Department of Business and Management

Chair of Advanced Corporate Finance

The profitability of Capital Structure Arbitrage from 2015 to 2017: evidence on volatility estimator and companies' leverage

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Contents

1 Introduction

The topic of this thesis will be the investment strategy known as Capital Structure Arbitrage and the predictive models that serve to implement this strategy.

Capital Structure Arbitrage prescribes to trade one security against another security issued by the same firm. A common way to implement the arbitrage is to trade the debt against the equity of a given firm. Generally, it is implemented trading stocks and CDSs.

The willingness to deepen the knowledge on this arbitrage strategy comes from the scarcity of academic research on the subject and the will to deepen the knowledge on models developed to estimate default probability. In fact, how it will be later clearer, a correct implementation of the Capital Structure Arbitrage requires, as input, a correct and timely estimation of default probability of companies through time. The success of Capital Structure Arbitrage is therefore strictly linked to the effectiveness of these models.

In particular, this work will enquiry if Capital Structure Arbitrage is still a profitable investment strategy and if there is, eventually, room for improvement in strategy execution. The last found paper written on the subject, in fact, dates back to 2014 and it concludes that the profitability of the strategy seems to be linked to specific time periods.[1] Moreover, the Capital Structure Arbitrage profitability could have been explained, in past years, by a low liquidity of credit default swap (CDS) market. It is therefore of interest to understand if the development of derivatives trade during last years affected the profitability of the strategy. The strategy, in fact, earns from the mispricing of credit default swaps. Therefore, an increase in CDSs liquidity could have led to a higher market efficiency in pricing these derivative products and no profit left for arbitrageurs. This vision is shared by Cserna & Imbierowicz (2008), that found that the average returns of the strategy appears to decline over time, and that this phenomenon could be explained by an increased efficiency of the credit default swap market.

[1] Wojtowicz, M. (2014). *Capital Structure Arbitrage Revisited*. Duisenberg School of Finance - Tinbergen Institute Discussion Paper; Working Paper.

At the same time, several authors remarked the importance of model's parameters setting to have acceptable CDS spread previsions.[2] In particular, the parameter that has mostly been subject of study is the equity volatility.[3]

I will start the discussion of the topic with a literature review on debt riskiness and capital structure decisions. The arbitrage strategy under analysis, in fact, feeds on the inconsistent valuation of debt and equity of the same entity. A review of the more common theories on capital structure composition is therefore proposed. Those are, in fact, theories that try to explain the relation between the value of the firm as a whole and the value of the single parts of its capital structure, that is equity and debt.

Hence, an historical digression on structural models is reported. Starting from the model proposed by Merton in 1974, the other structural models developed on it are analyzed. Structural models are models developed to formally link firm's asset value with debt and equity value. The improvements of new models are highlighted and a synoptic table is proposed.

Then, the features of Capital Structure Arbitrage are analyzed. The investment strategy will be dissected and the various approach reported in academia will be compared, as well as the result obtained by various authors.

Since one of the main point of discussion on Capital Structure Arbitrage is represented by the correct way to calibrate the equity volatility in the structural model chosen to implement the arbitrage, an innovative approach to volatility calibration will be proposed.

Finally, the results of a simulation of the analyzed strategy is proposed. The simulation is performed through a back-testing of the arbitrage in the period from August 2015 to August 2017.

The aim of the strategy back-testing is to understand if Capital Structure Arbitrage is still able to produce attractive returns and if the introduction of GARCH as volatility estimator can have a positive effect on strategy effectiveness.

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[2] See, for instance, Bajlum, C. & Larsen, P. T. (2008). *Capital Structure Arbitrage: Model Choice and Volatility Calibration*. Copenhagen Business School, Department of Finance, Working Papers.

[3] See Bajlum & Larsen (2008), Avino, D. & Lazar, E. (2013). *Rethinking Capital Structure Arbitrage: A Price Discovery Perspective*. MPRA Paper, University Library of Munich and Wojtowicz (2014).

Interestingly, the strategy simulation shed light on a feature of structural models used that was not mentioned in no one of previous works on the matter. In particular, the role of leverage seems to play a fundamental role on the ability of the model to predict market spreads. A possible explanation of the phenomenon is proposed.

2 Capital structure and debt riskiness

2.1 Introduction

This chapter will illustrate the determinants of the riskiness of corporate debt and the effects of capital structure composition on companies' market value.

The implementation of an arbitrage on firms' capital structure requires, in fact, that debt and equity are not priced consistently. Debt and equity are the two components of the capital structure of every firm and their characteristics, in terms of riskiness and value, are linked to the same entity, that is the assets of the firm.

The effect of different shapes of capital structure on assets' value has raised debates in academy. Different theories arose, from the famous irrelevance of capital structure, firstly theorized by Modigliani and Miller (1958) to the more recent Pecking Order Theory. Anyway, it is undeniable that the value of firm's debt and equity are, in some way, affected by the firm's capital structure and are both derivative of the firm's asset value.

Therefore, this chapter will, first of all, present the more relevant theories produced on the topic of capital structure.

Successively, the more relevant literature on structural models will be reported. Structural models are models developed to formally link firm's asset value and the value of its capital structure components. Structural models make use of theories on capital structure and go beyond in the determination of the mechanism that links the two side of the "market value balance sheet". Most of the early structural models, in fact, stately relies on the theory of Modigliani and Miller (1958). The usefulness of these models to the purposes of this thesis relies on the fact that structural models can predict from market variables the probability of default of a firm.

The purpose of this chapter is therefore to introduce and explain the relevant literature on capital structure theory and the development, through the years, of models for debt pricing.

2.2 Capital Structure Theory

The arbitrage strategy I am going to analyze in this work has its reason in the mispricing of one part of the capital structure respect to another. According to Pedersen (2015), this trade is based on the idea that all claims to the firm are derivatives of the firm value and if these are not priced consistently, arbitrage opportunities arise. Therefore, a discussion on the more common theories on capital structure composition appear useful, since debt and equity valuation start from the comprehension of their interrelations with company's asset value.

Many research papers on the effects of capital structure composition on the firm's value and the determination of an optimal leverage ratio has been produced during last decades. No one produced a definitive answer. On the contrary, different theories arose, testifying how the capital structure valuation of firms is still a discussed topic. The theories on the effect of capital structure on firm's value and the resultant effect on the valuation of capital structure's components are an element to take under consideration in implementing an arbitrage strategy that exploits the pricing of debt and equity. These theories, in fact, give the basis to understand the elements affecting debt and equity pricing.

2.2.1 The irrelevance of capital structure

The most popular seminal work on capital structure composition is the paper from Modigliani and Miller of 1958. They claim that the capital structure is not relevant in determining the value of a firm. In their work, the author approaches the discussion on capital structure under the hypothesis of uncertain outcomes of firm's operations. Their theory relies on the assumption of perfect capital markets. This assumption entails a range of features on the environment of their research: particularly relevant is the absence of frictions and taxes in the market. The starting point of this theory is that the value of a firm comes solely from the expected return on its assets. In their proposition I, in fact, the authors say that *the average cost of capital of any firm is completely independent of its capital structure and it is equal to the capitalization rate of a pure equity stream of its class.*[4] Hence, the average

[4] Miller, M. & Modigliani, F. (1958). *The Cost of Capital, Corporation Finance and the Theory of Investment*. The American Economic Review, 48(3), 261-297.

cost of capital of a firm is derived by the expected returns of the firm's asset and by the volatility of these returns. The cost of equity and debt is therefore direct function of the expected return on the assets. Value of equity and of debt are given by the level of leverage of the firm, and their sum equals the value of the firm's assets. This implies that for higher level of debt, the equity becomes riskier and therefore the required return on it increases but its weight on the average cost of capital decreases, leaving the expected return on assets constant. Similarly, debt becomes more risky for higher level of indebtedness, but in a different way respect to the equity. While the cost of equity rises as a compensation for the higher volatility of its return, debt's price increases when the variability of firm's return produces the risk of default on debt. High level of debt, in fact, entails the real possibility of default on debt, making it more similar to equity. As the leverage increase, the cost of debt will therefore increase to reach, in the extreme case, the cost of risky equity. The dynamic of debt's cost for different level of leverage is a direct consequence of the variability of the streams of revenues of the firm.

Anyway, the total cost of capital for the firm is its average cost of capital and it is determined exclusively by the expected return of the firm's assets, no matter how the capital structure is composed.

The relation among the return on asset and the cost of debt and equity, according to the theory from Modigliani and Miller, is expressed in the proposition II by the following equation:

$$r_A = \frac{E}{V}\, r_E + \frac{D}{V}\, r_D$$

where r_A is the expected return on assets, r_E is the expected return on equity and r_D the required return on debt. E, D and V are, respectively, the market value of equity, debt and the whole firm.

The previous equation can be rearranged to solve for r_E as

$$r_E = r_A + \frac{D}{E}\,(r_A - r_D)$$

that is, the expected yield of a share is equal to the appropriate capitalization rate r_E of a pure equity stream plus a premium for the financial risk coming from the level of leverage and the spread between r_A and r_D.[5] If the firm were financed solely through equity, in fact, r_E would equal r_A. Introducing debt, the return on equity requires a premium for the additional risk.

If we refer to the proposition II's equation in terms of the beta of each segment of the capital structure, we would have that

$$\beta_A = \frac{E}{V}\,\beta_E + \frac{D}{V}\,\beta_D$$

Given that the beta of stock *i* can be expressed as

$$\beta_i = \frac{cov(r_i, r_M)}{var(r_M)}$$

and the covariance between stock *i* returns and market returns as

$$cov(r_i, r_M) = \sigma_i\,\sigma_M\,\rho_{i,M}$$

where r_i is the return of stock *i,* r_M is the return of market portfolio and $\rho_{i,M}$ is the correlation among r_i and r_M, the equation of β_A can be rewritten as

$$\frac{cov(r_A, r_M)}{var(r_M)} = \frac{E}{V}\,\frac{cov(r_E, r_M)}{var(r_M)} + \frac{D}{V}\,\frac{cov(r_D, r_M)}{var(r_M)}$$

If we express the covariance as the product of the volatility of the two variables and their correlation, the above equation becomes

$$\rho_{A,M}\,\sigma_A\,\sigma_M = \frac{E}{V}\,\rho_{E,M}\,\sigma_E\,\sigma_M + \frac{D}{V}\,\rho_{D,M}\,\sigma_D\,\sigma_M$$

Rearranging and solving for σ_E and σ_D we have

$$\sigma_E = \frac{\rho_{A,M}}{\rho_{E,M}}\,\sigma_A + \frac{D}{E}\left(\frac{\rho_{A,M}}{\rho_{E,M}}\,\sigma_A - \frac{\rho_{D,M}}{\rho_{E,M}}\,\sigma_D\right)$$

$$\sigma_D = \frac{\rho_{A,M}}{\rho_{D,M}}\,\sigma_A + \frac{E}{D}\left(\frac{\rho_{A,M}}{\rho_{D,M}}\,\sigma_A - \frac{\rho_{E,M}}{\rho_{D,M}}\,\sigma_E\right)$$

Looking at the theory of Modigliani and Miller by this perspective highlights the link between the volatility of the assets' return, the volatility of debt and equity and the level of leverage of a firm. Both the volatility of debt and equity are function of asset's volatility and capital structure.

[5] Ibid.

Since the asset of a firm are not traded, the parameters σ_A and r_A are not variables that can be observed in the market. The prediction of theoretical value for r_E and r_D therefore required the creation of sophisticated models, that will be debated later.

2.2.2 The Trade-off Theory

A theory, that evolves from the theory of Modigliani and Miller, is the Trade-off theory. This theory maintains the basic assumptions made by Modigliani and Miller but furthermore takes under consideration the costs of financial distress. Under perfect capital market's assumptions, in fact, the default would simply produce the passage of the firm from the shareholders to the debtholders without affecting the total value available to investors as a whole. Debtholders are remunerated for the risk of suffering the cost deriving from a potential poor economic performance of the firm and the consequent loss in value. Under the Modigliani and Miller model the risk of bankruptcy is not a disadvantage of leverage.[6] In the real world, the financial distress and the default implicate costs for the firm. A firm that is no longer able to repay its debt will likely face the costs of debt restructuring, the cost of lawyers, problems with supplier and the loss of corporate going concern, just to report someone. This implies that a higher level of debt, and hence a higher probability of distress, will affect negatively the ability of a firm to raise new debt and will increase its cost of capital.

The trade-off theory says that the value of a levered firm is equal to its unlevered value plus the present value of the tax benefit minus the present value of the distress costs. This theory says that exists an optimal capital structure that maximize the value levered of a firm, minimizing its cost of capital.

The equation of the required return on assets can be easily modified to consider the effects of taxes and costs of distress. Taxes are in fact a benefit of leverage: a higher level of debt produce higher interest expenses that will reduce the taxable income. On the other hand, debt entails the risk of default. The equation of the required return on asset under the hypothesis of taxes and distress cost will hence appear to be

[6] Berk, J. & DeMarzo, P. (2014). *Corporate Finance, Third Edition.* Pearson.

$$r_A = \frac{E}{V} r_E + \frac{D}{V} r_D (1 - \tau) + (PD \cdot DC)$$

where $(1 - \tau)$ and $(PD \cdot DC)$ are corrective factors that take into consideration taxes and distress costs: τ is the tax rate for the firm while $(PD \cdot DC)$ is the probability of default given that level of leverage times the cost of default. It is important to note that while τ is a fixed percentage, $(PD \cdot DC)$ is a function of the level of indebtedness and hence the probability to suffer from financial distress. By the equation above follows that the arbitrageur should take into account, when trying to price fairly debt and equity, the effect of taxes and the probability of financial distress.

2.2.3 The Pecking Order Theory

Another diffused theory regarding capital structure is the Pecking Order Theory. This theory does not try to individuate an ideal level of indebtedness, but rather it provides the order the firm will use in raising funds. According to the pecking order theory a firm will firstly use internal funds, then debt, finally equity. The reasons behind this theory are in the asymmetric information and in the opportunistic behavior of management that debt incentivizes.

The presented theories all try to explain the effect of capital structure's choices on the value of a firm and of the components of its capital structure. The theories presented show how the capital structure influences the value of the company and how it is a determinant of the value of single segments of the structure.

Of higher interest for this work are those theories that try to formally link the value of the firm to the value of its capital structure components. The paper from Modigliani and Miller started to approach the problem by this standpoint and gave rise to further development of their theory.

