the annualized realized variance during the contract period, K_{Var} denotes the annualized fair value of variance during the contract period and $N_{Variance}$ is the notional amount of one variance point, typically called the variance notional. (Bossu 2006, 50; Demeterfi et al. 1999, 3) Let us look at a long variance swap contract in which the fair value of variance, also called the strike, is 4%[26], the maturity of the contract is 12 months, and variance notional is €1000. If realized volatility during the 12 month contract period is 25%, i.e. variance is 5%, the payoff is then $(5\% - 4\%) \times 1000 = 1000$.[27] To make matters simpler, market participants typically like to write the notional amount in terms of volatility and not variance. In this instance, the profit and loss of a long volatility position can be written

$$P/L = \frac{(\sigma_R^2 - K_{Var})}{2K_{Var}} \times N_{Vega},$$

where N_{Vega} is the notional amount per 1% of volatility, also called vega notional.[28] (Allen et al. 2006, 12)

At this stage, one might wonder why do not make a contract purely based on volatility instead of variance. Frankly, a contract based on volatility could be created. However, only variance swaps can be hedged and thus replicated with a static options portfolio and a dynamic futures position. This hedging argument is the main reason why variance swaps are mostly used and discussed instead of volatility swaps. (Bossu 2006, 50; Mougeot 2005, 13) To focus on the pricing of a variance swap, it is important to note that the net present value of the contract at initiation is zero. Hence, the expected payoff of a long variance swap contract in a risk-neutral world is

$$\mathbb{E}^{\mathbb{Q}}[P/L] = \mathbb{E}^{\mathbb{Q}}[e^{-rT}(\sigma_R^2 - K_{Var})] \times N_{Variance},$$

where $E^{\mathbb{Q}}$ is the expected return operator under risk-neutrality, r is the risk-free rate, and T is the tenor of the swap. (Demeterfi et al. 1999, 2,15) For the net present value of the contract to be zero, it must hold that

$$K_{Var} = \mathbb{E}^{\mathbb{Q}}[\sigma_R^2].$$

[26] Equivalent to 20 % volatility.
[27] Variance figures can be multiplied by 100 depending on the terms of the contract.
[28] As can be seen, these two P/L equations are equivalent.

In other words, the fair value of variance should equal the estimated realized variance at time zero.

To derive an expression for the expected realized variance, and eventually for the replicating portfolio, let us assume that the return dynamics of the underlying instrument can be written as follows

$$\frac{dS_t}{S_t} = \mu(t, ...) + \sigma(t, ...)dW_t, \tag{27}$$

where S_t is the price of the underlying instrument at time t, $\mu(t, ...)$ is the drift dependent on time and other parameters and $\sigma(t, ...)$ represents the volatility that depends similarly on time and other parameters. W_t denotes a Wiener process. Additionally, let us define realized variance here as (Demeterfi et al. 1999, 15)

$$\sigma_R^2 = \frac{1}{T}\int_0^T \sigma^2(t, ...)dt.$$

Now, when the Itô–Döblin theorem is applied to $\ln(S_t)$, we get

$$d\ln(S_t) = \left(\mu - \frac{1}{2}\sigma^2\right) + \sigma dW_t. \tag{28}$$

Furthermore, by deducting Equation (28) from Equation (27) it can be seen that

$$\frac{dS_t}{S_t} - d\ln(S_t) = \frac{1}{2}\sigma^2 dt.$$

Finally, by integrating from time 0 to time T, realized variance σ_R^2 can be expressed as

$$\sigma_R^2 = \frac{2}{T}\left[\int_0^T \frac{dS_t}{S_t} - \ln\left(\frac{S_T}{S_0}\right)\right]. \tag{29}$$

Simply by utilizing this expression, one can now build a continuously rebalanced replicating portfolio that hedges the variance swap, assuming that the stock price moves continuously, i.e., that it does not exhibit jumps. To get a conceptual idea of the replicating portfolio, the first term $\int_0^T \frac{dS_t}{S_t}$, can be thought as of the profit or loss of a continuously rebalanced portfolio that consists of a long position of $1/S_T$ shares worth €1. The second term, on the other hand, denotes a short position in a log contract. This contract, initially introduced by Neuberger (1994), pays the holder the logarithm of the underlying asset's total return. (Demeterfi et al. 1999, 16–17)

To analyze the replicating portfolio more thoroughly, let us take a risk-neutral expectation of Equation (29) and write

$$K_{Var} = \frac{2}{T}\mathbb{E}^{\mathbb{Q}}\left[\int_0^T \frac{dS_t}{S_t} - \ln\left(\frac{S_T}{S_0}\right)\right].$$

Given the asset dynamics presented in Equation (27), the first term under the risk-neutral expectation reduces to

$$\mathbb{E}^{\mathbb{Q}}\left[\int_0^T \frac{dS_t}{S_t}\right] = rT.$$

Hence, the continuously rebalanced portfolio worth €1 at all times has a forward price equal to the risk-free rate. Due to the fact that one cannot trade with log contracts, the payoff profile must be constructed with a forward contract and with out-of-the-money put and call options. By decomposing the log contract into two separate parts, and introducing a new arbitrary parameter S_* that signifies the strike level between call and put options, we get

$$-\ln\left(\frac{S_T}{S_0}\right) = -\ln\left(\frac{S_T}{S_*}\right) - \ln\left(\frac{S_*}{S_0}\right).$$

As can be seen, only the first term depends on the future asset price S_t while the second term is static. Thus, it is solely necessary to replicate the first part of the payoff structure. The portfolio that replicates this first term is given by

$$-\ln\left(\frac{S_T}{S_*}\right) = -\frac{S_t - S_*}{S_*} + \int_0^{S_*} \frac{1}{K^2}\max(K - S_t, 0)dK + \int_{S_*}^{\infty} \frac{1}{K^2}\max(S_t - K, 0)dK, \tag{30}$$

where the first term denotes a short position in a forward contract, the second term is a portfolio of long put options with strikes ranging from 0 to S_* weighted as the inverse of the squared strike, and correspondingly, the last term represents a portfolio in long call options with strikes ranging from S_* to ∞ weighted as the inverse of the squared strike. Taking this all together, the fair value of variance at time 0 can be written as

$$K_{Var} = \frac{2}{T}\left[rT - \left(\frac{S_0}{S_*}e^{rT} - 1\right) - \ln\left(\frac{S_*}{S_0}\right)\right] + e^{rT}\Pi_{CP},$$

where Π_{CP} denotes the options portfolio consisting of put and call options described in Equation (30). (Demeterfi et al. 1999, 18–20)

After the variance swap position has been established, it might be interesting to know the contract's mark-to-market value. Especially if the contract will be closed before expiration, the mark-to-market value is of particular interest. The fact that variance is additive makes the calculation procedure to be a relatively easy one (Allen et al. 2006, 15). Mark-to-market of a long variance swap contract, MTM_L, can be written as

$$MTM_L(t,T) = N_{Variance}\left[\frac{t}{T}(\sigma^2_{R:0,t} - K_{Var:0,T}) + \frac{T-t}{T}(K_{Var:t,T} - K_{Var:0,T})\right],$$

where t is the time at mark-to-market, T represents time to expiration, $\sigma^2_{R:s,t}$ is realized variance from time 0 to time t, and $K_{Var:0,t}$ is the variance strike in a period ranging from time 0 to time t. (Allen et al. 2006, 15–16)

Focusing on other characteristics related to variance swaps and the replication methodology, it is relevant to highlight, that well-known volatility indices, such as the Chicago Board of Exchange's VIX index and its European counterpart, called the VSTOXX index, rely on a similar calculation methodology discussed above (Bossu 2006, 54–55). However, there are some clear issues with variance swaps as well. The assumption regarding the continuous price process of the underlying instrument is somewhat unrealistic in practice. If the underlying instrument exhibits major jumps during the contract period, the replication might turn out as inaccurate. This might happen even if there is an infinite continuum of strikes, which is not a realistic assumption either. (Demeterfi et al. 1999, 29) The lack of out-of-the-money options might turn out to be a second issue from the perspective of replication. Another problem related to the options market is liquidity, especially with single-name options. Typically, with indices the liquidity is not that big of an issue, whereas with single-name stocks, the lack of options and liquidity might make it impossible for the dealer to hedge the variance position, thus leading to non-existent variance swap liquidity (Allen et al. 2006, 24–25). All in all, variance swaps offer an investor an efficient way of placing bets on the difference between implied and realized volatility while the main challenges are related to replication and, especially, option market liquidity.

4.2.2 Hedge vega instead of delta

In almost all of the previous capital structure arbitrage studies, the CDS positions have been hedged with plain vanilla equity positions, i.e., with delta. The first study in which the hedge is constructed with volatility positions, in this case, deep out-of-the-money (OTM) puts, is conducted by Zeitsch (2017). In other words, CDS leg's exposure to changes in equity volatility, i.e., vega, is hedged. The rationale behind this approach is both theoretical and technical. As Carr & Wu (2009) and Cao et al. (2010) highlight, implied equity volatility plays an important role in explaining CDS spreads. This is so because CDS spreads behave somewhat similarly than deep OTM puts, and are thus linked to the market pricing of future equity volatility. Moreover, implied volatility reflects the prevailing variance risk premium, which is in itself time-varying. According to Cao et al. (2010), the existence of the time-varying variance risk premium can be seen as a central factor behind the explanation power of implied volatility.

In previous capital structure arbitrage studies, models calibrated with implied volatility have outperformed models based on historical volatility (Bajlum & Larsen 2008; Huang & Luo 2016; Zeitsch 2017). Given this evidence and the notion that volatility is the single most important input in a structural model, it is sound, at least in theory, to trade an instrument closely tied to the synthetic and market spread. Additionally, as Zeitsch (2017) highlights, there are no significant differences in CDS spread correlations between equities and implied volatilities. In that case, why should equity, i.e., delta, be the hedge of choice? Furthermore, vega hedge requires a lot less capital compared to the common delta hedge. If delta hedge is utilized in a capital structure arbitrage setting, building a risk equivalent position requires significantly more capital compared to other common fixed income arbitrage strategies (Duarte et al. 2006, 790). Large positions are needed because of the low sensitivity between the equity market and CDS spread movements. This finding coincides with the ones made by Zeitsch (2017) regarding CDS sensitivities.

Considering the strategy is based on relative value positions, the level of cointegration between the different traded markets is of high importance. However, the field is relatively mixed when it comes to the lead-lag relationship of the equity and CDS market. According to Byström (2005), Norden & Weber (2009) and Kiesel et al. (2016) equity market leads its CDS counterpart. However, Zhu (2006), Acharya & Johnson (2007) and Amadori et al. (2014) see the relationship is lead by the CDS market. Regarding the CDS market and implied equity volatility, Cao et al. (2010) find option markets to be more significant in the price discovery process, hence leading the CDS market. On another note, Trutwein & Schiereck (2011) analyze financial institutions during times of financial stress and discovered that no lead-lag relationship between CDS spreads and equity implied volatility could be found. What they do confirm is that the link between the two is very strong indeed. Based on previous studies, volatility cannot be said to dominate equity from a lead-lag perspective. However, the dislocations utilized by capital structure arbitrage strategies are not vanishing quickly but typically take, for example, 30 days or even longer to disappear. More specifically, spread convergence is not that fast in nature as the lead-lag times analyzed in these studies. All in all, if the strategy is profitable, it cannot be solely explained by simple lead-lag relationships.

The approach utilized in this study is built upon the idea of vega hedging. Compared to Zeitsch (2017), options are not used themselves, but instead, the hedge is constructed with variance swaps. As an instrument, they enable a purer exposure to volatility compared to, for example, delta-hedged straddles (Allen et al. 2006, 77). On the other hand, variance swaps and options overall have certain weak spots compared to equities. First, equity market is a lot more liquid than the single-name options market where broker-dealers must hedge their variance swap positions. Even though variance swaps are OTC instruments, the strike levels are closely tied to the options market. To hedge a variance swap, the broker-dealer must also buy deep out-of-the-money options, which might be rather illiquid. Liquidity issues in the options markets cast some size-related constraints on the tradable universe, but still, some names can be traded. Second, a concept linked closely to liquidity is trading costs. From a cost perspective, delta hedging is more efficient. With equity options and variance swaps, the bid-ask spreads are wider, making trading somewhat more costly. In the empirical analysis, trading costs have been factored in to make to results more significant from an economic perspective. Given the benefits and challenges discussed here, the vega hedging approach is an alternative that needs to be studied more closely in the field of capital structure research.

5 DATA AND STRATEGY IMPLEMENTATION

5.1 Description of data

The sample analyzed in this thesis consists of 102 European obligors. Sample period spans from 2.8.2010 to 30.7.2019 hence reflecting the financial conditions of the post-financial crisis era. Five-year euro-denominated mid-market CDS quotes with a modified-modified restructuring clause are used. Only companies with the most liquid quotes are included in the sample. More specifically, a company is left out of the sample if more than 20% of the CDS quotes during the sample period are deemed to be illiquid. No sector exclusions are made so that the arguments made by Zeitsch (2017) regarding the inclusions of financials can be tested. From the initial universe consisting approximately of 700 obligors, only the aforementioned 102 companies are selected. In total, the CDS sample consists of 239,394 individual quotes obtained from Thomson Reuters Datastream.

For other data used in the empirical part, Bloomberg serves as the source. To calculate the synthetic CDS spread with the selected structural model, market capitalization, and total liabilities for all the sample companies are needed. All the used fundamental data is denominated in euros. As discount and risk-free rates, deposit rates, i.e., EURIBORs in this instance, are used from one month to a year, and from thereafter euro-denominated swap rates are employed.[29] The following company-specific volatility data is used for model calibration: historical 360-day volatility, two-month 10-delta put implied volatility (IV), three-month 80% moneyness option implied volatility, and one-month and six-month variance swap rates. The output of the model calibrated with long-term historical volatility serves as a benchmark in the estimation error tests conducted later. Two-month 10-delta put IV is used to test the predictive features of put option supply and demand in terms of credit risk pricing. For all companies in the sample, put IV data is not available, and thus three-month 80% moneyness option implied volatility data is used as a substitute. The selection of the aforementioned IV data is mainly driven by quote liquidity and stability. One-month put IV data is likewise available for most of the sample companies. However, the data quality is relatively poor and contains a lot of noise, leading to somewhat unreliable trading signals. Given data availability and quality, three-month 80% moneyness option IV served as the best substitute.

In order to calculate the profit and loss (PL) of the variance swaps trades, the

[29] For the swap contracts, six-month EURIBOR acts as the floating leg.

term structure of the variance swap rates is needed. Hence variance swap rates starting from one-month and ranging to six months with one month increments are obtained from Bloomberg. To calculate variance swap rates, the company-specific volatility surface is constructed from current option prices by Bloomberg. A methodology similar to the one presented in the previous chapter is used to calculate the fair value of variance, which is then quoted in volatility points. Due to possible estimation errors and data quality issues, the variance swap data is analyzed so that inconsistent and outright untradable variance swap levels are removed by using the average between liquid quotes as an estimate. This way, the PL of the strategy explored later is more reliable and does not contain significant errors due to data quality issues.