Fundamental both in the Modigliani and Miller theory and in the Trade-off theory is to consider the expected return on equity and on debt derivatives of the expected return on the total assets. The value of debt and equity is simply given by the target leverage ratio of the firm. Fluctuations in the value of asset are followed by the rebalancing of the capital structure towards the desired level of leverage and the valuation of debt is obtained by multiplying asset value respectively for the percentage of debt on the total asset. Similarly is obtained the valuation of equity value. But if we consider the problem by the perspective illustrated by the Trade-off theory the valuation of equity and debt is not so straightforward as it is under the assumption of Modigliani and Miller. The level of leverage, in fact, has an impact on the value of total asset. The leverage produce both an increase and a decrease in asset value. The increase is due to the saving in tax that debt allows: interests paid on debt are deductible from the taxable income. The decrease is a consequence of the higher likelihood of default that leverage produces.

In both the case, anyway, the practical link between the asset and the capital structure remains to be solved, since, as previously noted, the firm’s assets is not something exchanged in the market.

Since that if the firm is financed only by equity, the problem would not exist, the role of debt has been subjected to an intense work of research. Many models have been developed, aiming to estimate the probability that a firm will suffer from financial distress and incorporating this information in debt pricing. Different theories raised, aiming at produce models able to embody the relevant factors that affects the pricing of debt on the market.

In the next section, I will present the more relevant structural models for the pricing of debt. These models play an important role in the implementation of the capital structure arbitrage, because represent the term of comparison of the observed values in the market with their theoretical values. The use of these models hence allows to have a signal of market’s mispricing and the rise of possibility of arbitrage. The ability of structural models to obtain a measure of the probability of default for a firm allows to understand if the credit default swaps on a given security are fairly priced. A broader description of the reasons for the use of CDSs in the implementation of capital structure arbitrage is reported in next chapters.

2.3 The evolution of structural models for debt pricing

The need to have a clear understanding and a theoretical term of comparison of the implication of a given level of leverage on the value of asset and consequently on the value of the component of its capital structure has been addressed creating models able to include the expectations that a firm will suffer from financial distress.

The prediction of parameters such as the probability of default and credit spread on corporate bonds is important for the purposes of this work because are these parameters that signal the presence of arbitrage opportunities. Typically, the implementation of the Capital Structure Arbitrage looks at the pricing of debt and at the implied probability of default and of recovery of a given firm perceived from the market and compare these values with the theoretical values that the model suggests.[7]

There are two basic approaches to modeling corporate default risk. The first one is the structural model approach, pioneered by Black and Scholes (1973) and Merton (1974) and extended then by various authors, such as Black and Cox (1976), Geske (1977), Kim, Ramaswamy & Sundaresan (1993), Longstaf & Schwartz (1995) Leland & Toft (1996) and Zhou (1997). The structural pricing models imply the definition of firm's value evolution as a variable observable by investors.[8] The firm defaults when its market value falls below an exogenously determined threshold, that in several models has been identified with the value of firm's debt.

Another fundamental feature of the models proposed by Merton in 1974, and common to most of its subsequent evolutions, is the assumptions that firm's value follows a diffusion process.

The second approach to default modeling is the reduced form approach. Under this approach, adopted, among the others, by Duffie & Singleton (1994), Jarrow, Lando, & Turnbul (1994), Jarrow & Turnbull (1995) and Madan & Unal (1994), the

[7] See, for instance, Bajlum & Larsen (2007), Avino & Lazar (2013), Yu, F. (2006). *How profitable is capital structure arbitrage?* Financial Analysts Journal, 62(5), 47-62 and Cserna, B. & Imbierowicz, B (2008). *How Efficient are Credit Default Swap Markets? An Empirical Study of Capital Structure Arbitrage Based on Structural Pricing Models*. 21st Australasian Finance and Banking Conference.

[8] Zhou, C. (1997). A Jump-Diffusion Approach to Modeling Credit Risk and Valuing Defaultable Securities.

relation between firm's value and default is not modeled in a structural way. This means that default could happen as a "surprise", being its happening not explicitly linked to firm's value. Default is treated in reduced form models as a random variable.

2.3.1 Merton Model

The work of research on structural models started after the publication of the paper from Merton (1974), that give further application to Black and Scholes (1973). Black, Scholes and Merton, in fact, introduced a contingent-claims approach to valuing corporate debt using option pricing theory.[9] In their model, the value of a firm's debt is contingent on the market value of its assets. In their paper, Black and Scholes (1973) propose a model for the pricing of European options, based on no-arbitrage principle, that can be extended to the valuation of corporate liabilities. The authors claim that, since all corporate liabilities can be viewed as a combination of options, the formula proposed for their pricing is also applicable to corporate liabilities. Further, their model could also be useful in deriving the discount to apply to corporate bonds because of the possibility of default. Their reasoning starts observing how, under certain assumptions, the value of common shares can be viewed as an option on the firm's assets. [10] Thus, the value of the common stocks is given by the formula Black and Scholes derived for the pricing of call options, where the strike price c is equal to the book value of the firm's debt, the variance of the underlying v^2 is the variance rate of return on firm's asset and the underlying's price $\varkappa$ is the total value of company assets. According to Modigliani and Miller proposition I, then they say that the value of the bonds will simply be the value of assets $\varkappa$ minus the value of the option on company's assets, that individuate the value of the equity. In this way, the authors propose the use of their option pricing formula to price the corporate debt, taking into account the volatility

[9] Bohn, J. R. (2000). *A Survey of Contingent-Claims Approaches to Risky Debt Valuation*. The Journal of Risk Finance, 1(3), 53-70.

[10] In their example, the authors consider a firm with common stocks and bonds outstanding. The bonds are pure discount bonds with no coupon payments, giving the holder the right to a fix amount of money at maturity. The bonds contain no restrictions on the company, except that the company cannot pay any dividends until the bonds are paid off. Finally, the company plans to sell all its asset at bonds' maturity, pay off the bond holders, if possible, and pay a liquidating dividend to the stock holders with any remaining money.

of company's assets and the linked probability of default. The authors propose also their model to figure out the discount that should be applied to bonds, due to the existence of default risk. The proposed procedure to individuate bond's spread consists on subtracting the value of the bonds, given by $\varkappa$ minus the value of the option on company' s assets, from the value they would have if there were no default risk.

Merton (1974) studies further the pricing of corporate debt, developing, along the Black-Scholes lines, a basic equation for the pricing of corporate debt. To develop his model, Merton makes a series of assumptions. In particular, the dynamics through time for the value of the firm V is described by the following stochastic differential equation

$$dV = (\alpha V - C)dt + \sigma_V V dz$$

where a is the instantaneous expected rate of return on the firm per unit of time, C is the total dollar payout by the firm to either shareholders or debtholders per unit of time and σ_V^2 is the instantaneous variance of the return on the firm per unit of time. Moreover, Merton assumes that the firm's asset value is observable and traded continuously.[11]

Hypothesizing the existence of a security whose market value, Y, at any point in time can be written as a function of the value of the firm and time, i.e. $Y = F(V, t)$, Merton obtains the equation for the parabolic partial differential equation of F as

$$0 = \frac{1}{2}\sigma_V^2 V^2 F_{VV} + (r\,V - C)F_V - r\,F + F_t + C_y$$

where C stands for the payout and r is the risk-free rate.[12]

This equation must be satisfied by any security whose value can be written as a function of the value of the firm and time. Merton remarks that the parameters that are present in the reported equation are those that affect the value of the security. These parameters are, in addition to the value of the firm and time, the interest rate, the volatility of the firm's value, the payout policy of the firm (C) and the promised payout policy to the holders of the security (C_y). However, F does not depend on

[11] The other assumptions the Merton model bases on are the absence of transaction cost and taxes, a constant interest rate, that the firm's liabilities consist of a single zero-coupon bond, that the short selling is allowed and that the Modigliani-Miller theorem obtains.

[12] For the derivation of the equation see Merton (1974).

the expected rate of return on the firm nor on the risk preferences of investors nor on the characteristics of other instrument available to investors.

If F is the value of the debt issue, the previous equation can be rewritten as

$$0 = \frac{1}{2}\sigma_V^2 V^2 F_{VV} + r\,VF_V - r\,F - F_t$$

because $C_y = C = 0$, since no cash out prior to maturity are allowed.

The application of the partial differential equation for F, when F represent the debt issue, entails the specification of further conditions, whose explanation can be found in Merton's paper.

Assuming that $V \equiv F(V,t) + f(V,t)$, where f is the value of equity, and observing that when the value of firm is zero, both the equity and debt value is zero, the author deduces the partial differential equation for f

$$\frac{1}{2}\sigma_V^2 V^2 f_{vv} + rVf_v - rf - f_t$$

subject to

$$f(V,0) = Max[0, V - B]$$

where B is the promised payment to the debtholders at maturity.

The author observes that the previous two equations are identical to the equations for a European call option on a stock that does not pay dividends, where B corresponds to the exercise price.

From the Black-Scholes equation, when σ_V^2 is a constant, and the relation between debt and firm's value $F = V - f$, Merton obtains that

$$F[V,t] = Be^{-rt}\left\{N[h_2(d,\sigma_V^2 t)] + \frac{1}{d}\mathrm{N}[h_1(d,\sigma_V^2 t)]\right\}$$

where

$$d \equiv \frac{Be^{-r}}{V}$$

$$h_1(d,\sigma_V^2 t) \equiv -\left[\frac{1}{2}\sigma_V^2 t - \log(d)\right]/\sigma_V\sqrt{t}$$

$$h_2(d,\sigma_V^2 t) \equiv -\left[\frac{1}{2}\sigma_V^2 t + \log(d)\right]/\sigma_V\sqrt{t}$$

The way to valuate debt proposed by Merton hence implicates that for a given maturity, the risk premium is a function of only the volatility of firm's operation and d, which is a measure of leverage. The measure d is a biased upward estimate of the actual market-value debt to value ratio, because B, the face value of debt, is discounted using the risk-free rate.

The debt-pricing model proposed by Merton relies on the unobservable variable V_t, whose dynamics are assumed to follow a geometric Brownian motion. The probability of default in the model is endogenous and determined by the capital structure of the firm: the fluctuations of firm's value, together with the target level of indebtedness of the firm, outputs a measure for the probability of default. [13] Moreover, Merton, modelling the equity value as a European call option, assumes that the debt is represented by a single zero-coupon debt instrument maturing at T, with face value F and current market value B_t. The default therefore can only happen at maturity of debt obligation.

The probability of default of the firm on its debt that is endogenous in the model is equal to the probability that shareholders will not exercise their option to buy the firm's asset for the price B at time T, that is

$$PD = N(-d_2)$$ [14]

The formulation of d_2 as reported in Black and Scholes (1973) is the following

$$d_2 = \frac{\ln(S_0/K) + (r - \sigma^2/2)t}{\sigma\sqrt{t}}$$

where S_0 is the price of the underlying stock at time zero, K is the strike price, r is the risk-free rate, σ^2 is the volatility of underlying's returns and t is the time to maturity. The model developed by Merton remarks the isomorphic price relationship between levered equity of the firm and a call option and rewrite d_2 in the following form

$$d_2 = \frac{\ln(V_0/D) + (r - \sigma_V^2/2)t}{\sigma_V\sqrt{t}}$$

where the stock price has been substituted by the value of asset in zero, the strike price by the face value of debt in T and the stock' return volatility with the asset value volatility.

[13] Crouhy, M., Galai, D., & Mark, R. (2000). *A comparative analysis of current credit risk models*. Journal of Banking & Finance, 24(1), 59-117.
[14] Hull, J., Nelken, I., & White, A. (2004). *Merton's model, credit risk, and volatility skews*. Journal of Credit Risk Volume, 1(1), 05.

Hence, under Merton's assumptions, the probability of default embedded in his model is

$$PD = N\left(-\frac{\ln(V_0/D) + (r - \sigma_V^2/2)t}{\sigma_V\sqrt{t}}\right)$$

The Merton model for the pricing of risky debt allows to obtain, through the Black and Scholes formula, a value for the equity, the debt and the probability of default that depends on the leverage, the time to repayment and the asset volatility. Whereas the leverage and the time to repayment are variables directly observable, the asset volatility needs to be estimated. Can be reported two approaches used in later works for the estimation of σ_V: the compound option approach, developed by Geske (1977), and the Ito formula approach.[15] These methods permit to have an independent valuation for V.

Merton solves the problem of unobservability of r_A and give a formal link to determine r_D, as a function of asset volatility, leverage and debt's time to maturity. He also proposes a way to determine the probability of default, producing a model able to output a credit spread for corporate bonds, under the framework of Modigliani and Miller (1958).

The aspects that more limit the model proposed by Merton are the restriction on the time of default, mapping all firm's debt into a single-zero coupon bond, the assumption that the risk-free interest rates are constant and that the firm's value is treated as a tradeable asset. More recent structural models, based on the one proposed by Merton, tried to improve the model in order to avoid these limitations. Anyway, all the structural models that followed share a bigger or smaller part of Merton's assumptions and of his framework. I will then report here the aspects, of these more recent models, that depart from the assumptions made by Merton.

2.3.2 Black and Cox Model

The so-called first passage models extend Merton model to comply with the possibility of default happening at intermediate time. This possibility has been first

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[15] For the compound option approach, see for example Hull et al. (2004). The derivation of σ_V trough Ito's lemma is documented, among the others, in Jones, E. P., Mason, S. P., & Rosenfeld, E. (1984). *Contingent Claims Analysis of Corporate Capital Structures: an Empirical Investigation*. The Journal of Finance, 39: 611–625.

addressed by Black and Cox (1976).[16] In their paper, Black and Cox introduce two assumptions, later became common in credit risk literature: a) default may happen at every time before maturity of debt and b) default is determined by the first passage of the diffused process of the firm's value hitting a lower barrier, that is the first time that V reaches a lower threshold. The authors in fact are interested in studying the effects of certain types of bond indenture provisions which are often found in practice. Specifically, they look at the effects of safety covenants, subordination arrangements and restriction on the financing of interest and dividend payments.[17] These safety provisions lead to default in the instant they are violated. Black and Cox start by the results obtained by Merton, developing a debt pricing formula that in addiction considers the probability that a given firm will hit the default boundary before maturity. The possibility of an early default is the consequence of the indenture agreements considered. The authors state that the indenture agreements they consider serve as a specified or induced lower boundary at which the company will be reorganized. In the same way as in Merton, the firm's value follows a diffusion process, but in Black and Cox the default happens the first time that the value of the firm goes beyond the lower boundary between time zero and debt maturity.

[16] Katz, Y. A. & Shokirev V. N. (2010*). Default risk modeling beyond the first-passage approximation: extended Black-Cox model*. Physical review. E, Statistical, nonlinear, and soft matter physics, 82 1 Pt 2 (2010): 016116.
[17] Black, F. & Cox, J. (1976). *Valuing Corporate Securities: Some Effects of Bond Indenture Provisions*. The Journal of Finance, 31(2), 351-367.

In figure 1 are illustrated the three possible scenarios of a firm having issued debt with maturity T under the Merton model and under the Black and Cox model. Looking at the figure, it appears how a firm can result to be in default in T or not, changing the model considered.

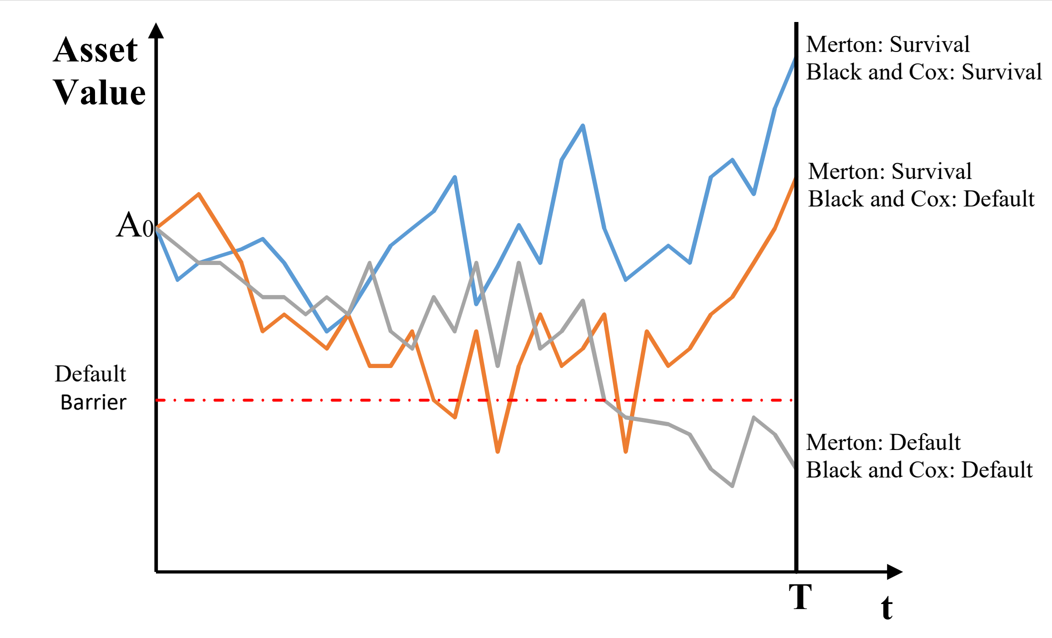

Figure 1 Definition of default under Merton (1974) and under Black and Cox (1976) models

The advantage of setting as exogenous the lower threshold and allowing the firm to default also before debt's maturity makes this model consistent with either net-worth or cash-flow based insolvency. This means that the Black and Cox model can be used to consider, in pricing the debt, both the eventuality that the firm will not be able to repay its debt because the value of its assets is lower than its obligation or that the default is determined by the incapability of the firm to pay back to bondholders the coupons or the principal because of lack of cash capacity.[18]

The authors find that the most basic properties of Merton's formula are shared also by the pricing-formula they propose: debt value is an increasing function of firm's value and time to maturity and a decreasing function of assets' volatility, risk-free rate and the expected rate of return on the firm. They also found that the debt's value is an increasing function of the boundary level: a higher boundary makes the debt safer. The authors, in fact, claim that premature bankruptcy is not itself

[18] Longstaff, F. A. & Schwartz, E. S. (1995). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. The Journal of Finance, 50(3), 789-819.

detrimental for bondholders: it is in their interest to take control of the firm as quick as possible in case of bankruptcy.

The conclusion of Black and Cox article is that provisions often found in bond indentures increase the value of bonds and that they may influence the behavior of the firm's securities. Anyway, in their analysis the authors point out that an important role in the results they obtain is played by the assumptions of no default costs: the default is, in fact, intended solely as the passage of the firm's ownership from stockholders to debtholders, and the probabilistic process governing the value of the firm.

2.3.3 Geske Model

A further development of the Merton model is proposed by Geske (1977). Geske applies the technique for valuing compound options to the case of risky coupon bonds. In this way, the author extends the Merton model to the case of bonds of different maturities and different coupon rates. To include in the analysis the hypothesis of intermediate debt payment, Geske observes as, in the case coupons on the debt are paid, the common stocks can be considered as compound options. At every coupon date until the final payment, the stockholders have the option to buy the next option by paying the coupon or default, leaving the firm to the bondholders. The author obtains a formula containing n-dimensional multivariate normal integrals, where n is measured by the number of payments and hence it also represents the number of nested options in the sequence of payout. This model allows to extend the result of Merton to debt paying periodic reimbursement to the bondholders. It also implicitly allows the possibility of default before the maturity of debt, at each coupon payment date.

2.3.4 Kim, Ramaswamy and Sundaresan Model

Kim, Ramaswamy and Sundaresan (1993) note that the yield spreads produced by Merton model and its following extensions are not able to predict the spreads which one observes in practice. The authors show that the conventional contingent claims model due to Merton is not able to generate default premium in excess of 120 basis point, even when excessive debt ratios and volatility parameters are used in the numerical simulation.[19] They argue that this maximum spread is not adequate if compared with the average spreads on high-grade corporate bonds and on lower grade corporate bonds. During the period 1926-1986, in fact, AAA corporate bonds' spread ranged from 15 to 215 basis point, with an average of 77 basis point and during the same period the BAA corporate bonds' spread averaged 198 basis point. This flaw is also recognized by Eom, Helwege and Huang (2004), which report that it is general wisdom that the credit spreads produced by Merton and Black and Cox models are too low if compared with those observed in the market.[20] Eom, Helwege and Huang stress the fact that these two models produce spreads that are lower than the real ones, in particular for the safer, short-term corporate bonds. Their explanation for this lack of real-word representativeness is that the discrepancies are related to the assumption of firm's value movement following a diffusion process.

The stated inability of contingent claims pricing models to account for the magnitude of the yield spreads between Treasury bonds and corporate bonds is the issue Kim, Ramaswamy and Sundaresan address in their paper. The focus of the model the authors propose is on the effect of the interest rate risk on the corporate bonds' yield and on the determination of default. The authors, in fact, capture the uncertainty in the term structure of interest rates in their model assuming that the short-term process of r is governed by a standard Wiener process. As in Merton and in Black and Cox, the value of the firm as well follows a standard Wiener diffusion process. This model hence embodies two stochastic variables, the firm's value and the risk-free interest rate movements.

With regard to the determination of default, this model is different from earlier contribution in the literature in the fact that bankruptcy is caused by the inability of the firm to cover its debt obligation using its cash-flows. The authors assume that the bond's indenture provisions prohibit the stockholders to sell the assets to pay dividends and that bondholders must be paid their coupon continuously. The omission of a coupon payments precipitates bankruptcy. This means that the net

[19] Kim, I. J., Ramaswamy, K., & Sundaresan, S. (1993). Does Default Risk in Coupons Affect the Valuation of Corporate Bonds?: A Contingent Claims Model. Financial Management, 22(3).
[20] Eom, Y. H., Helwege, J., & Huang, J. Z. (2004). *Structural models of corporate bond pricing: An empirical analysis*. The Review of Financial Studies, 17(2), 499-544.

cash-flow is a fundamental variable in the analysis. The cash-flows behavior over time and investors' preferences are both implicit in the log-normal diffusion process assumed for the firm's value.
Interesting is that under these assumptions the firm could default even though the value of assets is higher than the actualized value of debt repayment at the risk-free rate. From the restriction above mentioned, in fact, if the cash-flow in a certain moment is less than the obligation due the firm cannot sell its asset to repay its debt and is forced to bankruptcy.
Another point to consider of this model is that, modeling the interest payment as a continuous stream of coupons, allows the default to happen any time until debt maturity. Such a determination of default leads to the inclusion of this model in the category of the first passage models. Default happens the first time the firm is not able to repay its debt and the lower threshold is represented by the amount of the continuous coupon the firm owes to its bondholders.

2.3.5 Longstaff and Schwartz Model

The first passage approach is also adopted in a later paper by Longstaff and Schwartz (1995). The authors, as in Black and Cox (1976), develop a closed formula for the pricing of fixed and floating rate debt. The stated aim of Longstaff and Schwartz is to produce a simple new approach for debt valuation extending the model proposed in 1976 by Black and Cox. The assumptions made from the two authors in the attempt to improve the Black and Cox model reflect in part those of precedent works. The models from Longstaff and Schwartz, indeed, allows for complex capital structure including multiple issue of debt as in Geske (1977) and considers the interest rate as a stochastic variable, as previously hypothesized by Kim, Ramaswamy and Sundaresan (1993). An innovation in the assumptions of this model is represented by the possibility of deviation from the strict absolute priority rule. The deviation from the strict absolute priority rule is represented in the formula by the parameter ω, indicating the write-down on debt face value. The value of ω is fixed in the model and represent the outcome of the bargaining process for each tranche of debt. Debtholders, under this assumption, not necessarily receive all the residual value of the firm in case of default, but a fixed percentage of the debt face value. The authors suggest that the value of ω for a particular class of securities could be estimated from actuarial information.

The step forward made by the model of Longstaff and Schwartz is therefore the introduction of the possibility of deviation from the strict priority rule and the development of a single debt pricing formula including most of the features that previous works introduced.

An important implication of their result is that credit spreads for firms with similar default risk can vary significantly if the assets of the firm have different correlation with changes in interest rates.

2.3.6 Leland and Toft Model

The work from Leland and Toft (1996) that followed Longstaff and Schwartz, instead, bases on quite different assumptions from all the models that foreran. Leland and Toft model do not assumes the presence of stochastic risk-free rate, but rather the authors decide to use a nonstochastic default free rate. They argue that by previous works appeared that introducing a stochastic default free interest rate process does not affect heavily the credit spread, while significantly complicate the work.[21]

Leland and Toft introduced two other important features in their model, respect to the previous one: they focus on optimal amount and maturity of debt and they derive endogenous level of firm's value under which bankruptcy is declared. Their model allows for a closed form expression for the value of debt, equity and firm, where bankruptcy is endogenously determined. The model proposed is able to offer an optimal level of leverage for each maturity of debt and an optimal debt's maturity for each level of leverage. By the level of leverage and maturity chosen, the endogenous bankruptcy asset level follows.

[21] The works the authors refer to are Kim et al. (1993) and Longstaff & Schwartz (1995). Kim et al. (1993) found that although the yields on both treasury and corporate issues are significantly influenced by uncertainty in interest rates, the yields spreads are quite insensitive to interest rate uncertainty. Longstaff & Schwartz (1995) found that credit spreads are negatively related to the level of interest rates. This negative correlation would then result in lower level of credit spreads when stochastic risk-free rate is introduced. The low levels of credit spreads produced is one of the problem of structural models. The decision for nonstochastic interest rates is therefore due both to simplify the model both to avoid one of the factor responsible of low credit spreads produced.

The maturity is one of the determinant of debt value, while the total market's value of the firm is computed as asset value plus the value of tax benefits, less the value of bankruptcy costs. In this way leverage and debt's maturity participate in determining the total firm value. It also appears how Leland and Toft assume in their model that the tradeoff theory of capital structure holds, while in previous risk credit literatures the classic assumptions is the irrelevance of capital structure on firm value, as explained by Modigliani and Miller (1958).

It is interesting to note that in this model default is characterized both by flow and value conditions. Bankruptcy can occur at level that may be either lower or higher than the principal value of debt. Similarly, a cashflow shortfall relative to required debt service payments need not result in default, as long as the equity holders can raise funds to avoid bankruptcy. Bankruptcy is determined by that level of unleveraged firm value such that the change in equity value due to the raise of new funds just equal the additional cash flow they provide to avoid bankruptcy. A level of the unleveraged firm's value under the threshold would implicate that no equity capital can be raised to meet the debt obligation and then the firm will default. Default, in this model, produce a loss registered by bondholders given by a prespecified level of recovery rate.

Leland and Toft recognized the need to produce a structural model able to produce more realistic credit spreads and tried to accomplish their goal using a nonstochastic interest rate and computing a default threshold endogenous in the model. The endogenous default threshold is obtained considering, in the firm's market value function, the fiscal advantage of debt and the costs of default.

According to Bohn (2000) the model proposed by Leland and Toft could not be so effective. Bohn raise the question if including taxes and default costs into a structural model will really makes any difference. Moreover, the author advocates that the lack of reliable data on bonds' price and on taxes and default costs makes it difficult to empirically detect the influence of these factors.

2.3.7 Zhou Model

A different approach was proposed by Zhou (1997). Zhou recognized as well the necessity of models producing higher credit spreads, but modified the model by Merton in a different way respect to Leland and Toft.

Zhou, in fact, notes as, under all the structural model previously developed, the dynamics of the value of the firm is assumed to follow a continuous diffusion process. Such an arrangement of the firm's value process does not consent having a risk premium for the short-maturity corporate bond. In fact, a corporate that is in good health, whose asset value is above the debt value, under a continuous diffusion process would have a probability of default close to zero. This would signify no credit spread on short term debt and that the shape of the credit spread curve can only be upward sloping. In fact, classical structural models do not create downward shaped term structure of credit spread unless the firm is in financial distress. Zhou, together with Fons (1994) and Sarig and Warga (1989), observes that this behavior of credit spread is not coherent with reality. Zhou, in fact, points out that the shapes of credit spread curve observed on the market are sometimes flat or downward sloping.

Then, the ability of the model to predict positive credit spreads even on safe short-term bond is an important feature, that correct one of the limit that are recognized to classical structural models.[22]

The idea of Zhou develops from the observation that the continuous diffusion process cannot represent the unexpected default of the firm. Since no sudden drop in value are possible, default never happens by surprise.