Several euro-denominated monthly return time series are used as benchmarks of the broader market to discuss the possible drivers of the aggregate strategy returns. STOXX Europe 600 Total Return Index acts as the equity market benchmark. For fixed income, ICE BofA Euro Corporate Index represents the index for investment-grade bonds, whereas for high yield bonds ICE BofA Euro High Yield Index is selected. Furthermore, the VSTOXX Index is the implied volatility index of choice. Factoring in the effects of funding liquidity and counterparty credit risks in the interbank market, the euro-denominated equivalent of the TED spread is used. More specifically, this spread is calculated by deducting the yield of a three-month Germany government bill from the three-month EURIBOR. Let us call this spread EUR TED from now on. Starting from August 2011, monthly excess returns are calculated for the equity and fixed income benchmarks. With VSTOXX and the EUR TED spread, monthly changes are calculated.

In Table 2 the sample details are reported. As is evident, the sample consists mostly of investment-grade obligors. The issue is not CDS liquidity since there are multiple speculative-grade companies with liquid CDS quotes. The challenge arises from the fact that variance swap data for those companies is scarce, like the sample composition indicates. For later analysis, the sample is divided into two sub-samples based on the obligor's credit rating. Considering the overall structure of the sample, BBB and lower-rated firms are categorized to have lower credit quality whereas obligors with AA and A rating are allocated to the group with higher credit quality. Obligors that do not have a long-term credit rating issued by S&P at the beginning of the sample are analyzed separately, and their rating profile is determined by relying on other sources or ratings issued later. After this process, these unrated firms are allocated between the two sub-samples. By including BBB rated firms into the lower credit quality bucket, the analysis conducted in this thesis becomes more meaningful due to larger sub-sample sizes. If the typical investment grade and speculative grade dichotomy is followed, the speculative-grade sub-sample would consist only of 7 firms.

Continuing on the sample structure represented in Table 2, it can be said that the largest sector is financials. For example, Yu (2006), Wojtowicz (2014), Ju et al. (2015) and Huang & Luo (2016) exclude financial firms all together. They argue that the heavy capital structure of these companies poses challenges from the perspective of structural credit risk modeling. On the other end of the spectrum are Imbierowicz & Cserna (2008) and Zeitsch (2017), who both incorporate financials into the analysis. The argumentation supporting this inclusion is built upon default barrier adjustments. Here, financials are included so that the risk-neutrally calibrated default barrier introduced by Zeitsch (2017) can be tested. If financials are not taken into account, the sector allocation of the sample is relatively balanced.

Looking at the volatility figures in Table 2, it is evident that historical volatility is on average on a lower level than six-month variance swap rates and put implied volatilities. The spread between the historical and implied volatility figures reflect the variance risk premium incorporated in the implied volatility measures. Furthermore, analyzing the average correlations between the respective volatility measures and the CDS spreads, it can be seen that for the full sample variance swap rates dominate. Equity correlation denoted below average market capitalization is close with a correlation of -0.66. The two-month 10-delta put, on the other hand, shows correlations corresponding closely with historical correlations. For most of the rating buckets, equity correlation dominates. However, the differences on a sample level are small. The results regarding correlations are similar to Zeitsch (2017), thus supporting the notion that vega hedges could also be used in conjunction with CDS trades.

5.2 Strategy implementation

5.2.1 Synthetic spread construction

To calculate the synthetic CDS spread, Merton (1974) model is used as the underlying structural model. Then Moody's KMV methodology is applied to calculate the default probabilities used in the CDS pricing formula. For model calibration, different volatility measures, both historical and implied volatilities, are tested. This way, the risk-neutral calibration can be similarly tested against a methodology

Table 2: Sample description and statistics

N refers to the number of companies in each sample category, whereas S denotes the average CDS spread in basis points during the sample period. HV, Put IV, and VS IV represent the average historical 360-day volatility, two-month 10-delta put implied volatility, and six-month variance swap rate, respectively. With 12 companies in the sample, two-month 10-delta put IV is replaced with three-month 80% moneyness option IV. All volatility figures are denoted in percentage points. Below, the average volatility and size figures in the Full sample and Rating panel, average correlations between the respective category and CDS spreads are reported. Lev. reports the average leverage, which is calculated by dividing total liabilities with the sum of market capitalization and total liabilities. Size refers to the average market capitalization during the sample period. With Size, equity prices are used in the correlation calculation instead of market capitalization. Rating represents S&P's issuer long term credit rating on 2.8.2010. If the rating, as mentioned above, is not available for a company, it is categorized as not rated (NR).

Data descriptors	N	S	HV	Put IV	VS IV	Lev.	Size
Full sample	102	93.95	26.34	30.54	27.18	0.59	37,410
			(0.58)	(0.57)	(0.67)		(-0.66)
Rating							
AA	13	52.26	22.04	25.92	23.00	0.60	99,675
			(0.50)	(0.50)	(0.60)		(-0.74)
A	40	91.66	27.76	32.35	28.50	0.68	38,047
			(0.63)	(0.63)	(0.73)		(-0.53)
BBB	33	94.05	25.77	29.87	26.83	0.49	21,124
			(0.54)	(0.53)	(0.61)		(-0.67)
BB	7	194.04	31.98	35.52	32.21	0.61	13,447
			(0.72)	(0.67)	(0.80)		(-0.81)
NR	9	86.07	23.95	27.83	24.70	0.60	22,998
			(0.52)	(0.53)	(0.63)		(-0.72)
GICS sector							
Communication Services	7	69.81	22.40	26.95	23.85	0.52	33,655
Consumer Discretionary	10	110.86	27.85	32.41	28.89	0.54	22,446
Consumer Staples	16	83.42	21.65	26.94	23.71	0.43	37,517
Energy	4	69.15	23.06	27.40	23.77	0.53	113,688
Financials	24	96.99	30.42	34.70	30.41	0.94	35,703
Health Care	8	43.32	21.60	25.47	23.06	0.33	88,271
Industrials	15	79.05	25.07	28.65	25.90	0.49	22,146
Information Technology	1	237.02	40.17	42.26	39.75	0.48	22,537
Materials	13	149.05	30.50	33.66	30.61	0.52	18,622
Utilities	4	84.82	24.28	29.01	25.42	0.71	35,234

relying on historical, realized input data. Furthermore, the default barrier calibration follows the methodology introduced by Zeitsch (2017). Before any trades are initiated based on the calculated spread, a one-year calibration period ranging from 2.8.2010 to 2.8.2011 is introduced. The calibration period is primarily needed to calculate stable hedge ratios before the start of trading. Additionally, with some of the model variants, distributions are optimized during the calibration period. Both the hedge ratio calculation and distribution optimization are addressed later. All the following formulas are explained and derived in the theoretical section of this thesis and are thus covered here concisely.

The most critical input when calculating CDS spreads is the default probability. Before default probability can be calculated, a distance-to-default (DD) needs to be determined. Based on the Merton (1974) model and Moody's KMV methodology, distance-to-default is written

$$DD = \frac{\ln \frac{V_t}{B'(t,T)} + \left(r - \frac{\sigma_V^2}{2}\right)t}{\sigma_V \sqrt{t}},$$

where V_t is the asset value at time t, $B'(t,T)$ represents the default barrier at time t, r denotes the risk-free rate, and σ_V signifies the asset volatility. Following Zeitsch (2017), the default barrier $B'(t,T)$ is defined by following an iterative procedure so that the selected parameter satisfies the expression

$$\lim_{B'(t,T)\to 0} C_{\text{Black–Scholes}}[B_i'(t,T), \sigma_V, \tau, B_t] \approx 0,$$

where $C_{\text{Black–Scholes}}$ represents the Black & Scholes (1973) formula for a European long call option, and B denotes the total liabilities of the company. For the full representation of the Black & Scholes (1973) formula, see Equations (8), (9), and (10). Since the Black & Scholes (1973) formula is a set of non-linear non-negative equations, the root must be approximated. This is accomplished by utilizing the Broyden method. For more about the methodology, see Dennis Jr & Schnabel (1996). Now the asset value V_t is given by

$$V_t = B'(t,T) + S_t,$$

where S is the market capitalization of the company in question.

In the applied model specification asset volatility is given by the following expression

$$\sigma_V = \sigma_S \frac{S_t}{S_t + B'(t,T)},$$

where σ_s represents equity volatility. To test different calibration methods and model accuracy, historical and implied volatilities are used as inputs. Now that all the relevant model parameters have been determined, the default probability can be calculated by using the selected probability distribution. Assuming the normal distribution is applied, one can write

$$p_t = N\left[-\frac{\ln \frac{V_t}{B'(t,T)} + \left(r - \frac{\sigma_V^2}{2}\right)t}{\sigma_V \sqrt{t}}\right],$$

where N signifies the normal distribution. Student's t-distribution is tested as an alternative to the normal distribution in an effort to improve the model accuracy. During the calibration period, different degrees of freedom are tested. The selected degree of freedom is the one that produces the smallest CDS spread estimation error when compared to the market spread. To limit the calculation time of the spread, the maximum level for the degree of freedom is set to four.

Finally, the synthetic CDS spread can be calculated. Following the par spread approximation of O'Kane & Turnbull (2003), the spread of a CDS contract expiring at time t_N at the time of valuation t_v is

$$S(t_v, t_N) = \frac{(1 - RR)\sum_{m=1}^{M \times t_N} P(t_v, t_m)((Q(t_v, t_{m-1}) - Q(t_v, t_m))}{RPV01}, \tag{31}$$

where

$$RPV01 = \sum_{n=1}^{N} \Delta(t_{n-1}, t_n, DCC)P(t_v, t_n)Q(t_v, t_n). \tag{32}$$

In Equation (31), RR refers to the recovery rate which is assumed to be 0.40 thus corresponding to the market standard of CDS contracts with the modified-modified restructuring clause (Lipton & Rennie 2013, 89). Moreover, M is the number of times a credit event can occur during a year. During the contract period, this can happen $m = 1, ..., M \times t_N$ times. $P(t_v, t_m)$ represents the discount factor whereas $Q(t_v, t_m)$ denotes the cumulative survival probability between time t_v and time t_m. Equation (32), on the other hand, can be called as the risky present value of a basis point. Here $\Delta(t_{n-1}, t_n, DCC)$ marks the time between contractual payment dates t_{n-1} and t_n. DCC refers to the specific day count convention, which in the case of this thesis, is 30/360. The model used to calculate the par CDS spread omits the effects of accrued premiums. This is done because these effects are relatively small given that the spread level is not extremely high.[30] To come up with a time series of a company-specific synthetic spread, all the steps discussed here are repeated daily.

[30]For more about the effect of accrued premium, see O'Kane & Turnbull (2003, 8).

5.2.2 Trading signals

As with most of the prior capital structure arbitrage studies, the trading signal methodology of Yu (2006) is followed here. Compared to the Euclidean distance based strategy execution discussed by Zeitsch (2017), the selected methodology is somewhat more straightforward and more intuitive. Furthermore, the use of this methodology makes the results of this study more comparable to previous studies.

The strategy applied here works as follows. If the model spread, denoted $CDS_{model,t}$, is significantly higher than the market spread $CDS_{market,t}$, a misalignment has occurred. Mathematically one can write

$$CDS_{model,t} > (1+\alpha) \times CDS_{market,t}, \tag{33}$$

where α represents the trading trigger. In the empirical analysis, different alpha levels are tested. Given that Equation (33) is true, it can be interpreted that the market spread is too low according to the synthetic spread. In order to benefit from this misalignment, a long CDS position is opened on the next trading day. To hedge the risk, a short variance swap position is opened. A short CDS position is opened in a situation where the market spread is significantly lower than the spread implied by the model. In other words, if

$$CDS_{market,t} > (1+\alpha) \times CDS_{model,t},$$

then a short CDS position is established. This position is hedged by taking a long variance swap position on the next trading. After a signal is registered, both of the positions are opened and traded based on the following day's closing values.

To close a position, one of the following must be true: model and market spread have converged, the maximum drawdown limit is hit, or the maximum holding period is reached. Following Wojtowicz (2014), perfect convergence between the model and market spread is not needed. It is assumed in all the tested strategies that the convergence interval is 2.5%. More formally, a position is closed if

$$\begin{cases} CDS_{model,t} \leq (1+\varepsilon) \times CDS_{market,t}, & \text{if long CDS leg} \\ CDS_{model,t} \geq (1-\varepsilon) \times CDS_{market,t}, & \text{if short CDS leg,} \end{cases} \tag{34}$$

where ε denotes the convergence interval. A position is closed based on the closing values of the next trading day. Correspondingly trades might be exited if the maximum drawdown limit is hit. Here, the maximum drawdown limit is set to equal 50% of the invested capital. As the capital allocated to the trades is 50% of the traded CDS notional, the maximum drawdown limit stands at 25% of the

CDS notional traded. Furthermore, open positions are terminated if the maximum holding period of 180 days is reached. Before new positions can be opened after the maximum holding period is surpassed, there has to be a convergence similar to the one defined in Equation (34). Due to the fact that the sample ends at 30.7.2019, no new trades are opened after 29.1.2019. This way, all the open trades are terminated before the last sample date. All in all, the selected parameters are generally in line with previous studies. This allows us to focus on the effects of the instrument level execution, which, on the other hand, differs significantly from the preceding literature.

5.2.3 Hedge ratio, position mark-to-market and return aggregation

For the strategy to be profitable, it is essential to correctly size the CDS and variance swap positions. To do that, a hedge ratio must be calculated. If equities are used to hedge the CDS exposure, it is rather simple to determine the correct hedge ratio. For example, in the CreditGrades framework, the hedge ratio is defined by an analytical expression. Here, however, an empirical hedge ratio is used. This corresponds with the hedge ratio methodology applied by Zeitsch (2017). Before the strategy goes live, an initial hedge ratio based on regression is determined. As time goes by, the hedge ratio is updated with the latest data, and thus it reflects the possibly changing market conditions. As the PL of the variance swap depends on the realized and current fair value of variance, a statically calculated hedge ratio is never perfect. Here, the base assumption is that on average the positions are going to converge and ultimately be closed in a relatively short amount of time. In that case, the market pricing of future variance can be seen as the main contributor to the PL of the contract. Due to this assumption, the hedge ratio is based on the relationship between the CDS spread and the variance swap rate of the traded tenor. This tenor is fixed to six months with all the strategies. Naturally, as the position is open and time goes on, the hedge ratio becomes less accurate since realized variance starts to contribute more and more to the PL of the variance swap.

Approaching the hedge ratio more mathematically, one must start with the regression in which the variance swap rate's sensitivity to the CDS spread is determined. Starting from the first sample date, the sensitivity for date t_v is estimated with the following linear model

$$K(i)_{Var_m} = \hat{\beta}_0 + \hat{\beta}_1 S(i), \tag{35}$$

where $K(i)_{Var_m}$ is the time series of a variance swap rate with a contract tenor of m months, and correspondingly $S(i)$ represents the CDS time series. Regression parameters are denoted by $\hat{\beta}_0$ and $\hat{\beta}_1$, and i is defined as $i = 1, 2, ..., t_v$. Here, a crude assumption is made that, on average, $\hat{\beta}_0$ is zero. As the model in Equation (35) is updated daily with new data, the current hedge ratio $\hat{\beta}_1$ reflects changing market conditions dynamically and is used to scale the size of the opened variance swap position. Moreover, when a position is opened, the hedge is static, and thus, positions are not rebalanced during the holding period. This approach is in line with preceding studies.