The reduced form approach, instead, include the possibility of an unexpected default of the firm. The reduced form models treat default as an unpredictable Poisson event involving a sudden loss in market value, so default can never be expected. Even though the reduced form models solve the problem of unexpected default and are more tractable, they do not provide a structural argument as to why firms default.[23]

Zhou tries to create a model able to deal both with the unexpected default and with the interrelation between default and firm's value modeling the evolution of the latter as a jump-diffusion process. Under a jump-diffusion process default can happen expectedly, because a steady decline of firm's value protracted over time, or unexpectedly, because of a sudden drop in firm's value. The flexibility

[22] Eom et al. (2004)

[23] Bohn, J. R. (2000). *A Survey of Contingent-Claims Approaches to Risky Debt Valuation*. The Journal of Risk Finance, 1(3), 53-70.

introduced by the jump diffusion process bears positive implications for the results the model generate: the term-structure of credit spreads can assume more shapes than previous structural models were able to predict, the short-term credit spreads on high rated firm can be significantly higher than zero, the remaining value of a firm in the event of default is a random variable and the recovery rate in the event of default is positively correlated with the quality of the bond before default.

As explained, the recovery rate is endogenous in the model. Assuming a jump diffusion process for the value of the firm, in fact, implies that the lower threshold that determines default is "jumped" in the event of default. This means that, upon default, the value of the assets is a random variable that can assume values between zero and the value of asset at default triggering level.

The positive correlation between the recovery rate and the quality of bond before default comes by the fact that a firm having a more volatile jump component are more likely to default on its short-term obligations, while a firm whit a more volatile diffusion component is more likely to default on its long-term bonds. If default happens due to the jump component, the firm value could jump below the lower threshold without hitting it and the value left for the bondholder is a value in the interval between zero and the threshold itself. Instead, if the default is due to the continuous diffusion process, the default happens at the first passage to the default barrier. This means that bondholders will benefit of higher value of asset in the event of default. The fact that recovery rate and credit rating are positively correlated can be explained noting that higher credit rating signals that corporate liabilities are more subject to the diffusion component, rather than to the jump component.

The model proposed by Zhou is indeed innovative in its assumption on the dynamic of firm value. Nonetheless, it shares some of its features and assumptions with the credit model that foreran. In particular, Zhou maintained the same assumption of Longstaff and Schwartz (1995) on the default barrier and used a stochastic risk-free rate, as hypothesized by other authors before.

2.3.8 Briys and Varenne Model

Briys and Varenne (1997) proposed a model with the explicit aim to solve a flaw regarding the threshold introduced in the model by Longstaff and Schwartz. They argue that in Longstaff and Schwartz's model the firm could find itself at maturity in the situation to be "threshold-solvent" but unable to repay the face value of its debt. The firm's value could, indeed, remain at a value that allows the firm to remain solvent before maturity, that is when the assets' value is above threshold. But it could happen that, once maturity is reached, the value that allowed the firm to remain solvent is then not sufficient to reimburse the whole value of debt.

Another blemish the authors aim to solve is that the pricing equation in some of the previous models do not assure that the payment to bondholders is no greater than the firm value upon default.

The solution proposed is a model with a stochastic default barrier, based on the exogenous face value of corporate debt, that protect bondholders with a safety covenant. Thus, the model avoids the limitation of having a constant default boundary as in Longstaff and Schwartz (1995) and Kim, Ramaswamy and Sundaresan (1993) and ensures that bondholders do not receive a payment greater than the firm's value upon default.

In fact, the default barrier is determined discounting the face value of firm's debt using a stochastic risk-free interest rate. This formulation of the default boundary implies that the boundary is stochastic itself, since it is discounted using the risk-free rate. Moreover, such a determination of the default barrier protects the bondholders. If the bankruptcy is triggered when the asset value reaches the present value of debt at risk-free rate, the bondholders will be sure to receive the face value at maturity.

Anyway, the authors recognize that this theory implies that the strict priority rule is perfectly enforced and the shareholders do not receive nothing in the event of default. But this is not the situation that is often observed in practice. To take under consideration the deviations from the strict priority rule, the debt pricing formula proposed by the model incorporates two parameters, that represent the write-down on corporate bonds if default happens before maturity and the write-down if it happens at maturity.

Moreover, the presence of the face-value of corporate debt on the formula of the default barrier ensures that, in case of default, the bondholders will not receive a payment higher than the firm value at the moment of default. Default is in fact triggered when the assets value hits the present value of the payment due to bondholders and then bondholders have the assurance that the assets of the firm will be sufficient to pay their credit in the event of default.

2.3.9 Fan and Sundaresan Model

A conceptually innovative structural model is presented in 2001 by Fan and Sundaresan (2001). They, in fact, attempt to reconsider under the model the relative bargaining power of claimants. Specifically, they consider two possible bargaining formulations. The first one considers the borrower and the lender bargaining over the value of assets and no tax benefit is considered. In this setting, the authors study the debt-equity swap between debtholders and shareholders. The choice to do not consider the fiscal benefit of taxes has the advantage to make the model comparable respect to the previous ones.

Under the second formulation, the borrower and the lender bargain over the value of the firm. In this formulation, the role of debt tax benefit plays a crucial role, in that it represents one of the factors influencing the object of bargaining.

The model of Fan and Sundaresan shares part of its assumptions with previous models: the value of the firm follows a lognormal diffusion process, as proposed first by Merton (1974), and, as in Leland and Toft (1996), the effects of tax benefit and the explicit costs of default are reconsidered. The authors, anyway, point out that no one of the previous models distinguish between the value of the assets of the firm and the value of the firm as an ongoing entity in formulating strategic debt renegotiation.

The main innovation of this model is to have attributed to bondholders a bargaining power. Since in the event of insolvency the debt can be renegotiated with bondholders and considering that default and liquidation is inefficient, debtors can be interested in avoiding default.

The conclusion from their paper is that equity holders always pays themselves the maximal cash flow available as a dividend when they can optimally default on debt. Instead, when a cash-flow based covenant is present, as in the second formulation, the equity-holders may voluntarily cut their dividends just enough to avoid hitting the covenant inefficiently. The equilibrium in the model is reached in a game-theoretic setting.

The mentioned structural models differ in part of the assumptions and in the outputs produced in determining the credit spreads on corporate bonds. Anyway, they all are based on the first model proposed by Black and Scholes (1973) and Merton (1974) and share a similar set of core assumptions, such as the stochastic evolution of firm value.
According to Collin-Dufresne, Goldstein and Spencer Martin (2001) the factors studied in structural models presented in the literature on default risk explain only one fourth of the change in credit spreads. They also recognize that, although the test of early structural models proved to be disappointing, the more recent extensions, introducing agency theory (Fan and Sundaresan (2001)) or dynamic capital structure decisions (Leland and Toft (1996)), can improve the fit of the level of the credit spread. However, neither the earlier models nor their extensions can generate the kind of correlation in changes in credit spread uncovered in the analysis from Collin-Dufresne, Goldstein and Spencer Martin.[24]

2.3.10 CreditGrades Model

A more recent contribution to the scientific literature on structural models is represented by the CreditGrades model.[25] It was developed in 2002 by a project involving Deutsche Bank, Goldman Sachs, JPMorgan and RiskMetrics Group.
The aim of the model is to provide a transparent standard for quantitative credit risk. The CreditGrades model is built along a set of techniques that have been in use within a certain number of broker-dealers.
This model seems, then, to be more rooted in the practice of the financial markets respect to previous models, that also tried to give a vision representative of the credit risk dynamics. It tries to be accurate and transparent at the same time. To this end, the model appears to be quite simple, but its inputs have been chosen so to be purely market observables and the assumptions made have been designed to be accurate as a predictor of market levels.
The CreditGrades model, even though it can be enumerated among the structural models, differs from previous contributions in two aspects. First, it focalizes on

[24] Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). *The determinants of credit spread changes*. The Journal of Finance, 56(6), 2177-2207.
[25] Finger, C. G. (2002). *CreditGrades Technical Document*.

credit spread rather than on probability of default. This is reflected in the data used to train the model: parameter estimates and other model decision were made based on the model's ability to reproduce historical credit default swap spreads. Second, this model bypasses the strict definitions of classical structural models in favor of simple formulas tied to market observables. The previous models take literal interpretation of the structural model approach and tries to calculate fundamental parameters that are unobservable, namely the asset's value and volatility.
It appears how CreditGrades model uses a structural model framework where approximation for asset value, volatility and drift terms are related to market observables. One departure from the standard structural model's theory is to consider the default barrier as uncertain. The uncertainty in default barrier is a way used by this model to address the artificially low short-term spreads generally produced by previous structural models. In fact, the uncertainty in default barrier level allows also for instantaneous default, as in the former model by Zhou (1997). As in the classical structural models the firm's value is assumed to follow a standard Brownian motion. The default barrier is determined as the amount of the firm's assets that remain in the case of default. This amount is obtained as $L \cdot D$, where L is the average recovery rate in the event of default and D is the firm's debt on a per-share basis. As anticipated, the default barrier is uncertain in this model. The uncertainty is given by the randomness introduced to the average recovery value L. The variable L is assumed to follow a lognormal distribution, having mean $\bar{L}$ and percentage standard deviation λ. Hence, the default barrier is determined as $LD = \bar{L}De^{\lambda Z - \lambda^2/2}$, where Z is a standard normal random variable. The authors point out how, by letting Z be random, they are capturing the uncertainty in the actual level of debt-per-share. Such a formulation produces the possibility that the default barrier is hit unexpectedly, resulting in a jump-like default event.

In the figure 2 are represented the basic assumptions of CreditGrades model.

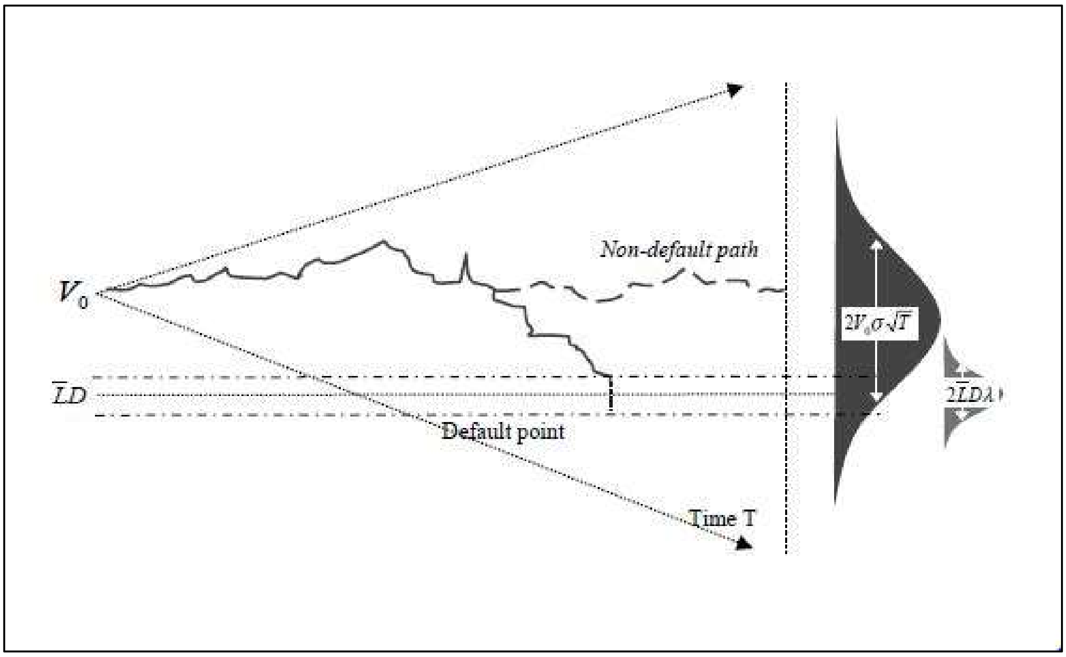

Figure 2 Firm's value process through time. Source: CreditGrades Technical Document (2002)

The value of the firm follows a stochastic process, starting from V_0 and moving in an interval whose scope is equal to $2V_0\sigma\sqrt{T}$. The default barrier moves around the value $\bar{L}D$ in function of the standard deviation of recovery rate, λ.

Given these assumptions, it is deduced as, for a starting value of V_0, default does not occur as long as

$$V_0 e^{\sigma W_T - \sigma^2 T/2} > \bar{L}De^{\lambda Z - \lambda^2/2}$$

The survival probability of the company is, hence, given by the probability that the asset value does not reach the barrier before time T. The model, in fact, adopts a first passage time approach. Default is triggered when the inequality above is no longer respected.

To compute the survival probability of the firm, the authors introduce then the process

$$X_T = \sigma W_T - \lambda Z - \sigma^2\, T/2 - \lambda^2/2$$

and rewrite the survival condition as

$$X_T > \log(\bar{L}D/V_0) - \lambda^2$$

Using the distributions for first hitting time of Brownian motion, the model derives a closed formula for the survival probability, $P(T)$, up to time T.[26]

It is interesting to note that to produce reasonable spreads for short maturity instruments the authors introduce a technical artifact: the movement of $X_T$start in the past, it means before time zero. This produce non-zero probability of default in time zero, replicating a situation like the one produced by a jump process.

To convert the CreditGrades survival probability obtained to a credit price, the model requires the specification of the risk-free rate and the recovery rate on the underlying debt. Now the recovery rate used is the recovery rate on the specific class of firm's debt considered, and not the value $\bar{L}$ used for the default barrier. $\bar{L}$ is, in fact, the expected recovery rate averaged over all the classes of debt.

The credit spread is then computed on a CDS solving for the continuously compounded spread c^* such that the expected premium payments on the CDS equate the expected loss payouts. For a given maturity T, the par spread for a CDS may be expressed as

$$c^* = r(1-R)\frac{1-P(0)+e^{r\xi}[G(T+\xi)-G(\xi)]}{P(0)-P(T)e^{-r} \ -e^{r\xi}[G(T+\xi)-G(\xi)]}$$

where $\xi = \lambda^2/\sigma^2$. The function G is, as proposed by Rubinstein and Reiner (1991),

$$G(u) = d^{z+1/2}\Phi\left[-\frac{\log(d)}{\sigma\sqrt{u}} - z\sigma\sqrt{u}\right] + d^{-z+1/2}\Phi\left[-\frac{\log(d)}{\sigma\sqrt{u}} + z\sigma\sqrt{u}\right]$$

where $z = \sqrt{1/4 + 2r/\sigma^2}$.