In the trading strategy, the used CDS notional (N_{CDS}) is one million euros. Now that the relationship between the variance swap rate and CDS spread is estimated, it is possible to size the notional of the variance swap contract so that the hedge is as accurate as it can be given the selected approach. If a trade is opened at time t_{v+1}, the variance notional is determined by

$$N_{Variance} = \frac{RPV01_{t_v} \times N_{CDS}}{\hat{\beta}_1},$$

where $RPV01_{t_v}$ is the risky present value of a basis point at time t_v as defined in Equation (32). Equivalently the vega notional is written as

$$N_{Vega} = N_{Variance} \times 2K_{Strike},$$

where K_{Strike} is the strike of the variance swap quoted in terms of volatility (Allen et al., 2006, 12). To avoid situations where the hedge ratio gives spurious signals, a limit is set regarding the value of $\hat{\beta}_1$. With a limited amount of data, the parameter might turn out to be negative, and thus corrupting the variance swap notional calculation. If extremely low $\hat{\beta}_1$ values are observed, and trades should be opened for that obligor, the last available sample mean $\hat{\beta}_1$ value is used instead. All things considered, these occurrences are rare in nature, but still, it remains essential to manage issues arising from spurious relationships.

Whenever positions are opened, the mark-to-market (MTM) of both the variance and credit default swaps must be calculated daily. This is done so that the preset trading rules, such as the maximum drawdown limit, can be monitored. Furthermore, the daily profit and loss for the sample must be calculated for the aggregate return calculation. With CDS contracts, the MTM is calculated based on the five-year on-the-run CDS quote. As noted by Wojtowicz (2014), this approximation can be considered to be a sound one due to the shape of the CDS curve. From the perspective of economic significance, trading costs should also be incorporated in the MTM calculation. Previous studies such as Yu (2006), Duarte et al. (2006), Imbierowicz & Cserna (2008) and Huang & Luo (2016) use a 5% bid-ask spread assumption. Wojtowicz (2014), however, use actual bid-ask spread from Markit to find that between the years 2010 and 2012, bid-ask spread ranged from 5.6% to as high as 12.2%. Based on these findings, the spread used in strategy calculations is simply the middle point of the range, i.e., 8.9%. This estimate better reflects true market spreads than the 5% level used in earlier studies.

The calculation process in itself is relatively simple as can be seen from Equations (26) and (25). The only challenge is to determine the term structure of default probabilities. Here, a simple approximation is used to estimate these probabilities. Generally, the default probability between time t and T is given by

$$Q(t,T) = e^{-(T-t)\Lambda_t},$$

where Λ_t is the constant zero hazard rate. To further approximate the constant zero hazard rate at time t, one can rely on the following expression

$$\Lambda_t = \frac{CDS_{market,t}}{(1-RR)},$$

where RR stands for the constant recovery rate assumption. In the empirical part, the recovery rate is assumed to equal 40%. To increase the accuracy of the hazard rate estimate, it is possible to utilize a CDS pricing model and optimize the hazard rate so that the model spread matches the market implied spread. However, the spread of the approximated hazard rate is accurate enough for this thesis's purposes. For a more thorough discussion regarding the constant hazard rate, see, e.g., White (2013).

With variance swaps, the mark-to-market calculation methodology is relatively simple because variance is additive. The PL of the contract is dependent on the realized and future fair value of variance. Put mathematically, the PL of a long variance swap at time t is determined by

$$MTM_L(t,T) = N_{Variance}\Big[\frac{t}{T}(\sigma^2_{R:0,t} - K_{Var:0,T}) + \frac{T-t}{T}(K_{Var:t,T} - K_{Var:0,T})\Big],$$

where T denotes the time to maturity, $\sigma^2_{R:0,t}$ represents the realized variance between time 0 and time t, and $K_{Var:t,T}$ is the fair value of variance for the remaining contract period. Moreover, $K_{Var:0,T}$ refers to the strike of the contract (Allen et al. 2006, 15–16). To calculate the realized variance, the so-called root-mean-squared methodology is applied. Realized variance is thus given by

$$\sigma^2_{R:0,t} = \frac{252}{T}\sum_{i=1}^{T}\left[\left(\ln\frac{S_i}{S_{i-1}}\right)\right],$$

where S_i is the stock price at time i and ln denotes the natural logarithm (Allen et al. 2006, 10). The fair value of variance $K_{Var:t,T}$ is estimated by fitting cubic splines into the prevailing term structure. By applying this simple interpolation methodology, the term structure is made continuous, and thus the roll effects are taken into consideration in the calculation process.

With variance swaps, a bid-ask spread of 5% is assumed. This represents the costs of trading. The assumption is partly based on the observations of Egloff, Leippold & Wu (2010) who estimate the bid-ask spreads for variance swap contracts underlying the S&P 500 index are somewhere around half and one percentage points. Filipović, Gourier & Mancini (2016) use actual bid-ask spreads sourced by a large broker-dealer, and discover that relative spreads for similar contracts with tenors from two to twelve months range from 2.3% to 1.2%. Moreover, they find that the bid-ask spread tends to increase while the tenor gets shorter. Addressing the lower liquidity with single-name contracts, the relative spread is set here to 5% of the variance swap rate. This way, higher variance swap rate levels lead to a higher bid-ask spread in absolute terms. Looking at the average six-month variance rate of the sample in Table 2, it can be seen that 5% constitutes approximately to a bid-ask spread of 1.4 percentage points or equivalently 1.4 vegas. Based on the information provided by Allen et al. (2006), who comments that in Europe, single-name bid-ask spreads are around 1 to 2 vegas, it can be said that the estimate is accurate enough. To make matters simple, the spread is not adjusted for different tenors, but instead it is assumed to remain static for all tenors. All daily MTM calculations with both CDS and variance swap are done so that the possible costs of closing these trades are reflected in the daily PL figures. More precisely, the round-trip cost, i.e., the bid-ask spread, is taken into account in the PL figures presented later.

To conduct a meaningful analysis of the strategy, company-level returns are calculated and then aggregated to the sample level. The process starts by calculating the company-specific daily returns based on initial invested capital and daily PLs. From the daily returns, the risk-free rate, in this case, 12-month EURIBOR, is subtracted. By following this approach, excess returns are obtained. When aggregating the returns, a standard methodology applied in earlier studies is utilized. All the opened positions can be thought of as single funds, which are opened and closed in conjunction with the trades. The same level of initial capital is committed to every "fund." All the open trades are given equal weight at any given moment, i.e., the s ample daily return is the mean daily return of all the open positions. From the daily data, an index is constructed so that logarithmic monthly excess returns can be calculated. These returns are utilized when the strategy's profitability is analyzed from the perspective of other market-level variables.

6 EMPIRICAL RESULTS

6.1 Model accuracy

The empirical part covered next can be divided into two sections based on the two-fold aim of this study. First, the effectiveness of model calibration methodologies in terms of model accuracy is analyzed. In the second part, holding period and monthly returns of the strategy variations are addressed. Before moving to this analysis, however, a case study of a global mining company Anglo American plc is presented to illustrate the dynamics of the trading strategy.

When discussing about model accuracy, it is essential to begin with the Merton (1974) model, which is used to calculate default probabilities. As noted widely in academic literature, the Merton (1974) model has a tendency to systematically produce spreads that are too low (see, e.g., Ogden 1987, Lyden & Saraniti 2001 and Eom et al. 2004). From the perspective of capital structure arbitrage, a biased spread estimate can lead to trades that should not have been opened in the first place, and thus the strategy PL is likely to be affected negatively. In Table 3, estimation error statistics for different model variations are reported in basis points. The estimation error is calculated by subtracting the model spread from the market spread. Eight separate model variants are presented here and used later to produce signals for the trading strategy. Models use four different volatility calibration methodologies, namely historical 360-day volatility (HVOL), two-month 10-delta put implied volatility (PUTIV), one-month variance swap rate (VS1M) and six-month variance swap rate (VS6M). Models M1 to M4 and M5 to M8 differ only in terms of the distribution applied in the default probability calculation. In all models, the risk-neutrally calibrated default barrier is used. To make the analysis more granular, the sample has been divided into two sub-samples based on the obligor's credit quality. Both the same model variants and sub-sample categorizations are used throughout this chapter.

Focusing on Panel A, which depicts model variants that utilize normal distribution in default probability calculations, it can be seen that with model M2 the underestimation issues mentioned widely in existing literature can be averted. The volatility calibration, in which primarily two-month 10-delta put implied volatility is used, can be identified as the main culprit behind the slight overestimation. As is evident, other model variants dominate model M1 in terms of total sample estimation error. This can be interpreted as partial evidence favoring models calibrated with implied instead of historical volatility. Still, models M1, M3, and M4 produce

Table 3: Model estimation error statistics categorized based on calibration methodology and sample credit quality

Table reports the estimation error statistics of different model specifications. Estimation error is defined as the daily difference between obligor's market CDS spread, and the model implied spread. Panel A presents models in which the normal distribution is used to map default risks, whereas models depicted in Panel B rely on Student's t-distribution. After model name (e.g., M1), the volatility calibration method is given. HVOL refers to historical 360-day volatility, and PUTIV to two-month 10-delta put implied volatility. VS1M and VS6M symbolize one-month and six-month variance swap rates, respectively. Model names are consistent throughout the empirical section. Statistics are reported on a sub-sample level. Total represents the whole sample, High consists of firms with credit ratings between AA-A, and Low reflects a sample of obligors with credit ratings between BBB-BB. Mean refers to average daily estimation error, Median gives the median daily estimation error, Std is the standard deviation of the error, Min corresponds with the largest daily spread overestimation, and Max denotes the largest daily underestimation in the sample. Statistics are calculated during the trading window ranging from 2.8.2011 to 30.7.2019.

Model	Sub-sample	Mean	Median	Std	Min	Max
Panel A: Normal distribution						
M1: HVOL	Total	71	57	68	-336	1153
	High	57	49	57	-268	961
	Low	87	68	75	-336	1153
M2: PUTIV	Total	-7	-1	69	-681	697
	High	-23	-11	69	-681	697
	Low	13	11	64	-587	668
M3: VS1M	Total	68	56	64	-884	856
	High	55	49	59	-884	705
	Low	84	67	66	-537	856
M4: VS6M	Total	70	57	60	-449	793
	High	57	49	54	-449	663
	Low	86	68	64	-378	793
Panel B: Student's t-distribution						
M5: HVOL	Total	17	14	65	-336	1081
	High	2	6	60	-321	891
	Low	35	25	67	-336	1081
M6: PUTIV	Total	-7	0	69	-765	697
	High	-22	-9	70	-681	697
	Low	11	11	64	-765	668
M7: VS1M	Total	14	14	63	-643	783
	High	1	6	61	-643	660
	Low	31	24	62	-501	783
M8: VS6M	Total	14	12	57	-414	790
	High	-0	4	53	-414	500
	Low	31	22	57	-345	790

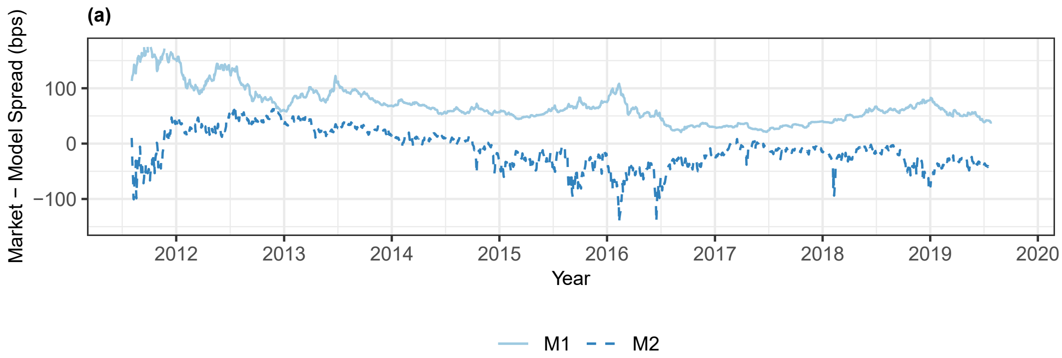
Table 4: Optimal degrees of freedom for models M5, M6, M7, and M8

Table reports the selected degree of freedom for the obligors in the sample. Results are presented for models in which the Student's t-distribution is applied for default probability calculations. The degree of freedom is selected by minimizing the estimation during the calibration period ranging from 2.8.2010 to 2.8.2011. The specification leading to the smallest error is selected. Estimation is made between freedom levels from 1 to 4.

	Degree of freedom				
Model	1	2	3	4	Median
M5: HVOL	92	4	1	5	1
M6: PUTIV	89	8	1	4	1
M7: VS1M	97	4	0	1	1
M8: VS6M	89	9	0	4	1

relatively biased estimates. And as documented, the estimation error is positive, and in this case signifying underestimation. With Table 3, more interesting results are observable in Panel B. Here, model variants have been optimized by minimizing the estimation error during the one-year calibration period by adjusting the degree of freedom in the t-distribution used to determine default probabilities. The distribution of selected degrees of freedom are presented in Table 4. For all models calibrated, the most common choice among the sample obligors is the first degree of freedom, hence the option with the fattest tails. By easing the restrictions posed by the normal distribution, estimation accuracy can be enhanced. Comparing model M6 to M2, the difference is negligible, but for models M5, M7, and M8, the improvement is significant. By using the t-distribution, estimation errors for these models can be lowered by approximately 55 basis points. Furthermore, the performance of models calibrated with implied volatility dominates historical volatility corresponding to findings of Panel A. Comparing the models calibrated with variance swap rates, the spread between the estimation errors narrows in Panel B. Moreover, looking at the standard deviation of the estimated error, it can be seen that M8 dominates M7. This might be due to the more stable characteristics of long-term implied volatilities.

To gain a better understanding of the longitudinal nature of model biases, model-specific errors are plotted in Figures 1 and 2. Indicated by the time series in Figure 1, the underestimation for models M1, M3, and M4 is quite systematic. From a stability perspective, the estimation error produced by model M4 is the least volatile, whereas M2 is clearly more responsive. In Figure 2, error dynamics are almost identical. However, with models M5, M7, and M8, a clear level shift can be identified compared to models presented in Figure 1. In these time series, market equity volatility seems to cause a similar volatile effect in the



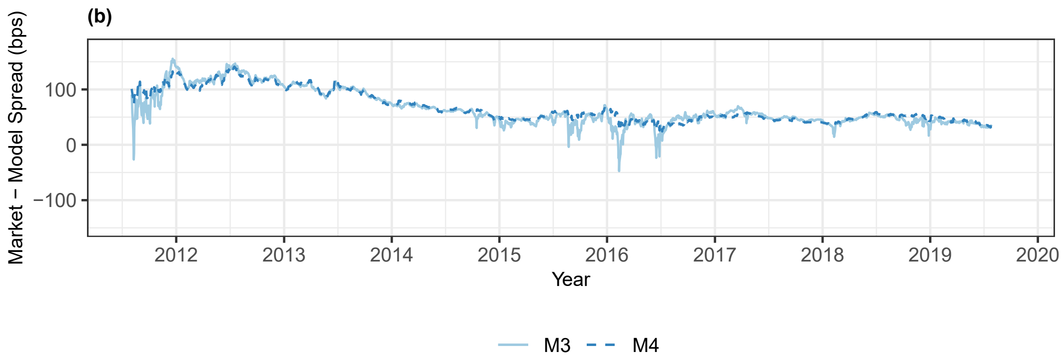


Figure 1: Mean daily estimation errors for models M1, M2, M3, and M4

Figure (a) depicts the average estimation error in basis points for models M1 and M2 during the trading period reaching from 2.8.2011 to 30.7.2019. Similarly, Figure (b) details the estimation error for models M3 and M4.

errors. Looking at the data through this lens, model M8 appears to be the most stable model in terms of estimation error volatility, while models calibrated with 10-delta put implied volatility lead to a higher level of responsiveness. This is line with a hypothesis made by Zeitsch (2017) regarding asset volatility calibration – utilizing deep out-of-the-money put implied volatility improves default probability estimation characteristics of the model.