---

[26] The derivation of the closed formula for the survival probability is obtained using an approximation of the process X, namely $\hat{X} = \sigma W_T - \frac{\sigma^2 T}{2}$. Moreover, the approximated process is assumed to start in the past, at $-\Delta T = -\lambda^2/\sigma^2$, and to have value of zero at the starting point. This means that $X_T = \sigma W_T - \lambda Z - \frac{\sigma^2 T}{2} - \frac{\lambda^2}{2}$ is approximated by $\hat{X}_{T+\Delta T} = \sigma W_T - \frac{\sigma^2 T}{2} - \frac{\lambda^2}{2}$. To obtain a survival probability is, then, used the distributions for first hitting time of Brownian motion. In particular, following Musiela & Rutkowski (1998), for the process $Y_T + bW_T$, with constant a and b, it can be written that

$$P\{Y_s > y, \forall s < T\} = \Phi\left(\frac{aT-y}{b\sqrt{T}}\right) - e^{\frac{2ay}{b^2}}\Phi\left(\frac{aT+y}{b\sqrt{T}}\right).$$

To apply this to $\hat{X}$, the constants a and b are set in the following manner: $a = -\sigma^2/2$, $b = \sigma$ and $y = \ln(\bar{L}D/V_0)$. Moreover, t is substituted with $t + \lambda^2/\sigma^2$. Is then obtained the following closed formula for the survival probability up to time T,

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{ln(d)}{2}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{ln(d)}{2}\right)$$

where $d = \frac{V_0 e^{\lambda^2}}{\bar{L}D}$ and $A_t^2 = \sigma^2 t + \lambda^2$.

The ability of this model to propose a theoretic credit spread for CDS based on market observables made this model the choice of a number of works on capital structure arbitrage.[27] It allows, in fact, to have a term of comparison for the credit spreads observed in the market. The incoherence between the theoretic and actual values could mean the presence of arbitrage opportunities.

2.3.11 Cremers, Driessen and Maenhout Model

Cremers, Driessen and Maenhout (2008) proposed a structural model based on option-implied jump risk premia. They use information on the market price of downward jump risk embedded in index put options to estimate a structural jump-diffusion firm value model. The authors claim that index put options constitute the prime liquid market for insurance against systematic jumps, that is the risk corporate bond investors are subject to. Henceforth, the asset value dynamic, similarly as modeled by Zhou (1997), is determined by both a continuous diffusion both by a jump diffusion process. The jump component is calibrated to fit option prices. Adding this specification, the authors want to capture the information contained on option prices on the jump intensity and jump size of firms' asset value process and therefore produce more realistic credit spreads.

2.3.12 Zhang, Zhou and Zhu Model

Zhang, Zhou and Zhu (2009) recognize the step forward made by models relying on option-implied jump risk measure. Anyway, they argue that none of the previously proposed structural model is efficient in predict credit spreads. The model they propose relies on high-frequency equity prices for volatility and jump risk. They argue that previous literature suggests that realized variance measures from high-frequency data provide a more accurate measure of short-term volatility, than do those from low-frequency data.

The model proposed by Zhang, Zhou and Zhu shares part of its assumptions with the original model from Merton (1974): default can only happen at maturity and the risk-free rate is fixed in the model. The dynamics of asset value is modeled according to Zhou (1974) and Cremers, Driessen and Maenhout (2008), combining

[27] See, among the others, Yu (2005), Bajlum & Larsen (2007), Cserna & Imbierowicz (2008), Avino & Lazar (2013).

a diffusion process and a jump process. The jump measures are constructed using high-frequency equity return data to better capture the potential effect on credit spreads from underlying asset dynamics.

2.3.13 Reduced form models

The other class of model mentioned above is represented by the reduced form models. The introduction of reduced form models is attributed to the work of Jarrow and Turnbull (1995), that was later improved by Jarrow, Lando and Turnbull (1997). [28] Other cited works on reduced form models literature are Duffie and Lando (1997), Duffie and Singleton (1998) and Cathcart and El-Jahel (1998).

Reduced form models were introduced to overcome the problem of the non-tradability of firm's asset and of non-observability of firm's asset value process that, instead, are key assumptions in structural models. Reduced form models, in fact, rest on the assumptions that default is an unpredictable event, governed by an intensity-based or hazard rate process. Here, it is the time of default to be stochastic. The time of default is assumed to follow a stochastic process governed by its own distribution that must be parametrized by an intensity or hazard rate process.[29] The process that leads the firm to default is totally inaccessible and unpredictable.

The extensions to reduced form models focus on more sophisticated determination of the hazard rate process. Many extensions explore assumptions surrounding the risk-free interest rate process and the recovery rates. These models are in fact quite flexible at changes on the assumptions on process governing the hazard rate, the risk-free rate and the loss given default.

Anyway, because the reduced form models do not link the default probability of a firm to its assets, these models are not useful to obtain predictions of credit spread. For the purposes of this analysis, then, the focus has been posed on the evolution, trough time, of structural models. Some of the more meaningful models have been proposed, highlighting the evolution of each model respect to the previous ones and explaining the innovation introduced by each one. The presented digression has the finality to understand the theory behind the structural models and the evolution of

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[28] Jarrow, R. A. (2009). *Credit risk models*. Annual Review of Financial Economics, 1(1), 37-68 and Bohn (2000).

[29] Ibid.

credit risk literature trough last decades. Anyway, the analysis proposed has not wish of completeness: many more are the models have been developed, other than those here proposed.

To summarize, the theory on credit risk modeling owes its birth to the works from Black and Scholes (1973) and Merton (1974). They first model the dynamics of firm value following a standard Brownian motion and apply the option pricing technique to debt valuation, recognizing that equity's value behavior can be assimilated to a European call option on firm's assets. In this way, Merton model can produce a term structure of risky interest rate. Later, Black and Cox (1976) introduced the possibility, not present in Merton (1974), of an early default. Modeling the equity as a European option, in Merton model default is possible only upon maturity. Black and Cox, instead, introduce an absorbing barrier, allowing the firm to enter default prior to maturity if its asset value hits this barrier any time up until maturity. Geske (1977) complicates the previous models introducing the hypothesis of bonds of different maturities and different coupon rates. Moreover, Geske uses a system of compound options to compute bonds' value. The author observes how the common stock can be considered a compound option: at every coupon date, the stockholders have the option to buy the next option by paying the coupon or forfeiting the firm to the bondholders. Kim, Ramaswamy and Sundaresan (1993) change part of the assumptions introduced by Merton, maintaining the possibility of early default, as in Black and Cox (1976). They, in fact, assumes the risk-free interest rate to be a stochastic variable, while it was previously assumed to be fix and known. Moreover, Kim, Ramaswamy and Sundaresan focus on the firm defaulting on its coupon obligation, rather than on default caused by assets' value falling beyond the threshold. Longstaff and Schwartz (1995) maintain the floating interest rates introduced by Kim, Ramaswamy and Sundaresan (1993), proposing a closed-form valuation expression for risky coupon bonds as well as risky floating-rate debt. Furthermore, they add the possibility of deviation from the strict priority rule. Another important difference introduced respect to the previous models is represented by the exogenous default threshold level. Default, here, is triggered the first time assets' value touch a certain lower threshold, that is not necessarily linked to the debt face value. This definition of financial distress is consistent with both the net worth default both with the cash-flow based default. The work from Leland and Toft (1996) drops the assumptions of stochastic risk-free rates, arguing that floating risk-free rate specification does not improve greatly the model, while making it more complex. An important innovation introduced by Leland and Toft is the determination of bankruptcy endogenously in the model. Moreover, the authors, state that their work is the first that focus on optimal capital structure, making explicit reference to the trade-off theory accounting equation. Zhou (1997) makes a radical change in the assumption on asset value process. In his model, the value of the firm follows a jump diffusion process, rather than the plan diffusion process, first introduced by Merton (1974). The jump component implies that the recovery rate is endogenously generated in the model. Whit the jump specification, in fact, in the event of default the residual value of the firm could be anywhere between the default threshold and zero. The default in Zhou is determined, as in Black and Cox and following models, by the first time the value of the firm hits the default barrier. The default barrier determination is borrowed by Longstaff and Schwartz (1995). Briys and Varenne (1997), aiming at improving the definition of threshold level proposed by Longstaff and Schwartz, propose to set the default barrier at the level of the discounted value, at risk-free rate, of the face-value of debt at maturity. They insert the assumption of stochastic risk-free rate, wich in turn determines that also the default barrier is stochastic, since it is determined discounting the fixed amount of debt at risk-free rate. They, in addition to previously proposed models, insert in the debt pricing formula parameters representing the write-down on debt, allowing deviations from strict priority rule. Fan and Sundaresan (2000) provides a framework for debt renegotiation where bargaining power of share-holders and debt-holders can be varied. They consider the effect of taxes, as in Leland and Toft (1996), assumes that the zero-rate curve is flat and the threshold barrier is endogenously determined. Fan and Sundaresan, in addition, impose that assets sale for dividend payment are prohibited. CreditGrades (2002) introduces the uncertainty in default barrier. The default barrier is here determined as the average recovery rate on debt times the debt value. The recovery rate considered is stochastic and hence also the default barrier is stochastic in the model. Another differentiating aspect of CreditGrades, respect to previous models, is the focus on valuation of credit spread rather than on default probability. The risk-free rate here is assumed constant.

Two more recent models, proposed by Cremers, Driessen and Maenhout (2008) and Zhang, Zhou and Zhu (2009), both follows Zhou (1997) in the definition of asset value dynamic. The introduction of the jump component, in fact, seemed to improve previous models in predicating more realistic credit spreads. Both the models propose, then, sophistication of the jump components estimation. Cremers, Driessen and Maenhout (2008) calibrate jump components consistently with index put options prices. Zhang, Zhou and Zhu (2009) identify the volatility and jump risks of individual firms from high-frequency equity prices.

It appears how the evolution of structural models passed through the modification and elaboration of certain parameters, while the core framework remained the same. In particular, the factors that mainly determine the differences among models are the dynamic of asset value, the dynamic of risk-free rate, the determination of the default barrier and the determination of the recovery rate.

The specification of these four measures for the models here reported are summarized in Exhibit 1 and Exhibit 2.

Reference	Asset value	Risk-free rate
Merton (1974)	$dV_A = \mu V_A dt + \sigma V_A dz$	$dr = rdt$
Black and Cox (1976)	$dV_A = V_A dt - Cdt + \sigma V_A dz$	$dr = rdt$
Geske (1977)	$dV_A = \mu V_A dt + \sigma V_A dz$	$dr = rdt$
Kim, Ramaswamy and Sundaresan (1993)	$dV_A = (\mu - \gamma) V_A dt + \sigma_1 V_A dz_1$	$dr = \kappa(\varepsilon - r)dt + \sigma_2 \sqrt{r} dz_2$
Longstaff and Schwartz (1995)	$dV_A = \mu V_A dt + \sigma_1 V_A dz_1$	$dr = (\varepsilon - \kappa r)dt + \sigma_2 dz_2$
Leland and Toft (1996)	$dV_A = \mu V_A dt - Cdt + \sigma V_A dz$	$dr = rdt$
Zhou (1997)	$dV_A = (\mu - \lambda c) V_A dt - \sigma dz_1 + (\Pi - 1)dY$	$dr = (\varepsilon - \kappa r)dt + \sigma_2 dz_2$
Briys and Varenne (1997)	$dV_A = rV_A dt + \sigma_1 (\varrho dz_2 + \sqrt{1 - \rho^2} V_A dz_1$	$dr = x(\tau)[b(\tau) - r]dt + \sigma_2(\tau) dz_2$
Fan and Sundaresan (2000)	$dV_A = (\mu - \gamma) V_A dt + \sigma V_A dz$	$dr = rdt$
CreditGrades (2002)	$dV_A = V_A \sigma dz + \mu_D dt$	$dr = rdt$
Cremers, Driessen and Maenhout (2008)	$dV_A = V_A[(r - C)dt + \sigma dz + dJ^Q - \lambda^Q \xi^Q dt + dJ^f - \lambda^f \xi^f dt]$	$dr = rdt$
Zhang, Zhou and Zhu (2009)	$dV_A = V_A[(\mu - \gamma - \lambda \mu_J)dt + \sigma dz + JdY]$	$dr = rdt$

Note: μ represents the instantaneous expected rate of return on the firm per unit of time; V_A represents the value of the firm's asset; C represent the firm's dollar payout for unit of time; σ is the instantaneous standard deviation of return on asset; dz is a standard Brownian motion; γV_A is the net cash outflow from the firm resulting from optimal investment decision; κ is the speed with which the interest rate r approach the long run mean rate; the scalar ε is the long-run mean rate of interest; c is the firm's payout rate; dY is a Poisson process with intensity parameter λ; Π is the jump amplitude with expected value equal to c+1; ρ represent the correlation coefficient between the riskless rate and the value of corporate assets; μ_D is the asset drift, J is the common jump process, in Cremers, Driessen and Maenhout (2008) J^Q is the jump process under the risk neutral measure and J^f is the jump specific jump process, ξ is the mean jump size.

Exhibit 1 Categorization of Structural Models I

Reference	Default barrier	Recovery
Merton (1974)	B	$V_{A(T)}$
Black and Cox (1976)	$LBe^{-r(\tau)}$; AB	$LBe^{-r(\tau)}rdt$
Geske (1977)	B	$V_{A(T)}$
Kim, Ramaswamy and Sundaresan (1993)	c/γ; AB	$\min[(1-L(\tau))P(r,\tau,c);V_A]$
Longstaff and Schwartz (1995)	K; AB	$(1-L)B$
Leland and Toft (1996)	$V^*_{A(\tau)}(\tau;c;t;\alpha)$; AB	$(1-L)V^*_{A(\tau)}$
Zhou (1997)	K; AB	$(1-L)B$
Briys and Varenne (1997)	$LBP(\tau)$; AB	$LBP(\tau)$
Fan and Sundaresan (2000)	$\frac{\gamma(1-t)}{r}\frac{-\lambda_-}{1-\lambda_-}\frac{1}{\eta\zeta}$; AB	$\frac{\gamma(1-t)}{r}\frac{-\lambda_-}{1-\lambda_-}\frac{1}{\eta\zeta}$
CreditGrades (2002)	LD; AB	LD
Cremers, Driessen and Maenhout (2008)	B; AB	$(1-L)B$
Zhang, Zhou and Zhu (2009)	B	$V_{A(T)}$

Note[1]: AB means that the default barrier is an absorbing barrier; B represents the debt's face value; L is a percentage that measure the write-down on debt in the event of default; T is debt's maturity; τ is the time to maturity; K is the asset level, specified in the bonds safety covenants, that triggers default; $P(r,\tau,c)$ is the value of a treasury bond with time to maturity τ; c is the contractual coupon rate; ; γV_A is the net cash outflow from the firm resulting from optimal investment decision; K is an arbitrary threshold value for the firm at which financial distress occurs; t represents the firm's tax rate; α is the bankruptcy costs as a fraction of the value of the firm in bankruptcy; $P(\tau)$ designates the price of a risk-free bond based on the stochastic process behind the risk-free interest rate.
Note[2]: In Leland and Toft (1996) the default barrier is determined endogenously.
Note[3]: In Zhou (1997) recovery rate is endogenous in the model.
Note[4]: The presented default barrier for Fan and Sundaresan (2000) refers to the deb-equity swap case. The choice to report the debt-equity swap case is due to comparability purposes. The value λ_- has, in this context, the value of elasticity of the probability of default with respect to the value of the assets of the firm. λ_- is expressed as $\left[0.5-\frac{(r-\gamma)}{\sigma^2}\right]-\sqrt{\left[0.5-\frac{(r-\gamma)^2}{\sigma^2}\right]+\frac{2r}{\sigma^2}}$ and is imposed to be strictly lower than zero.

Exhibit 2 Categorization of Structural Models II

2.4 Conclusion

This chapter went through two main topics: the capital structure theories and the structural models evolution. The theme that links these topics is the credit risk. Credit risk represent a core element in identifying opportunities of Capital Structure Arbitrage. This is the reason why a diffused discussion of the interrelation between capital structure, asset volatility, debt pricing and credit risk has been proposed.

The chapter starts, in fact, discussing the capital structure theories. Probably, the most famous theory on this subject is the irrelevance of capital structure, as presented by Modigliani and Miller. According to their theory the value of asset is determined by asset volatility and is not affected by the composition of firm's capital structure. The Trade-off theory, instead recognize to the composition of capital structure the power to influence the asset value. This theory asserts that increase in indebtedness has a dual effect on asset's value, first positive and then negative. Finally, the pecking order theory does not speculate on the effect of capital structure composition on firm's assets value, but illustrate how a firm should rank its source of financing.

The structural models, instead, propose a measure of credit spread and a way to price debt and equity by the observation of asset value movements. The evolution of these models has been presented, from the first idea of Merton (1974) to the more recent and diffused in practice CreditGrades model (2002). CreditGrades has been recognized by several authors as the current standard in credit risk identification and it appears to be used by the great majority of research on credit pricing and Capital Structure Arbitrage.

Therefore, the goal of this chapter has been to introduce the theoretical underlying of credit pricing and credit risk valuation as well as the theories on the role of capital structure on company valuation.

Indeed, these are also the elements that arbitrageur considers when chasing positive returns from the implementation of a Capital Structure Arbitrage.

3 Capital Structure Arbitrage

3.1 Introduction

This third chapter will go through the mechanism of Capital Structure Arbitrage investment strategy. This peculiar strategy relies on the debt pricing models that have been illustrated in the previous chapter. As a matter of fact, this strategy bets on the fact that, in the medium term the market value of debt and equity of a given entity will reach an equilibrium level and this equilibrium level is determined by the structural model chosen by the arbitrageur. In particular, structural models are fed with equity market value and volatility and debt face value to obtain a probability of default for the firm. Default probability, in turn, allows to predict a fair credit spread on company's credit default swaps.

What is interesting of the Capital Structure Arbitrage is that, if the strategy is able to produce positive returns, then it means that the structural model used to enquiry the real probability of default of a given entity was presumably right.

Therefore, hereinafter will be reported the main researches done on Capital Structure Arbitrage. The first complete work on this subject has been proposed by Yu (2004). Its work represents an empirical analysis of the arbitrage strategy as commonly implemented by traders. The relevance of Yu's work on the subject is witnessed by the fact that it is cited basically by all the subsequent works on Capital Structure Arbitrage. Hence, academic research that followed Yu will be here reported. Differences in strategy implementation will be highlighted, together with their effects on strategy's returns.

Then, the CreditGrades model will be presented in more depth. It, in fact, plays a key role on Capital Structure Arbitrage and a more detailed description of the parameters and assumptions that back the model appears to be essential. The choice of best inputs to correctly estimate parameters to feed the model, in fact, is at heart of the literature on Capital Structure Arbitrage. It will therefore be proposed a new way to calibrate the CreditGrades model through the use of GARCH model as estimator for equity returns variance.

Finally, the last section of this chapter will be dedicated to the credit default swap. The focus on this derivative instrument is dictated by the role that CDSs has assumed on the credit market during last years and consequently on Capital

Structure Arbitrage strategy. In fact, CDS's popularity increased greatly during the first decade of the century and the liquidity of this instrument reached a level like this of its underlying.[30] The high liquidity and the versatility offered by CDS in trading credit risk made of this credit derivative the preferred instrument in implementing the Capital Structure Arbitrage. Hence, a discussion on the mechanism and features of CDS will be presented.

[30] Oehmke, M. & Zawadowski, A. (2016). *The Anatomy of the CDS Market*. Review of Financial Studies, Forthcoming.

3.2 Strategy description and historical profitability

The term "Capital Structure Arbitrage" refers to those investment strategies seeking to exploit the inconsistent valuation of different parts of the capital structure of a same entity. Basically, it prescribes to trade one security against another security issued by the same firm.[31] These investment strategies do not care if the firm is in good condition or not as a whole entity, rather they look at the relative valuation of different parts of the company's capital structure. Since all the claims of a firm are really derivatives of the firm, their inconsistent valuation signals the presence on the market of a not univocal belief regarding one or more parameters that determine the firm value. The arbitrageur, hence, bets that the trade in the market will produce the convergence of those parameters towards an equilibrium value and gains buying the relatively cheap security while selling the expensive one.

A classical implementation of capital structure arbitrage is the trade of firm's debt against the firm's equity. What the arbitrageur looks for in this case is the consistent pricing of equity and debt given a certain riskiness level of firm's asset value. If debt and equity valuation is not consistent, the investor buy the relatively cheap segment of the capital structure and short-sell the relatively expensive one. Generally, this strategy is implemented using firm's stocks and credit default swaps written on firm's debt. The use of CDSs instead of bonds can be explained considering that during last years this instrument became quite liquid and easier to trade respect to bonds. In addition, it results much simpler and cheaper to open a CDS position rather than to short-sell bonds.[32] Moreover, the CDSs offer other advantages: CDS spread is in fact a function of the only default probability of the firm and is not directly affected by the risk-free interest rate, as bonds are. Moreover, the increased liquidity of this instrument produced a faster inclusion of market information on CDSs' spread rather than in bonds' price.[33] Support to this thesis comes by the observation that the expansions of CDSs' market and the popularity of capital structure arbitrage grew together. According to Wojtowicz

[31] Pedersen, L. H. (2015). *Efficiently inefficient: how smart money invests and market prices are determined*. Princeton University Press.
[32] Yu (2004) and Bajlum & Larsen (2007).
[33] One of the works that studied the responsiveness of CDSs to market condition is Zhu (2004). The author finds that CDSs' premia are more responsive to change in credit conditions respect to bonds.

(2014), the popularity of the arbitrage strategy grew starting from 2000, thanks to the increasing CDSs' market size and liquidity. Indeed, during the period from 2000 to 2005 the number of hedge funds using capital structure arbitrage increased five-fold, reaching over 300 active funds near the end of 2005.[34] The increasing interest in the Capital Structure Arbitrage during the early years of the new century is also documented by Currie and Morris (2002). In their article from 2002, the authors report as, according to traders at several investment banks, capital structure arbitrage is fast gaining ground as the next big trading strategy. [35] Currie and Morris, as well, recognize that the development of credit default market fueled the diffusion of the strategy. This is a point presented also by Skorecki (2004), in an article appeared on Financial Times. The article in question, proceeds further in explaining the reasons of the gained popularity of the Capital Structure Arbitrage, pointing out that other strategies, such as convertible bond arbitrages, which require a similar set of technical skills, are in the doldrums.[36] According to another article (James Drummond (2004)) it is the CDSs diffusion itself that has hurt the profitability of the convertible bond arbitrage. In fact, the opportunity offered by CDSs to be covered against the risk of default has led to a loss in value for convertible bonds as a class.[37] The expertise of investment banks on arbitrage involving debt and equity has therefore been reemployed on different arbitrage strategies. As a matter of fact, the weakened performances of similar investment strategies and the broadened CDSs' market led many funds and investment banks to study viable implementations of the idea behind the described arbitrage strategy. At the same time, various scientific paper exploring the potential of the capital structure strategy started to be written.

3.2.1 Capital Structure Arbitrage Literature Review

One of the first and more comprehensive work on Capital Structure Arbitrage is from Yu (2006). The aim of Yu is to present a comprehensive study of Capital Structure Arbitrage using a simplified version of the industry standard

[34] Wojtowicz (2014).
[35] Currie, A. & Morris, J. (2002). *And Now for Capital Structure Arbitrage*. Euromoney, December, 38– 43.
[36] Skorecki, A. (2004). *Hedge funds fill a strategy gap*. Financial Times, 21 July.
[37] Drummond, J. (2004). *Jury out on convertible arbitrage*. Financial Times, 19 December.

implementation procedure. Therefore, the author decides to back-test the strategy investing in credit default swaps and hedging his position buying or selling equity, depending on the position assumed in CDSs. To compute the risk-neutral survival probability, Yu utilizes the structural approach, that, how explained in the previous chapter, assumes that default occurs when the firm's asset level drops below a certain default threshold. The author uses the CreditGrades model. Yu, in fact, highlights how this model, on the practical side, provides a closed form solution to the survival probability and to CDS spread. Moreover, since the aim of the author is to test the profitability of capital structure arbitrage as implemented in the market by funds and investment banks, then its preference goes naturally for CreditGrades model. In fact, CreditGrades results to be largely adopted by major investors.

The spread produced by the model is then compared to the market spread. The difference by the theoretical and the observed spread is used as a signal for enter in or exit from the strategy.

The work by Yu was followed in subsequent years by other scientific paper that tried to replicate the strategy implementation, adding or modifying the parameters he set in order to improve strategy's returns.

Duarte, Longstaff & Yu (2007) conducted an analysis of the risk and return characteristics of a number of widely used fixed-income arbitrage strategies, Capital Structure Arbitrage included. Similarly to the approach presented by Yu (2006), Duarte, Longstaff and Yu implements the strategy trading stocks against CDS. They generate the predicted CDS spread using the CreditGrades model. Their work is anyway less specific on the subject, presenting the Capital Structure Arbitrage in the broader landscape of fixed income arbitrage strategies.

Bajlum & Larsen (2007) make explicit reference to the previous work from Duarte, Longstaff & Yu (2007) and Yu (2006). Their aim is to improve the return obtained by previous works on the subject using the more comprehensive structural model by Leland & Toft (1996). The authors, in fact, stress the focus of their study in the shortfalls of model's predictions. They point out how the observed difference in market and equity implied spread may be driven by model misspecification and inputs mismeasurement. What they find is that the exact model used for predicting CDS spread is a question of secondary importance. In fact, Bajlum and Larsen advocate that the real improvement is led by a correct estimate of key inputs used to feed the model. What they point out is that historical volatility may not be appropriate measure of the actual volatility. They find, instead, that using an option-implied volatility results in superior strategy execution. Anyway, such a determination of volatility could contribute to complicate even further the implementation of the strategy, that has been defined as "expensive" in terms of financial knowledge required to make it work.[38]

Cserna & Imbierowicz (2008) study the efficiency of CDS market by implementing a back test of a capital structure arbitrage in the period from 2002 to 2006. The simulation is performed using as signal the spread produced by three different structural models: the CreditGrades model, the Leland and Toft (1996) model and the model proposed by Zhou (2001). The originality of the work is in testing the structural model from Zhou (2001) as a predictor of credit spread. The result achieved by Cserna and Imbierowicz is that the mathematically more advanced Leland and Toft and Zhou models provide larger arbitrage return within their strategy. Moreover, the authors present a broader sample in the simulation, both in terms of time and of reference entities. The analysis is, in fact, conducted on a global set of firms, while most of the previous works were focusing only on North America.[39]

Avino & Lazar (2013) try to enhance the capital structure strategies proposing a set of new strategies aiming to solve the shortfalls the previous works highlighted. Namely, the authors propose four different strategies for capital structure arbitrage. The first one is a classic capital structure strategy, as explained by most of the previous works: theoretical spreads are estimated trough the CreditGrades model and the position in CDSs is hedged with stocks. The second proposed strategy is an augmented version of the first one. The enter signal is in this case given both by the structural model both by a price discovery measure. The price discovery measure adopted is the Information Share. The Information Share is a measure of the ability of the prices on a given market to reveal the prices on a different market. In this context, the Information Share is used to infer the ability of the equity market to

[38] Duarte, J., Longstaff, F. A. & Yu, F. (2006). *Risk and Return in Fixed Income Arbitrage: Nickels in front of a Steamroller?* The Review of Financial Studies, 20(3), 769–811.
[39] Cserna & Imbierowicz (2008).

reveal the spreads on the CDSs' market. This second strategy, hence, requires that the trade is started only if the market spread is away from the theoretical one from more than a given threshold and the information share is between two selected thresholds. Conceptually, this second strategy, respect to the first one, controls before starting the trade, that the equity price is a valid signal to discover the CDS spreads. The third suggested strategy entails trading only in one market, the CDS market or the equity market. The signals used are the same illustrated for the second strategy: the structural model and the price discovery measure. The trade is therefore executed only in the least efficient market. The fourth strategy focus on the determination of the minimum spread between model and market credit spread to generate a trading opportunity.

Avino and Lazar find that the role of the hedging is dependent on the state of the economy: during period of low volatility the hedge appears to be useful. On the contrary, during the crisis period, the strategies that avoid hedging performed better than these which hedge. The authors claim also to have produced investment strategies that are less correlated to the market respect to standard credit arbitrage strategies and that the introduction of the Information Share as a signal, in the second strategy, has improved the returns of the plain hedged strategy both during calm and crisis periods.