In Table 5, estimation errors are presented on a sector level for all model variants. Of all the sectors, especially financials is of particular interest due to the unconventional capital structures of financial institutions. Looking back at Table 2, the average sample leverage calculated by dividing total liabilities with the total balance sheet size is 0.59. The same number for financials is 0.94 striking as an apparent anomaly among sectors. Returning to Table 5 and analyzing models relying on the normal distribution, a definite spread underestimation can be observed throughout the sectors except for M2. With financials, the model produces spread estimates that are, on average, 45 basis points above the market spread. In the other model cohort, it can be seen that estimation errors become smaller for all

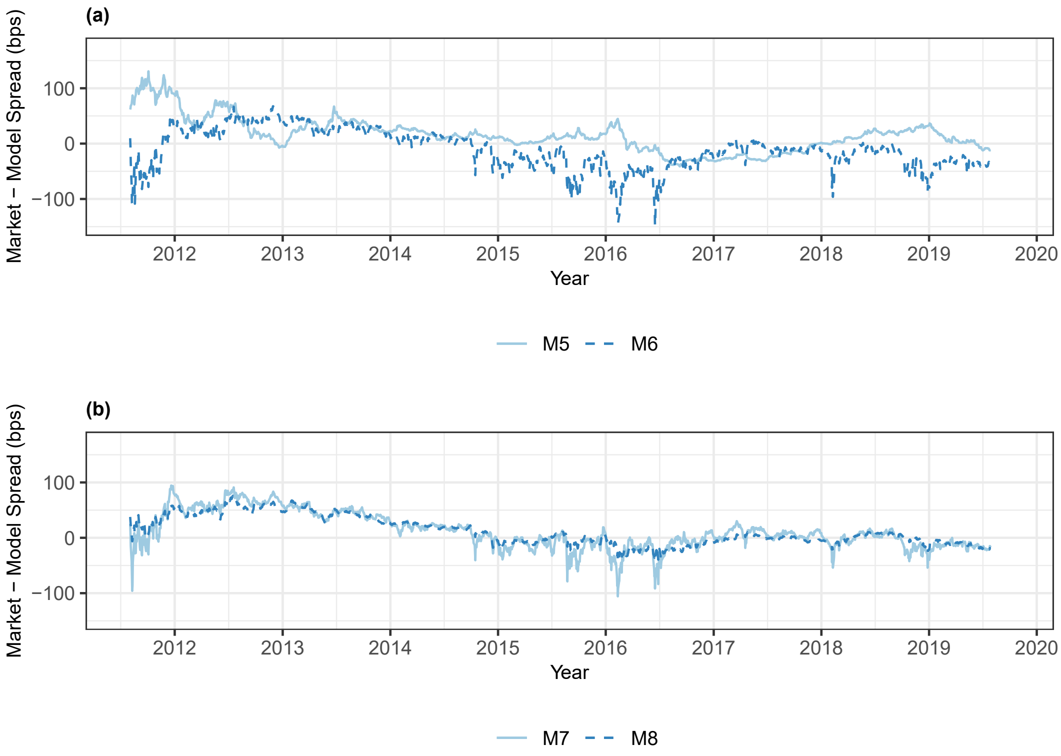


Figure 2: Mean daily estimation errors for models M5, M6, M7, and M8
Average estimation error in basis points for models M5 and M6 is portrayed in Figure (a). Errors for models M7 and M8 are depicted in Figure (b). The period under consideration reflects the time when trading took place, i.e., from 2.8.2011 to 30.7.2019.

sectors, and for financials turn negative with all model variants. Too high spread estimates are naturally due to higher than market default probabilities. However, by relying on the t-distribution instead of its normal counterpart makes estimates less biased, thus supporting the use of models M5 to M8 over models M1 to M4.

In previous studies conducted by Imbierowicz & Cserna (2008) and Ju et al. (2015), model estimation errors are analyzed so that effective comparisons can be made. Starting with the study of Imbierowicz & Cserna (2008) in which the CDS spread estimates are produced with either the CreditGrades, Leland & Toft (1996) or Zhou (2001) model. In this study, historical volatility is used in model calibration. During the analyzed sample window starting at the year 2002 and ending in 2006, the mean sample absolute estimation error for the CreditGrades, Leland & Toft (1996) and Zhou (2001) models are 32, 34 and 26 basis points respectively. The results indicate that the tested models systematically overestimate market spreads on an aggregate level. Taking into account that the sample consists partly of obligors with speculative-grade credit ratings, which have higher spreads in absolute terms, the errors in the investment-grade sub-sample are more

Table 5: Mean estimation errors for different model specification organized based on GICS sectors

Here, mean estimation errors are reported and divided into sub-samples corresponding with the obligor's GICS sector. Estimation error is the difference between obligor's CDS spread, and the synthetic model spread reported in basis points. Estimation errors are calculated during the strategy trading period. Model specifications and naming conventions correspond with Table 3.

	Normal distribution				Student's t-distribution			
Sector	M1	M2	M3	M4	M5	M6	M7	M8
Communication Services	62	-5	60	61	17	-5	12	11
Consumer Discretionary	83	-1	78	81	28	-5	19	22
Consumer Staples	77	14	70	72	39	14	29	31
Energy	61	-10	59	61	18	-10	12	10
Financials	54	-45	55	56	-18	-45	-14	-16
Health Care	41	-7	38	39	12	-6	4	5
Industrials	65	-4	64	64	15	-3	15	13
Information Technology	151	68	137	152	82	68	75	77
Materials	110	31	108	112	49	28	50	51
Utilities	67	-24	61	63	7	-22	2	2
Total	71	-7	68	70	17	-7	14	14

comparable given the sample of this study. These absolute errors for the models in the previous order are 31, 45, and 39 basis points. Most models constructed in this study, especially models M2 and M6, clearly outperform models tested by Imbierowicz & Cserna (2008) in terms of estimation errors. Moreover, smaller estimation errors cannot be explained by lower absolute spread levels during the sample window analyzed here. In fact, the average CDS spreads are higher than during the sample utilized by Imbierowicz & Cserna (2008). On a sector level, similar outperformance is observable with most sectors. Interestingly, estimation errors with financials are lower in Imbierowicz & Cserna (2008) than in models M5 to M8. This is perhaps due to the alternated default barrier methodology applied for financials in their study.

Continuing with the comparisons, Ju et al. (2015) test whether variants of an extended multi-period Geske & Johnson (1984) model can outperform CreditGrades in terms of responsiveness and model accuracy. All models are calibrated with 1000-day historical volatility, and the sample ranges from 2004 to 2008. With all model variants, the estimated spread for the total sample is higher than the market spread. CreditGrades leads to the highest average overestimation amounting to 185 basis points whereas extended Geske & Johnson (1984) model produces errors from 109 to 60 basis depending on the model variant. Considering only firms with high credit quality, model M2 and M6 still outperform all the models tested by Ju et al. (2015). On an aggregate level, additionally, models M5, M7, and M8 generate lower estimation errors. Furthermore, the estimates calculated here are significantly less volatile than estimates of Ju et al. (2015).

As expected, using risk-neutral measures such as implied volatility and variance swap rates in volatility calibration leads to improved model accuracy, as indicated by the lower estimation errors. The benefits of using these measures instead of historical ones are further confirmed by comparing the results to the discoveries made by Imbierowicz & Cserna (2008) and Ju et al. (2015). Additionally, results support the use of Merton (1974) model instead of more conventional, and perhaps mode complex models such as the CreditGrades and extended Geske & Johnson (1984). The key behind lower estimation error with models relying on other than the two-month 10-delta put implied volatility, is the use of Student's t-distribution instead of the normal distribution. As stated in Moody's KMV methodology, distance to default measures are mapped based on historical data instead of using the normal distribution to end up with default probabilities (Crosbie & Bohn, 2003, 18). Results uncovered here, suggest default probabilities follow a distribution with fatter tails than the ones of normal distribution. This corresponds with the comments made by Crosbie & Bohn (2003) concerning the differences between the normal distribution and the empirical default distribution.

However, one crucial aspect of the risk-neutral calibration methodology introduced by Zeitsch (2017) seems not to contribute to estimation accuracy positively. That is namely, the default barrier methodology. To test its effectiveness, spread estimates using total liabilities as a constant default barrier are calculated and analyzed. Comparing these results with the ones depicted in Table 3 and 5, no apparent differences can be found on an aggregate level. Negative interest rates introduced in the middle part of the sample might affect the results somewhat. Not to go further here into analyzing the connection between negative interest rates and the applied default barrier methodology, it can be, however, said that more research is needed when it comes to default barrier calibration for companies with unconventional capital structures.

6.2 Case study of the strategy: Anglo American plc

To gain a better understanding of the strategy dynamics, a case study of Anglo American plc is presented next. The British company specializing in copper, diamond, iron ore, and platinum mining among other metals and commodities, faced macroeconomic headwinds in the latter part of 2015 as China growth fears spread among market participants. Market volatility of mining companies increased during the fall as market discounted the effects of lower commodity demand from China. (Anglo American plc 2020; Financial Times 2015b) Moreover, as a large diamond produced, Anglo American was at the same time struggling with the global oversupply of diamonds making the company's outlook even grimmer (Financial Times 2015a). In Figure 3, the five-year EUR denominated CDS spread of Anglo American plc is depicted alongside with the synthetic model spread. The model spread in Figure 3 is calculated with model M8, i.e., the model is calibrated with six-month variance swap rates, and the t-distribution is applied in the calculation of default probabilities.

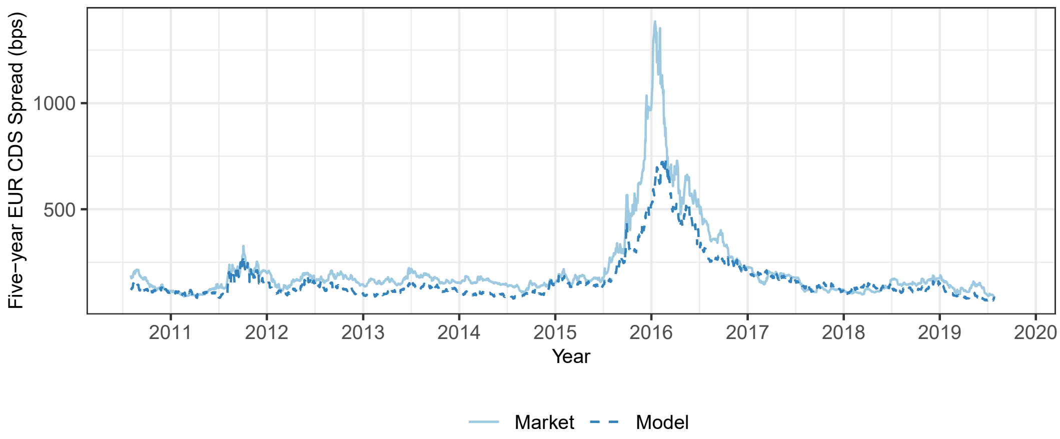


Figure 3: The five-year market CDS and M8 model spread of Anglo American plc
Spread is reported in basis points. The period under consideration corresponds with the full sample period starting at 2.8.2010 and ending 30.7.2019.

As can be seen, a clear divergence between the model and market spread starts to take place in the latter part of 2015, coinciding with macroeconomic challenges faced by the company. In Figure 4 (a), the capital structure of the company is depicted. The sliding market capitalization translates into a higher default probability, as shown in Figure 4 (b). At the peak of uncertainty, the company's asset value came rather close to the default barrier depicted in Figure 4 (a). As mentioned earlier, the default barrier in the negative interest rate environment is in close agreeance with total liabilities.

With the divergence ever-growing, the threshold indicating the need to open a position; in other words, a trading trigger of 1, is crossed on the 11.12.2015. At this stage, the model implied spread is approximately 480 basis points (bps), and the market spread is a bit over 960 bps, and hence the trading trigger is crossed.

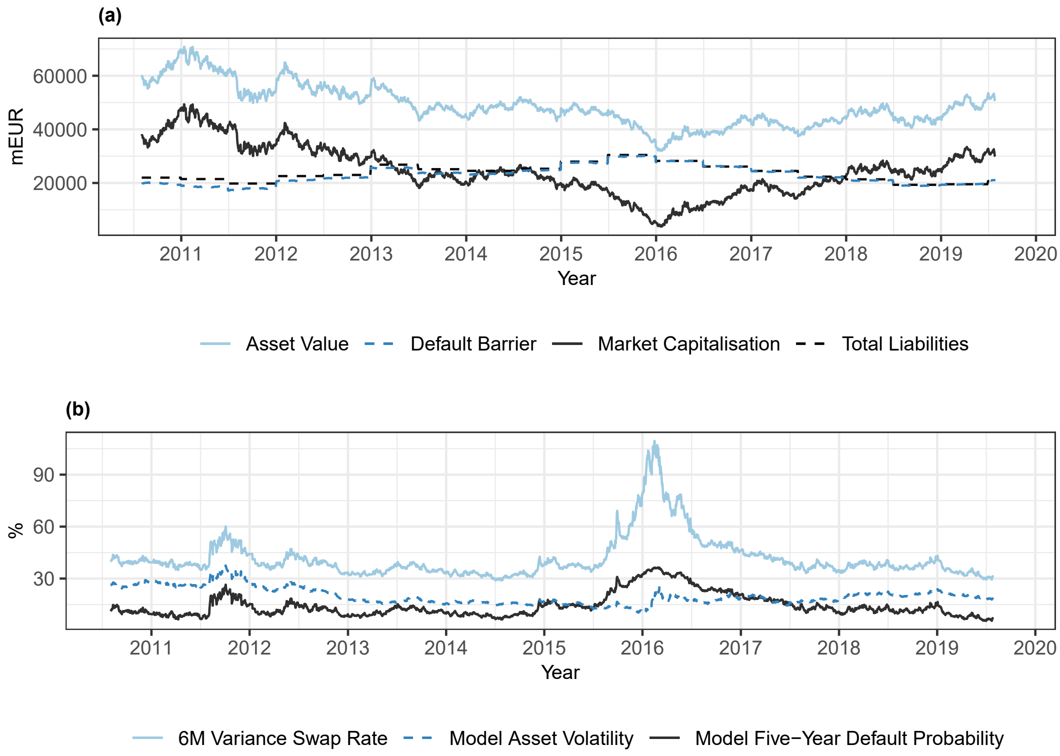


Figure 4: Model input and output for Anglo American plc

Figure (a) depicts the asset value, estimated default barrier, market capitalization, and total liabilities of Anglo American plc. In Figure (b), a six-month variance swap rate used in the calibration of model M8 is depicted alongside the model implied asset volatility and five-year default probability. Time series are presented for the full sample period.

According to the model, the market spread is too high, and it can be assumed to converge to the fundamental value calculated with the Merton (1974) model. This translates into a short CDS position with a strike of approximately 920 basis points after adjusting for the 8.5% bid-ask spread. To hedge the CDS leg, a long six-month variance swap position expiring on Wednesday the 8th of June in 2016 is opened with a strike of 75.1% expressed in vegas. The strike is similarly adjusted with the assumed bid-ask-spread of 5%. The notional of the variance swap is based on the hedge ratio calculated with Formula (35). Put simply, the variance swap position is sized based on historical co-movement of the six-month variance swap rate and the five-year CDS spread.

In Figure 5, the profit and loss (PL) of both the CDS and variance swap legs are depicted in addition to the total net PL of the position. In the first few days after positions are opened, the PL is negative partly due to the effect of bid-ask spreads. In early 2016, the variance swap trade PL turns positive as variance swap rates soar. Additionally, the realized variance of Anglo American's equity price is high

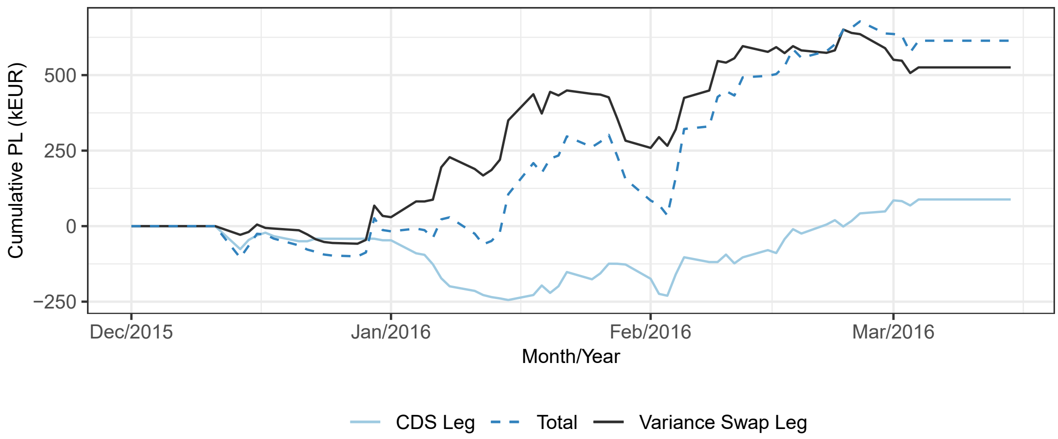


Figure 5: Trade PL breakdown
Profit and loss figures for the example trade are detailed here. Numbers reflect the daily PL calculated with hypothetical trade closing prices, thus incorporating transaction costs on a daily basis. Trade PL is achieved with model M8 accompanied by a trading trigger of 1.0.

during this time further boosting the positive PL. In late February and early March of 2016, as the market pressure starts to ease, the company's CDS spread starts to come down quickly and eventually converges with the model spread on the 4th of March. At this stage, the market spread is at 707, and the model spread stands at 691. To achieve a higher rate of convergence, a perfect match between the spreads is not needed. With the convergence threshold being 2.5%, the two spreads are within the limits of this threshold, and hence the positions can be closed. Because the bid CDS spread of Anglo American plc has come down to 737 bps, the PL is positive. With the CDS notional being one million euros and the risky present value of a basis standing at approximately 484 euros, the total PL is close to 89,000 euros.[31] The long variance swap leg made a total PL of approximately 526,000 euros. This because the annual realized variance expressed in terms of volatility was 118% and the fair value of variance, i.e., the variance swap rate for the rest of the contract period, stood close to 98% in volatility terms. Given the strike of 75.1% and the time-weighted average of the realized and fair value of variance being approximately at 107.6%, the PL can be calculated. Considering that the variance notional of the trade is close to 88.5 euros per variance point, the total PL of the leg is 526,000 euros.[32] Hence, the total net PL of the position accumulates to 615,000 euros. With the initial capital of 500,000 euros in mind, the trade turned out to be extremely profitable. Of course, it is important to mention that

[31] $(920 - 737) \times €484 \approx €89,000$.
[32] Using variance points to do the PL calculation, you get $(11,578 - 5,640) \times €88.5 \approx €526,000$.

most trades rarely generate comparable returns, and typically trades can lead to a clearly negative net PL. Anglo American Plc is a great example of how the strategy should ideally work, and that is the primary reason it was discussed here.

6.3 Strategy returns

6.3.1 Holding period returns

In order to find out whether capital structure arbitrage opportunities can be found during the post-financial crisis sample period, a trading strategy must be implemented and tested based on the model signals discussed earlier. In this section, the results generated by this exact implementation are covered. First, strategy holding period returns are analyzed. Second, monthly returns of the constructed strategy indices are discussed. And lastly, tests are conducted to find out if common market risk factors can explain the monthly strategy excess returns. The implemented trading strategy follows the same general trading rules with every model variant: five-year CDS contracts are traded in conjunction with six-month variance swaps by limiting the maximum holding period to 180 days. Trading triggers of 0.5, 1.0, and 1.5 are tested. Furthermore, the sample is divided into sub-samples based on obligor's credit quality. To increase the economic significance of the analysis, transaction costs are factored into the returns.

In Table 6 and 7, holding period return statistics for all model variants are reported. Table 6 contains results of returns produced with models M1 to M4, which use normal distribution in determining default probabilities. Table 7, on the other hand, reports holding period returns for models relying on optimized t-distributions. Starting with the strategy characteristics of different model variants, some overarching observations can be made. More specifically, models calibrated with either two-month put implied volatility (M2 and M6) or with one-month variance swap rate (M3 and M7) lead to higher trading activity. For example, with models M2 and M3, there are many times more trades opened during the trading window compared to models M1 and M4. A similar observation can be made based on results illustrated in Table 7. Another corresponding observation is that with these more responsive models, the convergence rates are significantly higher than with models relying on the more static six-month variance swap rate and historical volatility. With the average convergence rate of over 85%, models top the 70% level reported by Zeitsch (2017). Improved convergence behavior is likewise reflected in shorter mean holding periods and in the relatively lower number of trades exceeding the maximum holding period limit of 180 days. Furthermore, by introducing a more responsive signal, a higher portion of the sample obligors can be traded. In Table 7, for example, the sample coverage, referring to the percentage of traded companies in the sample, is 100 percent with almost all of the different trading triggers tested with models M6 and M7. These observations are mostly consistent regardless of the applied trading trigger or obligors credit quality.

As the results indicate, the most responsive model variants, as could be expected based on model accuracy tests, are M2 and M6. However, with neither of these models or with models M3 and M7, positive mean holding period returns can be achieved on a sample level. In fact, these returns range from -0.61 to -0.54 percent. In addition to mean holding period returns, also median returns for most of the tested strategies for these models are negative. Interestingly, the returns' behavior seems not to be due to systematic long or short CDS positioning. Models M2 and M6 are on average net long CDS, i.e., short six-month variance swaps, and models M3 and M7 are short CDS and hence long six-month variance swaps as can be seen in the column called "Long (%)" in both Tables 6 and 7. If both models exhibited a similar bias to long or short positions, that could be seen as a possible culprit behind strategies' performance. Poor returns might also be attributed to strategy implementation and especially to tenor selection with variance swaps. More often, it seems that changes in the short-term pricing of options are not fully reflected in the longer maturity bands. If market participants expect risks to rise or fall in the short-term, this might not have an effect on the six-month contracts due to the mean-reverting nature of volatility. A genuinely fundamental shock is needed to see high a beta across the variance term structure. To truly test whether positive returns with these models could be generated, short-term variance swaps or deep out-of-the-money options, like in the implementation tested by Zeitsch (2017), should be used instead. The observation that the mean holding period with models M2, M3, M6, and M7 ranges from 49 to 60 days supports the use of two-month contracts. Strategy implementations with short-term volatility instruments are left in the hands of future research.

Table 6: Holding period return statistics for models M1, M2, M3, and M4

This table reports the holding period return statistics for models M1, M2, M3, and M4. In the Table, α refers to the trading trigger, N denotes the number of trades during the sample period, Cnvg is the number of converged trades, Pos (%) stands for the fraction of trades generating positive holding period returns, Max DD tells how many times the maximum drawdown limit is hit, Max HP represents the number of trades when maximum holding period limit is reached, Mean HP denotes the length of mean holding period in days, Long (%) is the percentage of long CDS trades, Cvge (%) symbolizes the percentage of sample obligors traded, Mean reports the average percentage profit and loss of the trades, Median is the median holding period return, Std is the standard deviation of holding period returns in the sample, Min refers to the minimum and Max to the maximum holding period return.

											Return (%)				
Model	Sub-sample	α	N	Cnvg	Pos (%)	Max DD	Max HP	Mean HP	Long (%)	Cvge (%)	Mean	Median	Std	Min	Max
M1:HVOL	Total	0.50	78	11	51	0	67	121	28	35	2.10	0.07	11.58	-16.05	47.76
		1.00	67	2	49	0	65	127	19	35	3.93	-0.02	11.82	-7.68	47.76
		1.50	66	7	52	0	59	127	15	35	4.43	0.40	12.81	-6.64	47.76
	High	0.50	60	9	55	0	51	119	33	43	2.76	0.14	11.18	-16.05	47.76
		1.00	51	2	57	0	49	127	24	43	4.80	0.86	11.47	-4.97	47.76
		1.50	50	7	56	0	43	126	18	43	5.30	0.81	12.89	-5.25	47.76
	Low	0.50	18	2	39	0	16	124	11	26	-0.11	-3.20	12.90	-12.57	47.21
		1.00	16	0	25	0	16	128	6	26	1.15	-1.61	12.86	-7.68	47.21
		1.50	16	0	38	0	16	128	6	26	1.72	-1.75	12.57	-6.64	47.21
M2: PUTIV	Total	0.50	1819	1588	38	6	225	51	56	100	-0.61	-0.36	6.92	-75.41	143.98
		1.00	787	595	45	2	190	73	62	99	-0.65	-0.27	5.04	-76.51	30.26
		1.50	436	280	48	2	154	85	70	96	-0.35	-0.11	5.40	-57.99	15.89
	High	0.50	911	776	35	5	130	53	63	100	-0.81	-0.37	5.95	-56.13	107.68
		1.00	411	296	45	1	114	78	73	100	-0.59	-0.28	4.66	-57.99	30.26
		1.50	246	150	48	1	95	89	80	96	-0.42	-0.06	5.51	-57.99	15.89
	Low	0.50	908	812	42	1	95	48	49	100	-0.40	-0.33	7.76	-75.41	143.98
		1.00	376	299	45	1	76	66	50	98	-0.73	-0.27	5.43	-76.51	8.38
		1.50	190	130	47	1	59	81	57	96	-0.27	-0.12	5.27	-47.16	14.17
M3: VS1M	Total	0.50	830	689	40	0	141	60	30	75	-0.60	-0.37	7.54	-42.08	129.38
		1.00	549	407	42	1	141	74	19	75	-0.81	-0.28	8.44	-53.05	118.52
		1.50	424	282	40	1	141	82	11	75	-1.27	-0.68	7.16	-46.61	46.36
	High	0.50	604	519	37	0	85	53	31	77	-0.89	-0.42	5.58	-42.08	46.36
		1.00	400	314	38	1	85	67	21	77	-0.96	-0.37	8.65	-53.05	118.52
		1.50	304	218	38	1	85	75	13	77	-1.33	-0.70	6.75	-46.61	46.36
	Low	0.50	226	170	47	0	56	68	27	72	0.19	-0.10	11.18	-26.10	129.38
		1.00	149	93	48	0	56	83	14	72	-0.40	-0.05	7.85	-26.10	38.28
		1.50	120	64	46	0	56	92	4	72	-1.12	-0.47	8.13	-26.10	38.72
M4: VS6M	Total	0.50	227	146	57	0	81	75	22	45	0.82	0.57	8.10	-34.09	72.15
		1.00	127	48	39	0	79	103	15	45	0.64	-1.32	10.17	-18.40	72.15
		1.50	104	32	38	0	72	109	14	45	1.42	-1.05	10.75	-12.38	72.15
	High	0.50	173	113	55	0	60	74	25	57	0.42	0.40	7.86	-34.09	72.15
		1.00	92	33	35	0	59	105	17	57	0.24	-1.38	10.00	-18.40	72.15
		1.50	74	22	36	0	52	110	18	57	1.08	-1.05	9.90	-9.57	72.15
	Low	0.50	54	33	65	0	21	77	11	30	2.08	1.94	8.79	-16.37	44.63
		1.00	35	15	49	0	20	99	9	30	1.70	-0.61	10.66	-12.93	44.63
		1.50	30	10	43	0	20	106	7	30	2.24	-1.07	12.75	-12.38	44.63

Table 7: Holding period return statistics for models M5, M6, M7, and M8

This table reports the holding period return statistics for models M5, M6, M7 and M8. Column names follow the same convention as in Table 6.

											Return (%)				
Model	Sub-sample	α	N	Cnvg	Pos (%)	Max DD	Max HP	Mean HP	Long (%)	Cvge (%)	Mean	Median	Std	Min	Max
M5: HVOL	Total	0.50	282	83	48	0	199	116	41	86	1.79	-0.13	12.08	-28.08	100.56
		1.00	141	21	55	0	120	123	40	74	3.58	0.40	16.75	-22.04	100.56
		1.50	89	4	60	1	84	125	38	52	3.65	0.55	17.36	-49.66	98.26
	High	0.50	186	63	52	0	123	112	48	91	2.82	0.14	13.78	-28.08	100.56
		1.00	93	18	58	0	75	119	47	80	5.16	1.01	19.26	-20.98	100.56
		1.50	62	3	58	1	58	124	45	64	3.78	0.52	19.38	-49.66	98.26
	Low	0.50	96	20	42	0	76	121	29	80	-0.23	-0.61	7.47	-19.34	38.49
		1.00	48	3	48	0	45	128	25	65	0.53	-0.26	9.77	-22.04	38.49
		1.50	27	1	63	0	26	128	22	37	3.36	0.57	11.81	-27.22	38.49
M6: PUTIV	Total	0.50	2015	1786	38	6	223	49	55	100	-0.59	-0.37	6.27	-75.41	143.98
		1.00	912	719	44	3	190	69	59	99	-0.57	-0.24	5.18	-76.51	37.31
		1.50	521	368	48	1	152	81	66	96	-0.23	-0.11	4.51	-57.99	15.89
	High	0.50	1019	885	35	5	129	51	61	100	-0.77	-0.37	5.63	-56.13	107.68
		1.00	491	375	43	1	115	75	67	100	-0.53	-0.22	4.29	-57.99	30.26
		1.50	302	207	50	1	94	85	73	96	-0.34	-0.00	5.00	-57.99	15.89
	Low	0.50	996	901	41	1	94	45	49	100	-0.40	-0.35	6.85	-75.41	143.98
		1.00	421	344	45	2	75	62	51	98	-0.62	-0.25	6.05	-76.51	37.31
		1.50	219	161	45	0	58	76	57	96	-0.08	-0.24	3.75	-16.68	14.17
M7: VS1M	Total	0.50	1832	1587	43	4	241	51	45	100	-0.54	-0.22	5.95	-61.31	105.03
		1.00	887	669	48	2	216	71	43	100	-0.43	-0.12	7.39	-52.72	149.36
		1.50	475	302	51	1	172	87	43	100	-0.66	0.03	5.71	-51.95	30.26
	High	0.50	1026	886	43	3	137	51	49	100	-0.72	-0.18	5.28	-61.31	46.10
		1.00	492	367	49	2	123	72	52	100	-0.80	-0.02	5.29	-52.72	30.26
		1.50	263	163	54	1	99	85	55	100	-0.61	0.14	6.22	-51.95	30.26
	Low	0.50	806	701	43	1	104	51	39	100	-0.31	-0.31	6.71	-47.24	105.03
		1.00	395	302	46	0	93	70	33	100	0.03	-0.30	9.35	-44.87	149.36
		1.50	212	139	47	0	73	89	29	100	-0.72	-0.18	5.02	-22.60	12.66
M8: VS6M	Total	0.50	507	283	62	3	221	89	44	96	1.30	0.88	9.27	-61.31	99.90
		1.00	201	61	59	1	139	113	40	89	1.73	0.76	14.15	-47.16	122.78
		1.50	109	25	58	0	84	117	39	73	2.25	0.46	14.22	-18.11	133.17
	High	0.50	295	169	62	2	124	88	52	98	0.97	0.73	9.10	-61.31	99.90
		1.00	110	30	62	0	80	114	57	95	2.07	0.86	13.60	-31.19	111.52
		1.50	59	8	58	0	51	118	56	80	2.90	0.13	18.15	-16.15	133.17
	Low	0.50	212	114	62	1	97	92	34	93	1.76	1.34	9.51	-55.19	74.85
		1.00	91	31	56	1	59	113	20	83	1.32	0.44	14.86	-47.16	122.78
		1.50	50	17	58	0	33	116	20	63	1.49	0.90	7.41	-18.11	41.59