Wojtowicz (2014) presents a revisited way to implement capital structure arbitrage.[40] His work is mainly based on the previous works from Yu (2006) and Bajlum and Larsen (2007). The innovation added by the Wojtowicz's paper are focused mainly on the calibration of recovery-rate volatility as input in CreditGrades model. The author, in fact, believes that the approach suggested by Yu (2006), that prescribes to calibrate the volatility minimizing the squared pricing error between model spread and market spread at the beginning of the sample period, could produce heavy bias in the model. Wojtowicz argues that if the calibration made according to Yu (2006) is performed in a period when the Capital Structure Arbitrage would have been profitable, then the estimated parameter would be biased by market temporary anomalies. Instead the use of a rolling CDS-implied volatility would produce a better estimate. The assumptions behind this approach is

[40] Wojtowicz (2014).

that the market pricing of debt and equity is correct most of the time. To obtain a rolling CDS-implied volatility the author first compute for each trading day that level of volatility that, if used as input in the CreditGrades model will produce a credit spread equal to this observed in the market. Next the 1-year moving average volatility based on the past CDS model implied volatility is computed. Finally, this is used as input in the CreditGrades model to obtain the theoretical credit spread for the firm.

The contribution to the existing literature added by the work of Wojtowicz is not confined to this new approach to calibrate model parameters. He also analyzes the profitability of capital structure arbitrage in a relatively recent period, when the CDS market was yet highly developed. He conducts his study in the period from July 2010 to November 2012. Moreover, the author advocates that, despite what reported in various previous works, Capital Structure Arbitrage return indices are associated with common risk factors.[41]

Summarizing, the literature on Capital Structure Arbitrage is not so sparse and the study of this investment strategy followed the expansion of CDS market. It is, in fact, the expansion of credit derivative markets that fueled the adoption of the arbitrage strategy among funds and investment banks' desks. The reminded work from Yu (2006) represents, in this context, the first comprehensive analysis of the arbitrage strategy and the point of departure for the following related literature. I will therefore report here in detail the approach to the study of the strategy as implemented by Yu, highlighting the aspects of its study that the following works on credit arbitrage have questioned. I will then report in more depth the relevant findings of these works.

3.2.2 Strategy Implementation

Yu, noticing a complete lack of evidence in favor or against this strategy, conducts an empirical analysis of capital structure arbitrage as commonly implemented by traders. Hence the author relies on the use of a structural model to estimate the real

[41] Among the authors that did not find a correlation between the returns on the arbitrage strategy and common risk factors is Yu (2006). Yu reports that "*the monthly excess returns cannot be explained by several well-known equity and bond market risk factors*".

survival probability of the reference entity and the spread consistent with that probability.

The model chosen by Yu, as previously mentioned, is the CreditGrades model. The decision to use the CreditGrades derives by its practicality and because it is reputed to be the model used by most capital structure arbitrage professionals. The utility of the structural model here comes by its ability to output a measure for the risk neutral probability of default of the reference entity and, consequently, to produce a theoretical credit spread on its obligations.

In the implementation of the arbitrage strategy, the use of a structural model results to be useful both in order to have a theoretical spread on CDSs to compare with market CDSs'spread, both to compute the change in value of a contract after it is started.

The pricing process of a credit default swap starts by observing that, for the counterparty that sell protection, the value of the CDS is determined by the premium he will earn and by the probability that the reference entity will default, forcing him to reimburse the other part. The present value of the premium payments is equal to

$$E\left(c\int_0^T exp\left(-\int_0^s r_u du\right)1_{\{\tau>s\}}ds\right),$$

where c denotes the CDS spread, T the CDS contract maturity, r the risk-free interest rate and τ the default time of the obligor.

The author explains how, assuming independence between the default time and risk-free interest rate, the reported formula can be re-written as

$$c\int_0^T P(0,s)q_0(s)ds,$$

where $P(0,s)$ is the price of a risk-free zero-coupon bond with maturity s and $q_0(s)$ is the survival probability of the obligor, hence the probability that τ is higher than s, at the starting time.

The present value of the protection bought by the counterparty corresponds to

$$E\left[(1-R)exp\left(-\int_0^\tau r_u du\right)1_{\{\tau<T\}}\right],$$

where R measures the recovery rate, in the event of default, of bond market value as a percentage of par in the event of default.

Again, assuming independence between default and the risk-free interest rate and a constant value of the bonds' recovery rate, the present value of the protection can be expressed as

$$-(1-R)\int_0^T P(0,s)q_0'(s)ds,$$

where $q_0'(t)$ is the probability density function of the default time and is linked to the survival probability by the following relation $q_0'(t) = -dq_0(t)/dt$.

The initial value of the contract is zero: the value of the payments must be equal to the value of the protection bought. Hence, the present value of payments is equal to the present value of credit protection

$$c\int_0^T P(0,s)q_0(s)ds = -(1-R)\int_0^T P(0,s)q_0'(s)ds.$$

Rearranging this equation, it is possible to determine the CDS spread c as

$$c = -\frac{(1-R)\int_0^T P(0,s)q_0'(s)ds}{\int_0^T P(0,s)q_0(s)ds}.$$

The CDS spread so derived is the spread on a newly minted contract. It is such a spread that assure that at initiation the value of the contract is zero for both the parts. As the market conditions change, the value of the contract moves away from zero. To someone who holds a long position in a CDS contract with maturity T, from time 0 to t, this change in value is determined as

$$\pi(t,T) = [c(t,T) - c(0,T)]\int_t^T P(t,s)q_t(s)ds,$$

where $c(t,T)$ is the CDS spread on a new contract initiated at time t, having maturity date T, and $q_t(s)$ is the survival probability trough s at time t.

The risk-neutral survival probability is computed, as explained, in accordance with CreditGrades model. A further explanation of CreditGrades model is reported later in this chapter.

The author proceeds further with strategy implementation. The implementation of the strategy requires the computation of a theoretical CDS spread, given the observables required by the chosen structural model. In this case, the author needs as inputs for CreditGrades model, the equity price, the debt per share, the mean global recovery rate, the standard deviation of the global recovery rate, the bond specific recovery rate, the equity volatility and the risk-free interest rate. Different authors have variously addressed the setting of some of these parameters. Yu identifies the debt per share as the ratio between total liabilities and the number of common shares outstanding. The leverage level input is updated every quarter, taking data from companies' report releases. This seems to be a choice shared by all the works that followed. On the contrary, the equity volatility represents a point of divergence in the literature. Yu's approach prescribes to use the 1,000-day equity volatility to feed the model. Bajlum and Larsen (2007) instead test both the 250-day historical volatility and the implied volatility from equity options. The choice to use also the option-implied volatility is based on the findings of Cremers et al. (2006) and Cao et al. (2006): the authors found as the implied volatility contains important and timely information about credit risk different from the historical measure.[42] This characteristic could indeed lead to superior entry and exit decisions and trading returns, given that the strategy earns from the different reactivity of capital structure components to change in credit risk.

Wojtowicz (2014) adopts the approach to compute the stocks' volatility implied in the CDS spread by finding the level of volatility that when used as an input to CreditGrades produces CDS premium that is equal to the actual CDS premium. Then compute for each company in the sample the 1-year moving average volatility using the CDS-implied equity volatility so obtained and finally use this information as input to feed the model and produce the benchmark CDS premium.

The mean global recovery rate, as well as the standard deviation of the global recovery rate, are parameters whose value is suggested by the CreditGrades technical documents itself. The mean and the percentage standard deviation of the recovery rate are estimated using proprietary databases, the Portfolio Management Data and Standard & Poor's database. The databases contain actual recovery data for approximately 300 non-financial U.S. firms that defaulted in the period from 1987 to 1997. Defaulted instruments include bonds and bank loans. Based on the

[42] Cao, C., Yu, F., & Zhong, Z. (2010). *The information content of option-implied volatility for credit default swap valuation*. Journal of financial markets, 13(3), 321-343 and Cremers, M., Driessen, J., Maenhout, P., & Weinbaum, D. (2008). *Individual stock-option prices and credit spreads*. Journal of Banking & Finance, 32(12), 2706-2715.

study of these historical data, the mean recovery rate and the standard deviation of recovery rate are estimated to be, respectively, 0.5 and 0.3.[43]

The value of the bond specific recovery rate is also obtained from proprietary database from JP Morgan. Yu observes as, instead, traders usually leave the bond specific recovery rate as a free parameter to fit the level of market spread. It seems appealing to the author to assume a fixed debt recovery rate and let the data speak to the value of mean global recovery rate, which determines the default barrier. In this way, to obtain the mean global recovery rate, Yu fit the ten daily CDS spreads at the start of the sample period to the CG model by minimizing the sum of squared pricing errors over the average global recovery rate. The obtained average global recovery rate is then taken as a fixed parameter for the following period. This approach is agreed and implemented by most of the work on capital structure arbitrage. However, Wojtowicz argues as this way to set the average global recovery rate could generate large bias in the model. The author asserts that this approach ensures that the model and market spreads are at similar levels at the beginning of the sample, but afterwards the model and market premia can diverge and remain at different levels. Persisting deviations could be a problem that arise from change in market or company specific conditions. Using the first ten days at the beginning of the sample period, in fact, crystallizes all the variables that are no longer updated thereinafter. Moreover, Wojtowicz argues that, if the first ten day are a period of actual mispricing, the parameters would result distorted. If this happens, the arbitrageur would likely find itself opening positions when the equity and debt are well aligned. The author proposes to overcome the delineated problem by setting parameters on recovery rate how suggested from CreditGrade Technical Document and then using a rolling CDS implied volatility. Wojtowicz believes that by daily fitting the model with the 1-year moving average of CDS implied volatilities, the strategy would overcome the problem of insensibility of the model to structural change in market or company-specific conditions.

Finally, the risk-free rate is set equal to the five-year constant maturity Treasury Yeld. The use of the five-year zero rate to parametrize the model represents a common choice in academia.

[43] Finger (2002).

The reported parameters serve as input to the chosen model to produce a theoretical credit spread. The value produced by the model represents a fundamental information for the arbitrageur: it is the primary input that determine the presence in the market of an arbitrage opportunity. If the credit spread produced by the model for a certain obligor and the prevalent credit spread on the same obligor observed in the market differs, two scenarios arise: the CDSs do not incorporate relevant information, that instead stocks incorporate, or, on the contrary, stocks are slower than bonds in incorporating relevant news in their price. Actually, a third possibility exists, both debt and equity are fairly priced and the model is unable to represent the relation existing between them. This is the risk the arbitrageur is not hedging away and hopes to be remunerated for bearing.

Once obtained the theoretical credit spread the investor must decide the level of divergence of the theoretical value from the actual one that justify the implementation of the investment strategy. Generally, that value is indicated whit the letter α. The entry signal is therefore triggered when

$$c_t > (1+\alpha)c_t' \text{ or } c_t' > (1+\alpha)c_t$$

where α represents the trading trigger, c_t is the observed credit spread and c_t' is the theoretical credit spread produced by the model.

It appears how the entry signal is valid both in the case that the theoretical spread is higher than the observed one both in the opposite situation. The signal, in fact, communicates the presence of a misalignment in the market between the valuation of corporate debt and equity. Descending from the fact that the actual spread is higher than the theoretical one or that the opposite is true, follows the direction the investor should bet on. If the theoretical spread results to be higher than the observed one follows that the CDSs are undervalued or that the CDS spread is right and stocks' volatility is undervalued and consequently stocks are expensive. In fact, if we believe that the model and market spread will converge, we expect one of the two happening: or the model spread will decrease or the market spread will increase. The model spread decreases if the equity volatility decreases, and hence the stock price increases. If the equity valuation, instead is correct, the market spread will increase. The correct way to exploit the individuated opportunity will therefore be to buy credit protection and hedge the position by buying stocks.

On the contrary, if the CDSs are overpriced or the stocks are undervalued (as effect of an overvalued equity volatility), then the correct way to implement the arbitrage is to sell credit protection and sell short stocks as a hedge.

To see this mechanism more clearly, we can assume that the theoretical pricing relation is given by $c_t' = f(S_t, \sigma;\ \theta)$, where S_t is the equity price, σ is an estimate of asset volatility and θ represents the other fixed parameters presented in the model. The actual CDS spread, on the other hand, is given by $c_t = f(S_t, \sigma^{imp};\ \theta)$, where σ^{imp} is the implied asset volatility obtained by inverting the pricing equation.[44] If $c_t > c_t'$, it may be that the implied volatility σ^{imp} is too high and shall decline to a lower level σ. The correct strategy in this case is to sell overpriced credit protection and sell equity as a hedge. That is similar to sell overpriced stock options and delta hedging to neutralize the effect of a change in stock price.

Another possibility is that the CDS is priced fairly, but the equity reacts too slowly to new information. In this case, the correct strategy would be to short sell the overpriced stocks and hedge the position selling credit protection.

If instead $c_t' > c_t$, the opposite is true: it may mean that σ^{imp} is too low or that the equity is undervalued. In the first case, the correct strategies would be to buy credit protection and buying stocks as a hedge. In the second case, it would be to buy stocks and hedging buying credit protection.

It appears how if $c_t > c_t'$ the correct strategy is to sell CDSs and sell equity, both if the misalignment is due to the implied asset volatility or to the stock price. Similarly, if $c_t' > c_t$ the correct strategy is to buy CDSs and buy equity, whichever between σ^{imp} and stock price is not correctly priced.

Anyway, a theoretical credit spread value departing from the observed value could be explained by other factors. It could be that the volatility estimator underestimates the true asset volatility, sending a false signal of mispricing in the market. Another possibility is that other parameters of the model, such as debt per share or recovery rate, are mis-measured. Finally, the gap between c_t' and c_t could be simply due to model misspecification.

[44] The reported example is first proposed by Yu (2006).

Once the arbitrageur has entered the market according to the signal received, she also need to know when to liquidate the positions. Yu (2006) assumes that exit will occur when one of the following conditions are met: 1) the misalignment between model predicted credit spread and market credit spread disappears, or 2) convergence has not occurred by the end of a pre-specified holding period.

The subsequent movements of the CDSs and equity price after the arbitrageur has implemented the trading strategies can be summarized in the following three situations:

1. Both credit spreads and stock price rise or both decrease, according to the expectations of the arbitrageur. This is a case of convergence. In this case, the arbitrageur profits from both positions.
2. Spread c_t and equity price moves in the opposite directions. In this case the arbitrageur suffers loss on one side while earnings in the other. Depending on the exposure, the investor will report an overall profit or a loss.
3. Both credit spreads and stock price rise or both decrease, in the opposite direction respect to what the arbitrageur expected. This a sure case of divergence. The investor suffers losses from both positions.