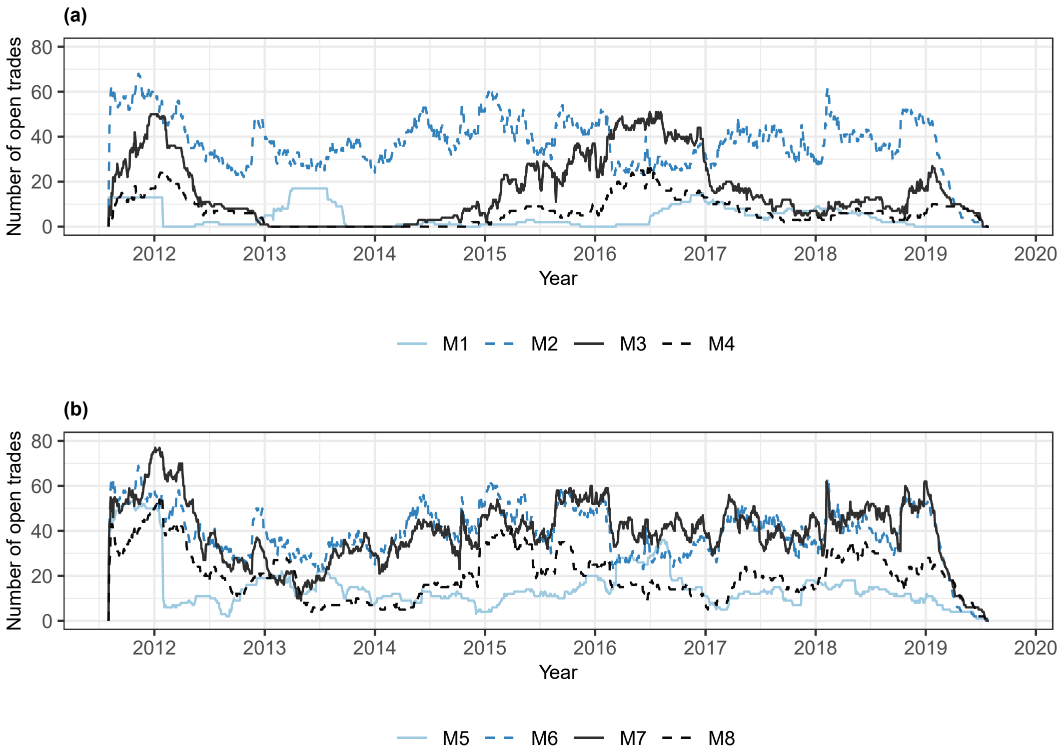


Figure 6: Number of open trades during the trading window

Figure (a) reports the total number of open trades at a given time for models M1, M2, M3, and M4. Correspondingly, Figure (b) reports the same figures for models M5, M6, M7, and M8. To specify, one trade consists of a CDS and a variance swap leg.

Models with which positive mean and median holding period returns can be attained are the ones calibrated with historical volatility (M1 and M5) and with the six-month variance swap rate (M4 and M8). Models M1 and M5 generate mean holding period returns from 1.79 to 4.43 percent, whereas with models M4 and M8 returns fluctuate between 0.64 and 2.25 percent on a sample level. When t-distribution is applied instead of the normal distribution, mean returns for models analyzed here are generally higher or remain largely unchanged. Comparing M1 to M5, mean returns are lower with model M5, but median returns are higher with trading triggers of 1.0 and 1.5. With all of the models, the use of t-distribution leads to higher trading activity, and thus the sample trading coverage increases, especially with models M5 and M8. The number of open trades is depicted in Figure 6. As can be seen, the change is dramatic with models M5, M7, and M8. When it comes to strategy performance, however, the change is the most significant between models M4 and M8. Mean and median returns with M8 are markedly higher as more trading opportunities arise. Moreover, with a trading trigger of

0.5, approximately 62% of opened trades generate a profit. Convergence rates are not as high as with models M6 and M7. Still, over 50% of the trades converge before the maximum holding period is reached given a trading trigger of 0.5. With M8, the maximum drawdown limit is hit less often than with models M7 and M6. Furthermore, based on the minimum and maximum returns, the strategy returns seems to be asymmetric. This is a sign that the imposed maximum drawdown limit is indeed effective.

Comparing these holding period returns and statistics to previous studies that rely on equities instead of equity variance, few themes come to the forefront. First, in studies conducted by Yu (2006), Bajlum & Larsen (2008) and Ju et al. (2015), who mainly utilize the CreditGrades model and similar strategy specifications in terms of maximum holding period and trading trigger, the amount of trading is many times higher than even with models M2 or M6. Additionally, convergence rates are relatively poor in those studies mentioned above. Continuing on these studies, returns with a 180-day maximum holding period and a trading trigger of 0.5 are somewhat in line with the models M1, M4, M5, and M8. It is essential to highlight that transaction cost assumptions made here are higher compared to these studies. As one of the most comparable studies in terms of strategy implementation details, Wojtowicz (2014) reports significantly fewer trades than other preceding studies. With a convergence rate and positive holding period return rate of over 60%, mean holding period returns of 6.59% can be generated. Using the CreditGrades model calibrated with, CDS implied volatility and following a maximum holding period of 180 days and a trading trigger of 0.5, the reported sample mean return can be regarded to be high. The reported mean is skewed due to large, over 40% holding period returns with B to CCC rated obligors. With companies whose credit ratings vary between AAA and A, mean holding period returns adjusted for transaction costs range from 0.24% to 0.91%. Hence, the returns generated by, for example, with model M8 are inline or even higher with the strategy tested in this thesis. Interestingly, in the strategy implementation discussed here, higher mean holding period returns cannot be generally linked to lower obligor credit quality as is the case in Yu (2006), Duarte et al. (2006), Bajlum & Larsen (2008) and Wojtowicz (2014) for example. Furthermore, the linkage between higher trading triggers and higher mean holding period returns is not coherent among tested model variants and different strategy specifications. Nonetheless, if only returns between trading triggers of 0.5 and 1.5 are compared, the relationship exists with almost all the model variants regardless of obligors' credit quality.

6.3.2 Strategy monthly returns

Based on holding period returns, it can be noted that model calibration significantly affects the performance of the capital structure arbitrage strategy tested here. To analyze this strategy from a more systematical perspective, an equally-weighted strategy index capturing all trades made during the trading window starting at 2.8.2011 and ending in July of 2019 is constructed. From this index, monthly excess returns can be calculated. In Tables 8 and 9, excess return statistics are presented for all model variants and tested trading triggers. With models relying on more short-term equity implied volatility, the mean monthly excess returns fluctuating on a sample level between -0.17% and -0.30% are indeed negative as the holding period returns suggested.

With models M4 and M8 positive monthly excess returns are attained with all trading triggers and in all sub-samples. Model variants calibrated with historical volatility offer generally positive returns on a total sample level as well. However, none of these positive returns are significant on a 95% confidence interval when adjusting the t-statistic for the first-order autocorrelation. Putting high p-values aside, and comparing risk-adjusted returns of the strategies, it is evident that following signals produced by model M8 is the best alternative. Sharpe ratios between 0.43 and 0.59 on a sample level can be acknowledged to be in the same range with ratios reported by Yu (2006), Duarte et al. (2006) and Imbierowicz & Cserna (2008). This can be seen as evidence in support of capital structure arbitrage strategies utilizing volatility and variance hedging methodologies instead of the traditional delta hedging approach.

Previous studies such as Yu (2006), Duarte et al. (2006), Bajlum & Larsen (2008) and Huang & Luo (2016) have found strategy returns to be largely positively skewed thus indicating that the profitability cannot be attributed to selling tail risk insurance. With strategies such as M5 and M8, which generate positive returns with all trading triggers, excess returns are indeed positively skewed, and minimum monthly excess returns are outweighed by positive and maximum monthly excess returns. Also, the use of models M1 and M4 leads to positively skewed returns. Another common observation holds here: on average, a higher trading trigger leads to higher excess returns. Nevertheless, no clear connection can be found between obligor's credit quality and corresponding monthly mean excess returns. Considering strategies with a trading trigger of 0.5, with six out of eight tested strategies, lower credit quality is linked to higher mean monthly excess returns. However, with a trading trigger of 1.5, the linkage inverts, and six out of eight strategies produce higher returns among obligors with higher credit quality. Perhaps misalignments of such proportions are relatively rare among companies with lower credit ratings. Instead, for companies with low absolute spread levels, there is room for large moves in both absolute and relative terms, and thus more lucrative trading opportunities can arise. If the sample would include obligors with credit ratings between B and CCC, the results might differ.

Table 8: Monthly strategy excess return statistics for models M1, M2, M3, and M4

Table reports the monthly return statistics of the constructed strategy index for models M1, M2, M3, and M4. The time under consideration represents the trading window starting at 2.8.2011 and ending 30.7.2019. Like in Table 6 and 7, α represents the trading trigger. N is the number of months, whereas N_{neg} gives the number of months with negative mean returns and N_{zero} the number of months when no positions were open. Mean is the average monthly excess return, and t-stat is the t-statistic of the mean monthly return adjusted for first-order autocorrelation. Median, Std, Kurt, and Skew denote the median, standard deviation, kurtosis, and skewness of the monthly returns, respectively. Corr stands for the first-order autocorrelation of mean monthly returns. Min and Max report the minimum and maximum monthly excess returns in decimal format, and Sharpe is the annualized Sharpe ratio of the strategy in question. Finally, P-value is linked to the t-statistic reported after mean excess returns.

Model	Sub-sample	α	N	N_{neg}	N_{zero}	Mean (%)	t-stat	Median (%)	Std (%)	Skew	Kurt	Corr	Min	Max	Sharpe	P-value
M1: HVOL	Total	0.50	95	47	19	-0.37	-0.97	0.00	3.20	0.64	15.16	0.10	-0.13	0.17	-0.39	0.33
		1.00	95	38	31	0.24	0.80	0.00	2.60	3.06	20.37	0.16	-0.06	0.17	0.32	0.43
		1.50	95	40	24	0.61	1.43	0.00	3.99	3.20	16.40	0.04	-0.06	0.23	0.55	0.16
	High	0.50	95	41	24	-0.26	-0.68	0.00	3.13	0.70	16.77	0.10	-0.13	0.17	-0.28	0.50
		1.00	95	31	32	0.28	0.96	0.00	2.59	3.18	21.30	0.13	-0.06	0.17	0.38	0.34
		1.50	95	36	27	0.68	1.68	0.00	3.83	3.72	19.19	0.04	-0.05	0.23	0.64	0.10
	Low	0.50	95	33	40	-0.24	-0.71	0.00	2.85	1.56	14.31	0.10	-0.09	0.16	-0.29	0.48
		1.00	95	27	46	-0.03	-0.13	0.00	3.05	0.89	13.79	-0.08	-0.13	0.16	-0.04	0.89
		1.50	95	29	47	0.06	0.20	0.00	3.17	1.17	14.77	0.02	-0.14	0.15	0.07	0.84
M2: PUTIV	Total	0.50	95	56	0	-0.28	-1.41	-0.12	1.77	-1.78	14.26	0.09	-0.09	0.06	-0.53	0.16
		1.00	95	54	0	-0.27	-1.29	-0.16	1.87	-2.48	18.22	0.08	-0.10	0.07	-0.48	0.20
		1.50	95	49	0	-0.22	-1.26	-0.02	1.82	-2.41	20.07	-0.10	-0.12	0.07	-0.41	0.21
	High	0.50	95	57	0	-0.29	-1.51	-0.19	1.99	0.21	18.54	-0.06	-0.10	0.10	-0.50	0.14
		1.00	95	57	0	-0.21	-1.13	-0.17	1.82	-1.52	16.05	-0.02	-0.11	0.07	-0.39	0.26
		1.50	95	48	0	-0.21	-1.24	-0.08	1.85	-2.20	19.84	-0.11	-0.12	0.07	-0.40	0.22
	Low	0.50	95	51	0	-0.23	-0.98	-0.07	2.14	-2.30	20.82	0.14	-0.14	0.08	-0.37	0.33
		1.00	95	61	0	-0.35	-1.21	-0.20	2.42	-4.32	32.91	0.15	-0.18	0.05	-0.49	0.23
		1.50	95	53	0	-0.37	-1.48	-0.10	2.28	-1.98	11.28	0.10	-0.12	0.05	-0.56	0.14
M3: VS1M	Total	0.50	95	50	14	-0.32	-0.89	-0.10	2.49	0.95	10.84	0.20	-0.09	0.12	-0.43	0.37
		1.00	95	50	14	-0.37	-1.03	-0.06	2.94	2.26	20.16	0.12	-0.11	0.18	-0.42	0.30
		1.50	95	54	14	-0.42	-1.34	-0.12	2.62	1.34	12.61	0.10	-0.09	0.14	-0.54	0.18
	High	0.50	95	51	15	-0.01	0.61	-0.27	4.63	5.80	48.72	0.21	-0.10	0.38	-0.01	0.54
		1.00	95	50	15	-0.26	0.03	-0.05	4.10	3.26	23.63	0.29	-0.12	0.26	-0.21	0.98
		1.50	95	52	14	-0.29	-0.19	-0.16	3.55	2.61	20.98	0.25	-0.12	0.22	-0.28	0.85
	Low	0.50	95	43	21	-0.25	-0.93	0.00	2.96	1.94	12.51	-0.13	-0.08	0.15	-0.29	0.36
		1.00	95	44	22	-0.29	-1.25	0.00	2.83	2.60	18.80	-0.23	-0.06	0.17	-0.35	0.21
		1.50	95	42	22	-0.35	-1.44	0.00	2.79	2.01	13.36	-0.17	-0.07	0.15	-0.42	0.15
M4: VS6M	Total	0.50	95	45	21	0.27	0.96	0.00	2.73	4.73	28.60	0.46	-0.03	0.18	0.35	0.34
		1.00	95	47	23	0.40	0.87	0.00	4.01	5.74	37.82	0.44	-0.04	0.29	0.35	0.39
		1.50	95	43	20	1.09	1.27	0.00	6.10	5.13	30.28	0.37	-0.04	0.42	0.66	0.21
	High	0.50	95	47	22	0.14	0.64	0.00	2.22	3.91	22.25	0.42	-0.03	0.14	0.22	0.52
		1.00	95	47	23	0.20	0.59	0.00	2.95	5.35	40.09	0.28	-0.05	0.23	0.23	0.56
		1.50	95	43	20	0.83	1.24	0.00	5.43	6.03	41.64	0.20	-0.04	0.41	0.55	0.22
	Low	0.50	95	27	45	0.37	0.96	0.00	3.88	6.11	47.20	0.34	-0.05	0.32	0.34	0.34
		1.00	95	29	43	0.34	0.74	0.00	4.19	5.69	38.82	0.33	-0.05	0.31	0.28	0.46
		1.50	95	36	33	0.42	0.88	0.00	4.63	5.35	34.06	0.40	-0.04	0.31	0.32	0.38

Table 9: Monthly strategy excess return statistics for models M5, M6, M7, and M8

Table reports the monthly return statistics of the constructed strategy index for models M5, M6, M7, and M8. Period under consideration represents the trading window starting at 2.8.2011 and ending 30.7.2019. Column names follow the same convention as in Table 8.

Model	Sub-sample	α	N	N_{neg}	N_{zero}	Mean (%)	t-stat	Median (%)	Std (%)	Skew	Kurt	Corr	Min	Max	Sharpe	P-value
M5: HVOL	Total	0.50	95	50	0	0.03	0.18	-0.08	2.11	4.24	29.85	0.16	-0.04	0.15	0.04	0.86
		1.00	95	45	0	0.37	0.99	0.11	3.28	3.51	21.55	0.14	-0.06	0.21	0.40	0.32
		1.50	95	43	0	0.48	1.10	0.10	3.87	3.83	21.74	0.11	-0.05	0.24	0.44	0.27
	High	0.50	95	53	0	0.05	0.25	-0.09	2.49	3.35	25.07	0.20	-0.08	0.17	0.07	0.80
		1.00	95	50	0	0.32	0.82	-0.04	3.40	4.15	24.62	0.17	-0.04	0.22	0.33	0.41
		1.50	95	41	12	0.18	0.41	0.00	4.42	2.94	17.65	0.17	-0.10	0.25	0.14	0.68
	Low	0.50	95	49	6	-0.10	-0.43	-0.05	1.90	1.92	14.75	0.09	-0.05	0.11	-0.18	0.66
		1.00	95	48	1	0.31	0.81	-0.05	3.75	2.85	17.59	-0.01	-0.09	0.21	0.29	0.42
		1.50	95	32	17	0.54	1.57	0.00	3.12	3.63	24.36	0.08	-0.08	0.21	0.62	0.12
M6: PUTIV	Total	0.50	95	57	0	-0.29	-1.58	-0.17	1.68	-1.69	13.34	0.07	-0.09	0.06	-0.59	0.12
		1.00	95	54	0	-0.28	-1.57	-0.16	1.79	-1.95	15.21	-0.03	-0.10	0.06	-0.54	0.12
		1.50	95	47	0	-0.17	-1.01	0.00	1.81	-1.92	17.34	-0.16	-0.11	0.07	-0.32	0.31
	High	0.50	95	59	0	-0.31	-1.66	-0.18	1.95	-0.11	17.51	-0.06	-0.10	0.09	-0.55	0.10
		1.00	95	56	0	-0.23	-1.28	-0.13	1.79	-1.60	16.24	-0.04	-0.10	0.07	-0.44	0.20
		1.50	95	48	1	-0.19	-1.17	-0.04	1.84	-2.33	20.57	-0.18	-0.12	0.07	-0.35	0.24
	Low	0.50	95	53	0	-0.22	-1.09	-0.13	1.87	-2.40	18.38	0.07	-0.12	0.05	-0.40	0.28
		1.00	95	59	0	-0.38	-1.46	-0.19	2.45	-3.32	21.21	0.03	-0.16	0.06	-0.52	0.15
		1.50	95	53	0	-0.23	-1.12	-0.10	2.08	-0.80	7.04	-0.07	-0.09	0.07	-0.37	0.27
M7:VS1M	Total	0.50	95	60	0	-0.25	-2.69	-0.19	0.98	-0.09	3.69	-0.05	-0.03	0.02	-0.89	0.01
		1.00	95	54	0	-0.21	-1.35	-0.10	1.44	-2.20	13.01	0.06	-0.08	0.03	-0.50	0.18
		1.50	95	50	0	-0.30	-1.49	-0.02	1.91	-2.14	13.17	0.02	-0.11	0.05	-0.53	0.14
	High	0.50	95	61	0	-0.36	-3.34	-0.29	1.16	-0.84	6.78	-0.11	-0.05	0.03	-1.04	0.00
		1.00	95	50	0	-0.31	-1.63	-0.08	1.74	-2.74	17.05	0.06	-0.11	0.03	-0.61	0.11
		1.50	95	45	0	-0.26	-1.04	0.09	2.37	-2.00	13.15	0.01	-0.12	0.07	-0.37	0.30
	Low	0.50	95	47	0	-0.15	-1.02	0.04	1.43	0.27	4.82	-0.02	-0.04	0.05	-0.35	0.31
		1.00	95	48	0	-0.07	-0.39	-0.01	1.84	0.16	4.30	-0.02	-0.04	0.06	-0.14	0.70
		1.50	95	51	0	-0.22	-1.19	-0.14	1.89	-0.76	5.63	-0.08	-0.08	0.04	-0.39	0.24
M8: VS6M	Total	0.50	95	41	0	0.23	1.44	0.14	1.35	2.50	16.18	0.16	-0.02	0.08	0.59	0.15
		1.00	95	45	1	0.26	1.32	0.05	2.07	2.45	14.52	-0.11	-0.06	0.12	0.43	0.19
		1.50	95	42	3	0.36	1.45	0.03	2.29	3.36	24.09	0.06	-0.04	0.16	0.56	0.15
	High	0.50	95	42	0	0.07	0.35	0.11	1.71	1.76	20.66	-0.24	-0.07	0.11	0.15	0.73
		1.00	95	48	3	0.43	1.05	-0.04	4.41	4.89	32.84	-0.12	-0.07	0.32	0.35	0.30
		1.50	95	45	7	1.01	1.12	0.00	8.96	8.79	82.94	-0.03	-0.08	0.85	0.41	0.26
	Low	0.50	95	47	0	0.33	1.40	0.01	2.16	2.04	9.78	0.10	-0.04	0.10	0.55	0.17
		1.00	95	46	6	0.28	0.90	0.00	2.52	2.75	19.47	0.14	-0.06	0.16	0.39	0.37
		1.50	95	33	14	0.64	1.34	0.00	4.45	6.93	59.54	0.05	-0.07	0.39	0.52	0.18

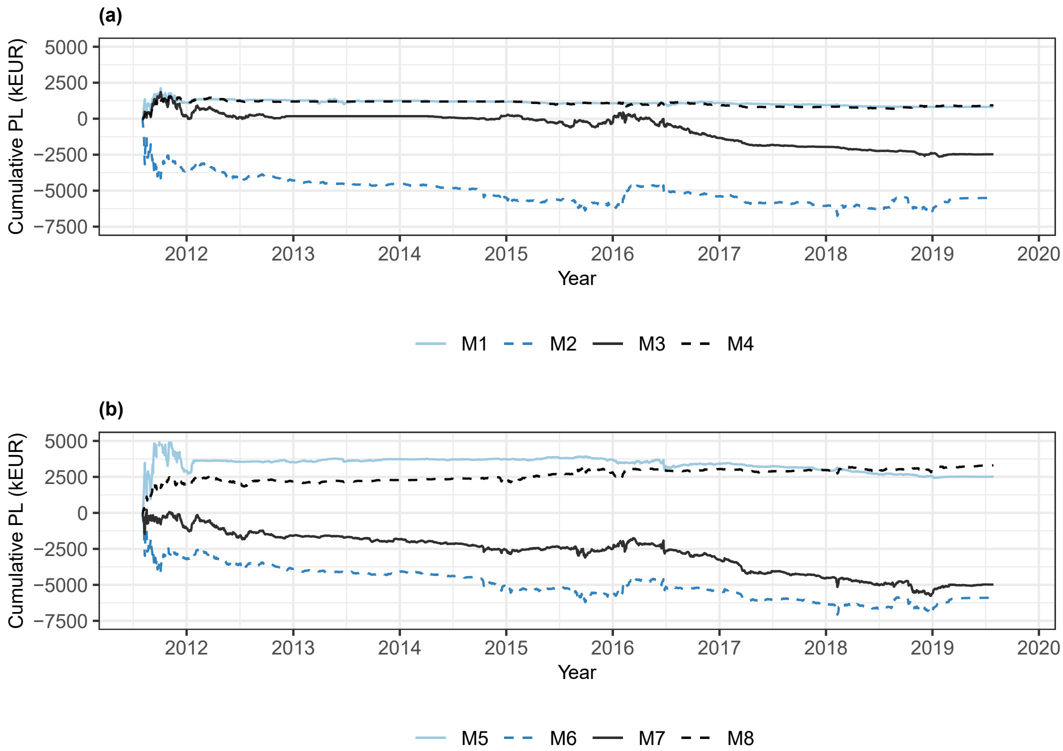


Figure 7: Total cumulative PL of strategies with a trading trigger of 0.5

Figures (a) and (b) illustrate the net mark-to-market value of all open positions at a given moment. In mark-to-market calculations, the prices reflect the hypothetical transaction costs given that the positions are closed. All CDS contracts have a notional of one million euros. Variance swap notional is determined based on a dynamic company-specific hedge ratio.

To understand better how these strategies behaved during the trading window, total cumulative PLs of strategies with a trading trigger of 0.5 are plotted in Figure 7. Additionally, net positioning of the different strategies are depicted in Figure 8. Here, a positive number implies a net long CDS and, correspondingly, net short variance swap positioning. Starting with Figure 7 (a), it can be seen that with models M2 and M6 large losses occur in 2011. After that, returns have a negative drift with occasional large positive trades affecting the PL positively. Models M1, M3 and, M4 offer positive returns in the volatile market conditions of the second half of 2011. However, after these sharp positive returns, M1 and M4 remain relatively static with low trading activity, whereas with M3 losses start to accumulate after year the 2016. Models using the t-distribution are depicted in Figure 7 (b). From a PL perspective, following the model calibrated with one-month variance swap rates leads here to a more sour result than the use of model M3. Model M6 behaves similarly compared to its variant M2. With higher trading activity, PL generated with models M5 and M8 are higher than with models M1 and M4 in the Figure above. The start for M5 is especially volatile, and later on, it offers flat or negative returns. With M8, the return profile is significantly more stable. Moreover, the positive drift in the PL curve is a sign of more balanced return characteristics than with model M5.

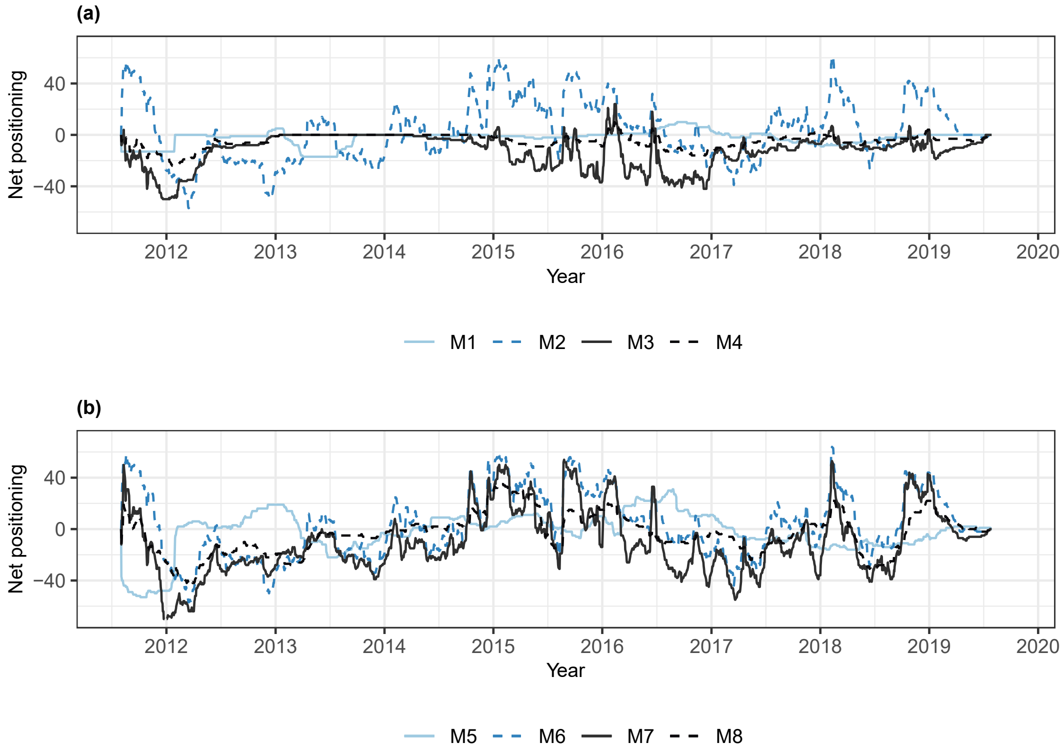


Figure 8: Net positioning of strategies with a trading trigger of 0.5
Here, Figures (a) and (b) reflect whether all the open trades at a given moment are net short or long the CDS leg. Positive value indicates net long positioning in CDS legs, i.e. net short variance swaps, and negative number represents net short positions in CDS contracts corresponding to net long variance swap positioning.

In Figure 8 (b), it can be seen that the net positioning of strategy M8 varies between net long and short, hence an additional signal of model stability. If the model exhibited persistent long or short biases, the argument of market neutrality would not be valid. High realized returns of M5 in the second part of 2011 could be somewhat explained by the net short CDS and net long variance positioning. In these market conditions, variance swap curves were shifted sharply higher as a sign of higher level of uncertainty in the marketplace. Even though the use of model M8 leads to a net long CDS positioning similarly than with models M6 and M7 during this volatile time, with M8, a positive overall PL could be attained while the use of M6 and M7 leads to poor performance. Taking into account that the one year calibration period ended at the beginning of August in 2011, which also marked the beginning of a new, more volatile market regime, especially model M8 performed smoothly. In line with the findings of, for example, Zeitsch (2017) and Wojtowicz (2014), it can be said that the strategy M8 exhibited higher returns during volatile market regimes such as the ones experienced in 2011 and 2015. Generally, the performance of this strategy indicates that in the post-financial crisis world, capital structure arbitrage can still be profitable given the right calibration methodology and trading strategy. Furthermore, variance and volatility-based hedging strategies should be considered as an alternative to the vanilla delta hedging strategy.

6.3.3 Explaining strategy returns

Finally, it is interesting to discover if strategy returns can be explained with common market risk factors. Here, the main focus is on model variant M8, but regression results for models M5 to M7 with a trading trigger of 0.5 can be found in the Appendix as well. To conduct a more comprehensive analysis compared to previous studies, eight regression models are tested per strategy. Selected regressors are generally comparable to the ones used broadly in the literature. Presenting the European stock market, monthly excess returns of STOXX 600 Total Return Index are used. For the credit market, ICE BofA Euro investment grade and high yield corporate indices are both included. To reflect general market risk sentiment and funding pressure, VSTOXX Index and so-called EUR TED spread are additionally utilized. The first five models presented in regression tables are individual regressions based on all the selected regressors. In the two following multivariate models, regressors are combined based on their overall importance. Lastly, all the regressors are combined in model specification number 8.

Focusing primarily on the most promising strategy in terms of risk-adjusted returns, regression results for model M8 with a trading trigger of 0.5 are reported in Table 10. The key observation is that none of the factor loadings are statistically significant. However, with model specifications 1, 3, and 6 alphas are positive at a 10% significance level. Another striking result is the relatively low R^2 readings reported. To make further conclusions, other trading triggers of this model are analyzed similarly. Regression results for those model variants are presented in the Appendix in Tables 14 and 15. With a trading trigger of 1.5, none of the variables are significant – this holds for the alphas as well. If a trading trigger of 1.0 is applied, equity and high yield market are statistically significant with sig-

Table 10: Regression results of monthly returns – Model M8 with a trading trigger of 0.5

Table reports the results of various regressions based on strategy returns generated with model M8 combined with a trading trigger of 0.5. Period under consideration corresponds with the trading period, i.e., ranging from 2.8.2011 to 30.7.2019. As the first variable, STOXX600 stands for monthly excess returns of the STOXX Europe 600 Total Return Index. ER00 represents monthly excess returns of the ICE BofA Euro Corporate Index, while HE00 denotes the monthly excess returns of the ICE BofA Euro High Yield Index. Moreover, V2X stands for VSTOXX Index and EUR TED factors in the monthly change in the spread between three-month EURIBOR and three-month government bill issued by the Federal Republic of Germany. Standard errors are reported below factor loadings. RSE refers here to Residual Standard Error.

	M8 ($\alpha = 0.5$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STOXX600	−0.027					−0.020	−0.016	−0.043
	(0.039)					(0.058)	(0.059)	(0.074)
ER00		−0.023					0.116	0.114
		(0.159)					(0.246)	(0.251)
HE00			−0.046			−0.019	−0.064	−0.062
			(0.073)			(0.109)	(0.145)	(0.148)
V2X				0.001				−0.007
				(0.007)				(0.011)
EUR TED					0.003			0.002
					(0.007)			(0.008)
Constant	0.002*	0.002	0.003*	0.002	0.002	0.002*	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	95	95	95	95	95	95	95	95
R^2	0.005	0.0002	0.004	0.0002	0.002	0.006	0.008	0.013
Adjusted R^2	−0.006	−0.011	−0.006	−0.011	−0.009	−0.016	−0.025	−0.043
RSE	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
F Statistic	0.486	0.021	0.403	0.022	0.160	0.256	0.244	0.229

Significance levels: *p<0.1; **p<0.05; ***p<0.01.

nificance levels of 10 and 5 percent, respectively. With multivariate models, none of these variables are significant. With all trading triggers, low and comparable R^2 are reported. Focusing on the sings of the factor loading in different regression model specifications, a pattern can be observed. Sings seem to be more in sync with trading triggers 1.0 and 1.5, especially in the multivariate regressions. An explanation might be found in Table 7 in which the holding period returns are reported. With a trading trigger of 0.5, mean holding period returns with lower credit quality obligors are significantly higher than with high-quality obligors. With other trading trigger specifications, the opposite results are observable. This dynamic might very well explain the mainly opposite factor loadings between these strategy specifications. With models M5, M6, and M7, the main observation here is that market risk factors largely explain the generated excess return figures.

Analyzing the F-statistics of the regressions, it can be seen that high yield market excess returns explain strategy returns with these model variants well. While market implied volatility in multivariate regressions is not significant, EUR TED spread, on the other hand, is. As discussed, the poor performance of models M6 and M7 might be explained by the mismatch between model calibration input and the tradable instruments.

Looking back at previous studies, the evidence is rather mixed when it comes to explaining excess returns generated with capital structure arbitrage strategies. Initially, Yu (2006) finds that common market risk factors are not significant in terms of strategy returns whereas Duarte et al. (2006), Bajlum & Larsen (2008), Wojtowicz (2014) and Huang & Luo (2016) provide evidence supporting the notion that, for example, the equity and the credit markets offer sometimes valuable clues in explaining the strategy returns. To emphasize, the results are not coherent, and no clear conclusions can be made based on previous research. Coming back to the performance of model M8, the assumed key driver behind positive returns is the strong link between model volatility calibration, i.e., six-month variance swap, and the traded instruments: CDS and six-month variance swap contracts. In the light of the evidence presented in this thesis, it can be noted that returns generated with this model variant can not be explained with common market risk factors, thus suggesting that misalingments between the pricing of credit risk and equity variance indeed occur. Moreover, the returns seem to be largely independent of the general markets supporting the notion of market neutrality.

7 CONCLUSIONS

In this master's thesis, a strategy called capital structure arbitrage is analyzed in detail. Briefly, the strategy relies on a structural credit risk model, which is used to identify misalignments in the pricing of a firm's capital structure. Based on model signals, positions in both the CDS and equity-linked markets are opened to capture the opportunities created by the hypothetical misalignments. The Merton (1974) Moody's KMV model is utilized here to calculate synthetic CDS spreads, and thus to identify discolorations in market pricing. For model calibration, both historical and market-implied data are tested. Furthermore, the strategy execution differs greatly from previous studies in which equities or equity options are used as the equity leg. Here, however, variance swaps are used for the first time in a capital structure arbitrage setting. Judging whether the Merton (1974) Moody's KMV model and the novel execution methodology are effective, a sample consisting of 102 European obligors is analyzed during the post-financial crisis era spanning from 2.8.2010 to 30.7.2019.

Given the two main areas of research addressed in this study, let us start with the model-specific results. First, based on the evidence presented here, it is clear that when computing default probabilities, the use of Student's t-distribution instead of the normal distribution leads to a significant improvement in model accuracy. On a total sample level, the improvement is, on average, approximately 55 basis points. Second, as prior research suggests, employing implied equity volatility measures in the model calibration process translates into enhanced model accuracy as well. On a broader level, when the Merton (1974) Moody's KMV model is compared to other previously tested structural models, such as the CreditGrades, extended Geske & Johnson (1984) and Leland & Toft (1996) models, it can be said that model accuracy is inline or even better when risk-neutral calibration methodology is followed. On another note, the comments made by Zeitsch (2017) regarding the effectiveness of a risk-neutrally calibrated default barrier with, e.g., financials, cannot be confirmed here. Results do not indicate that the proposed default barrier methodology leads to improved model accuracy.

Moving on to the strategy-related research questions, there is one essential observation that can be made based on the profitability of the tested strategy variants. Namely, the strategy's profitability is highly dependent on the linkage between the calibration input and the traded instruments. If equities are traded, this might not be an issue, but with volatility instruments with which different contract tenors can be used, this is of particular interest. Profitability-wise model variants calibrated with short-term implied volatility measures fare a lot worse than models calibrated with six-month variance swap rates or historical volatility. Concerning default probability determination, the use of t-distribution generally leads to improved profitability, higher trading activity, and a higher rate of convergence.

Considering that the applied variance swap tenor in the strategy is six months, it is rather straight forward to deduce that the model variant calibrated with a six-month variance swap rate, i.e., model M8, offers the best risk-adjusted returns. On a total sample level, Sharpe ratios between 0.43 and 0.59 are achieved after adjusting the returns for assumed transaction costs. Risk-adjusted returns are in same range with the figures provided by Yu (2006), Duarte et al. (2006), and Imbierowicz & Cserna (2008). Moreover, results indicate that models calibrated either with six-month variance swap rates or historical volatility produce positively skewed excess returns. This observation matches the results of Yu (2006), Duarte et al. (2006), Bajlum & Larsen (2008), and Huang & Luo (2016). Answering if general market risk factor are behind the strategy's returns, multiple regressions are conducted covering equity, credit, implied volatility, and funding liquidity related market variables. With model variants leading to negative monthly returns, market risk factors largely explained the results. However, with especially the model M8, results imply that the returns are not driven by market risk, but are instead broadly market neutral.

Putting it all together, the key findings here are that the risk-neutrally calibrated Merton (1974) Moody's KMV model can be regarded as a genuine substitute for the most often used structural models, such as the CreditGrades model. Additionally, based on the evidence provided in this study, the volatility, i.e., the vega hedging approach presented here is comparable to the plain vanilla delta hedging strategy explored in previous studies. The positive returns generated by some of the model variants support the notion that during the post-financial crisis era, misalignments in the pricing of firms' capital structure occasionally occur. What is left for future research is to test the variance swap implementation with varying tenors to see if models calibrated with short-term implied volatility can generate positive returns as well. Proposing and testing new dynamic default barrier methodologies to be used in the Merton (1974) model framework is likewise something that is preserved for subsequent research.

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APPENDIX

Table 11: Regression results of monthly returns – Model M5 with a trading trigger of 0.5

Table reports results of various regressions based on strategy returns generated with model M5 combined to a trading trigger of 0.5. Variable naming convention and the analyzed time frame correspond with Table 10.

	M5 ($\alpha = 0.5$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STOXX600	−0.127**					0.017	0.019	−0.015
	(0.060)					(0.087)	(0.088)	(0.110)
ER00		−0.524**					0.087	0.080
		(0.242)					(0.366)	(0.374)
HE00			−0.340***			−0.363**	−0.396*	−0.392*
			(0.109)			(0.162)	(0.215)	(0.220)
V2X				0.014				−0.009
				(0.011)				(0.017)
EUR TED					0.010			0.004
					(0.011)			(0.012)
Constant	0.001	0.002	0.002	0.0004	0.0004	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	95	95	95	95	95	95	95	95
R^2	0.046	0.048	0.095	0.018	0.009	0.096	0.096	0.100
Adjusted R^2	0.036	0.038	0.086	0.007	−0.002	0.076	0.066	0.049
RSE	0.021	0.021	0.020	0.021	0.021	0.020	0.020	0.021
F Statistic	4.494**	4.682**	9.789***	1.663	0.819	4.863***	3.228**	1.971*

Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 12: Regression results of monthly returns – Model M6 with a trading trigger of 0.5

Table reports results of various regressions based on strategy returns generated with model M6 combined to a trading trigger of 0.5. Variable naming convention and the analyzed time frame correspond with Table 10. Due to space constraints, numbers are mostly rounded up to contain only two decimal places.

	M6 ($\alpha = 0.5$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STOXX600	0.23***					0.04	0.02	0.06
	(0.04)					(0.06)	(0.06)	(0.07)
ER00		0.59***					−0.61**	−0.55**
		(0.19)					(0.24)	(0.24)
HE00			0.53***			0.47***	0.71***	0.67***
			(0.07)			(0.11)	(0.14)	(0.14)
V2X				−0.03***				0.01
				(0.01)				(0.01)
EUR TED					−0.03***			−0.01*
					(0.01)			(0.01)
Constant	−0.00***	−0.01***	−0.01***	−0.00*	−0.00*	−0.01***	−0.01***	−0.01***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	95	95	95	95	95	95	95	95
R^2	0.23	0.10	0.36	0.12	0.10	0.36	0.41	0.43
Adjusted R^2	0.22	0.09	0.35	0.11	0.09	0.35	0.39	0.40
RSE	0.01	0.02	0.01	0.02	0.02	0.01	0.01	0.01
F Statistic	28.12***	10.08***	52.62***	12.37***	10.00***	26.39***	20.97***	13.68***

Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 13: Regression results of monthly returns – Model M7 with a trading trigger of 0.5

Table reports results of various regressions based on strategy returns generated with model M7 combined to a trading trigger of 0.5. Variable naming convention and the analyzed time frame correspond with Table 10. Due to space constraints, numbers are mostly rounded up to contain only two decimal places.

	M7 ($\alpha = 0.5$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STOXX600	0.08***					0.003	−0.003	0.03
	(0.03)					(0.04)	(0.04)	(0.05)
ER00		0.22*					−0.21	−0.15
		(0.11)					(0.16)	(0.16)
HE00			0.19***			0.19**	0.27***	0.23**
			(0.05)			(0.07)	(0.10)	(0.09)
V2X				−0.01				0.01
				(0.01)				(0.01)
EUR TED					−0.02***			−0.01***
					(0.005)			(0.005)
Constant	−0.00***	−0.00***	−0.00***	−0.00**	−0.00***	−0.00***	−0.00***	−0.00***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	95	95	95	95	95	95	95	95
R^2	0.08	0.04	0.14	0.03	0.10	0.14	0.15	0.22
Adjusted R^2	0.07	0.03	0.13	0.02	0.09	0.12	0.13	0.18
RSE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
F Statistic	7.81***	3.84*	14.86***	2.76	10.81***	7.35***	5.48***	5.04***

Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 14: Regression results of monthly returns – Model M8 with a trading trigger of 1.0

Table reports results of various regressions based on strategy returns generated with model M8 combined to a trading trigger of 1.0. Variable naming convention and the analyzed time frame correspond with Table 10.

	M8 ($\alpha = 1.0$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STOXX600	0.098*					−0.004	−0.009	−0.007
	(0.059)					(0.087)	(0.088)	(0.110)
ER00		0.340					−0.181	−0.156
		(0.241)					(0.366)	(0.375)
HE00			0.253**			0.259	0.329	0.314
			(0.109)			(0.162)	(0.215)	(0.221)
V2X				−0.014				0.002
				(0.011)				(0.017)
EUR TED					−0.011			−0.005
					(0.011)			(0.012)
Constant	0.002	0.001	0.001	0.002	0.002	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	95	95	95	95	95	95	95	95
R^2	0.029	0.021	0.055	0.018	0.011	0.055	0.058	0.060
Adjusted R^2	0.018	0.011	0.045	0.007	0.0002	0.035	0.027	0.007
RSE	0.020	0.021	0.020	0.021	0.021	0.020	0.020	0.021
F Statistic	2.764*	1.998	5.428**	1.664	1.015	2.686*	1.857	1.129

Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 15: Regression results of monthly returns – Model M8 with a trading trigger of 1.5

Table reports results of various regressions based on strategy returns generated with model M8 combined to a trading trigger of 1.5. Variable naming convention and the analyzed time frame correspond with Table 10.

	M8 ($\alpha = 1.5$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STOXX600	0.035					−0.036	−0.051	0.025
	(0.066)					(0.098)	(0.098)	(0.122)
ER00		−0.023					−0.571	−0.587
		(0.269)					(0.410)	(0.418)
HE00			0.129			0.179	0.399	0.408
			(0.123)			(0.183)	(0.241)	(0.246)
V2X				0.003				0.020
				(0.012)				(0.019)
EUR TED					−0.004			−0.002
					(0.012)			(0.013)
Constant	0.003	0.004	0.003	0.004	0.004	0.003	0.004	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	95	95	95	95	95	95	95	95
R^2	0.003	0.0001	0.012	0.001	0.001	0.013	0.034	0.046
Adjusted R^2	−0.008	−0.011	0.001	−0.010	−0.010	−0.008	0.002	−0.008
RSE	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
F Statistic	0.275	0.007	1.105	0.055	0.101	0.615	1.061	0.856

Significance levels: *p<0.1; **p<0.05; ***p<0.01.