Once the strategy's entry and exit rules have been defined, it is important to define how the trading returns will be computed. While the computation of changes in value of the equity leg of the investment is straightforward, the value of the CDS position is not trivial. The solution adopted in literature is to calculate the value of CDSs trough the formula previously described

$$\pi(t,T) = [c(t,T) - c(0,T)] \int_t^T P(t,s) q_t(s) ds.$$

However, several simplifying assumptions have to be made when implementing this formula. First, the equation requires secondary market quotes on an existing contract, while CDS market mainly quotes spread on freshly issued contract. To overcome the problem in observing quotes on existing contract, various authors approximate $c(t,T)$ with $c(t,t+T)$. This allows to have a new contract spread in the formula, whit a marginal loss of accuracy, considering that the difference between two points on the term structure of CDS spread six months apart in maturities is likely to be much smaller than the time variation in CDS spreads over six months.

The second simplifying assumption consists in computing the survival probabilities by the structural model chosen to implement the strategy.

Another point to take under consideration is the fact that at initiation, the value of a CDS is equal to zero. Therefore, to have a basis to compute trading returns of the strategy, the cited works set an initial capital as a margin account. The definition of an initial margin account is necessary to have a back test attaining to reality, nevertheless the way the initial capital is determined differs among works proposed.[45]

Finally, Yu (2006) proposes the results of the described strategy. It will therefore be here reported the main findings of his work, together with the evidence from the subsequent studies.

3.2.3 Main findings on Capital Structure Arbitrage

Yu concludes that Capital Structure Arbitrage appears to offer attractive Sharpe ratios that are in line with other fixed income arbitrage strategies and hedge fund industry benchmark. The back-testing performed by Yu takes into account 261 obligors and assume an initial capital equal to 50% of CDS notional amount. He separates the results between investment grade and speculative grade obligors. Moreover, strategy returns are provided for different level of holding period and trading trigger value. The evidences are that, in general, longer holding periods produce higher returns. The level of the trading trigger, instead, has a different effect on investment and speculative grade obligors: for investment grade obligors, higher levels of the trading trigger increase strategy returns, while for speculative

[45] Indeed, solutions adopted by authors are not unique. Considering that at initiation, the market value of a CDS contract is zero, Yu (2006) opts for calculating returns by assuming that the arbitrageur has a certain level of initial capital in a margin account. The margin account is used to finance the initial equity hedge and cash flows deriving from the strategy are credited or deducted from this margin account. Yu simulates the strategy both with a $0.1 and $0.5 for each dollar of notional amount of CDSs traded. The author notes how returns roughly scale with the amount of initial capital: a lower initial capital allows a higher level of leverage, that scale up profits. Expectedly, higher returns are followed by a more pronounced volatility of returns. Avino & Lazar (2013) and Wojtowicz (2014) opt for an initial capital of $0.5 dollar for each $1 of notional CDS contract value.
It is worth noting that a lower margin account will force the position to be closed earlier if the model and market spread widen before converging.

grades obligors quite the opposite is true. Looking at the whole sample it appears how, in general, investment grade obligors perform better than speculative ones, except for long holding periods and small levels of the trading trigger.

Looking at the distribution of holding period returns, it appears how the distribution becomes tighter as the trading trigger increase. Moreover, the speculative grade distribution is more than twice as dispersed as the investment grade distribution.

Finally, the relationship of the strategy to market factors and its sensitivity to assumptions made are tested. The author find that do not appear to exist any apparent relationship between capital structure arbitrage monthly return and market factors.[46] The sensitivity analysis performed suggests that the strategy returns are not sensitive to the assumptions of the basic strategy.

Interesting appear also the study of the behavior of market and model spread for the obligors in the sample. The author found that they broadly fit into three categories. The first category is composed by obligors whose market and model spreads are closely related. These are the obligors that are expected to produce positive returns for the strategy: for these obligors, in fact, when the market spread deviates from the model spread, they inevitably converge subsequently to each other. The second category is composed by companies whose market spread and model spread are tightly linked only up to a point, after which they diverge from each other. Trades on this kind of obligors produce huge losses since once the two spreads start diverging, they do not later converge. Some of the obligors in this category are company that experienced a sudden decrease in CDS liquidity due to increased likelihood of Chapter 11 filings.

The third category group obligors whose market and model spreads, shortly after the coverage starts, diverge smoothly and persistently. Here, the most likely explanation for negative returns is a model misspecification. Indeed, these are cases where the model is not able to predict the behavior of the market.

[46] To investigate the relationship between the capital structure arbitrage profitability and systematic risk factors the following indices have been considered: The S&P Industrial Index (S&PINDS) to proxy for equity market risk, the Lehman Brothers Baa and Ba Intermediate Index (LHIBAAI and LHHYBBI) to proxy for investment grade and speculative grade bond market risk, the CSFB/Tremont Fixed Income Arbitrage Index (CSTINFA) to capture variations in monthly returns not attained to market factors.

Bajlum and Larsen (2007) obtains results similar to those reported by Yu (2006). As previously discussed, the authors back-test the arbitrage strategy using the structural model developed by Leland and Toft (1996) and the Creditgrades. Moreover, both the models are calibrated using the historical volatility and the option implied volatility. Hence, the authors perform the strategy in four ways: using the Leland and Toft model calibrated with the historical volatility, using the Leland and Toft model calibrated with the option implied volatility, using the Creditgrades model calibrated with the historical volatility and using the Creditgrades model calibrated with the option implied volatility. They find that higher the holding period, better are the performance of the arbitrage strategy, using both the model and the volatility measures.[47] This confirms the finding of Yu about the effect of holding period restrictions on strategy returns. Similarly, also the effect of variation of the trading trigger produces results as before highlighted by Yu: even though the distribution of returns becomes less dispersed, a higher level of trading trigger does not systematically lead to higher mean trading returns.

Comparing the relative value opportunity rising from the two volatility measure, the authors find that implied volatility leads to an higher number of initiated trades and to higher mean returns. This finding appears to be true for both the structural models. On the other hand, the authors notice as the choice of the structural model used to gauge arbitrage opportunity is of secondary order, if compared to the volatility measure.

The analysis of the relation between the arbitrage strategy and the systematic risk factors proposed by Bajlum and Larsen highlight results similar to those of Yu: excess returns do not appear to represent compensation for exposure to factors proxying equity and bond market.[48]

Cserna & Imbierowicz (2008) confirmed the profitability of the capital structure arbitrage in the period from 2002 to 2006, even though the average returns decline over time.[49] The reduced profitability of the strategy in the last part of the sample

[47] Bajlum & Larsen (2007), as well, perform the strategy's back-test assuming a maximum holding period of 30 and 180 days.

[48] Again, the indexes used are the S&P Industrial Index to proxy for equity market risk and the Lehman Brother Baa an Ba Intermediate Index to proxy for speculative grade bond market risk.

[49] When comparing this result with other works on Capital Structure Arbitrage one should note that the strategy implemented by Cserna and Imbierowicz is slightly different from others: namely,

is explained, according to the authors, by the increased efficiency of the credit default swap market.

It is also interesting to report the result of the comparison made by the authors between three different structural models in implementing the strategy. Cserna and Imbierowicz back-test the Capital Structure Arbitrage using the Creditgrades model, the Leland and Toft (1996) model and the Zhou model (1997). They find that, although the models differ substantially in their default barrier assumptions, complexity and following implementation costs, they all deliver credit spreads close to market observation. Therefore, concluding which one of the three models is preferable to others is not possible without objection. The authors find that until 2004 the model that better replicate the market spread is the Creditgrades. Afterward, the model from Leland and Toft and the model from Zhou work better. The authors hypothesize that, as the CDS market further develops, more mathematically advanced structural models are more able to predict market spreads. By a trading returns perspective, the Leland and Thoft model and the Zhou model offers higher mean returns than the Creditgrades model. Anyway, this general condition presents some exceptions: in 2002 the Creditgrades model offered the highest returns and considering the whole sample period, it performed better than other models for low credit quality obligors. Furthermore, when tacking into account the transaction cost, the advantage produced by the Zhou model respect to Creditgrades disappears. This is because the Zhou model produces more entry signals than Creditgrades, raising the total transaction costs.

How anticipated, Avino and Lazar (2013) study the role of the equity hedging in Capital Structure Strategy and they find that the role of the hedging is dependent on the state of the economy. In general, the role of the hedge has a positive effect on the strategy, in terms of risk and returns. Instead, during crisis period, the two alternative strategies proposed by the authors that do not hedge their positions performed better than hedged strategies. Moreover, the authors find that adding trading trigger to the plain Capital Structure Arbitrage strategy reduces the number

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if convergence does not occur, the individual positions are not terminated after a certain predetermined period, as in Yu (2006), Duarte, Longstaff, & Yu (2006) and Bajlum & Larsen (2008), but when losses amount to fifty percent of initial capital or aggregate returns reach five times the initial investment.

of trades and enhance its performances. Therefore, the three alternative strategies proposed, that add various signals to the plain strategy, results in better performances especially during crisis period.

Wojtowicz (2014) in his work find that, in the period from July 2010 to November 2012, the Capital Structure Arbitrage strategy in his sample have been profitable. However, the standard deviation of returns is large if compared to holding period returns. This implies, according to the author, that the overall profitability of the strategy is largely dependent on infrequent but large profits.

Differently from Yu (2006), Wojtowicz finds that the mean holding period returns are higher the lower the credit ratings. However, how one could have expected, the higher profitability of low rated obligors comes at the cost of higher returns volatility.

An interesting result of Wojtowicz's work is that low liquidity is not an explanation for capital structure arbitrage profits, but actually it seems to reduce arbitrage profitability. Moreover, the author finds that strategy returns are neither explained by low volume of trade, since highest returns are obtained by most traded companies. These findings are further clues of the fact that arbitrage opportunities are effectively produced from a real mispricing between equity and debt in the market.[50]

[50] The relation between arbitrage returns and liquidity is investigated portioning the sample used for the back-test based on Markit's liquidity scores. The liquidity scores incorporate several aspects of liquidity, such as bid-ask spread and market depth (number of dealers). The author finds that most liquid obligors obtains the highest holding period returns.

3.3 The CreditGrades model in more depth

By a rapid overview of the literature and of the research done on Capital Structure Arbitrage as investment strategy it clearly appears how the quantification of credit risk is reached in most of the cases using CreditGrades model. The large adoption of this model, that has been developed by some of the most famous and important investment banks of the world, has been explained by the fact that CreditGrades is considered a standard in credit risk valuation among professionals. The success of this model is probably due to its relative simplicity. Moreover, considering that this model has been developed, and probably used in everyday activities, by major actors in credit risk market, one can easily imagine that this lead by the adoption of the model at a broader level. In effects, Cserna & Imbierowicz (2008) recognize that during the two years after the publication of CreditGrades Technical Document (2002) the CreditGrades performed superior in replicating market CDS premium respect to other, more advanced, structural models. Anyway, the authors observe also as, some years after its publication, CreditGrades lost its superior ability in favor of more complex structural models, such as the ones from Zhou (2004) and Leland and Toft (1996). Nonetheless, in more recent paper verting on Capital Structure Arbitrage the CreditGrades model remain the favored choice, proving it is still a valid toll in credit risk valuation. Hence, it seems useful to report hereinafter a further description of this model, especially having regard to parameters calibration and estimation.

The formula proposed by CreditGrades for CDS pricing has been previously reported, together with the survival probability formula it relies on. Anyway, to implement the survival probability formula

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{ln(d)}{2}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{ln(d)}{2}\right),$$

where $d = \frac{V_0 e^{\lambda^2}}{\bar{L}D}$ and $A_t^2 = \sigma^2 t + \lambda^2$, it is necessary to link the initial asset value V_0 and the asset volatility σ to market observables. To this end, the two values, V_0 and σ, are determined in the following manner: the initial asset value V_0 is given by

$$V_0 = S_0 + \bar{L}D$$

where S_0 is the current stock price, consistently the asset volatility σ is determined as

$$\sigma = \sigma_S \frac{S}{S + \bar{L}D}.$$

Therefore, the survival probability $q(t)$ can be expressed as function of market observables parameters, expressing d and A_t^2 in the following manner:

$$d = \frac{S_0 + \bar{L}D}{\bar{L}D} e^{\lambda^2},$$

$$A_t^2 = \left(\sigma_{S_t} \frac{S_t}{S_t + \bar{L}D}\right)^2 t + \lambda^2,$$

where S_0 is the initial stock price, S_t is the reference stock price at time t, σ_{S_t} is the reference stock volatility at time t, D is the debt-per-share, $\bar{L}$ is the global debt recovery and λ is the percentage standard deviation of the default barrier.

The debt-per-share D is obtained from reference entity's financial statement. The debt-per-share is obtained considering all the liabilities that participate in the financial leverage of the firm, that is the principal value of all financial debts, short-term and long-term borrowings, convertible bonds and are also included capital leases, under-funded pension liabilities and preferred shares. The debt-per-share is then obtained as the ratio between total debt and number of outstanding shares.

The value of the mean global debt recovery $\bar{L}$ and of the percentage standard deviation of the default barrier λ are determined, in the CreditGrades technical document, from recovery rate databases. In particular, the value of $\bar{L}$ and λ are estimated using the Portfolio Management Data and Standard and Standard & Poor's database. The database contains recovery data for approximately 300 non-financial U.S. firms that defaulted in the period 1987-1997. As previously reported, based on the study on these historical data, $\bar{L}$ and λ are estimated to be 0.5 and 0.3 respectively. Values for $\bar{L}$ and λ seem to have been accepted in works on Capital Structure Arbitrage that implemented the CreditGrades. However, Yu (2006) prefers rather to fix the bond specific recovery rate and determining $\bar{L}$ fitting the 10 daily CDS spreads at the start of the sample period to the CreditGrades model by minimizing the sum of squared pricing errors over $\bar{L}$.

Finally, CreditGrades Technical Document explores what candidate volatility estimators would produce the more precise credit spread when used to feed the model. By comparing the historical CreditGrades implied asset volatility with the asset volatility computed on 252, 500, 750, 1,000 and 1,250 days and with the exponentially weighted moving average (EWMA). The evidences are that volatility estimates based solely on recent data are not appropriate. Longer historical periods seem to work better, with estimates based on 1,000 days of observation being optimal. Hence, according to CreditGrades Technical Document the simple measure of volatility based on the last 1,000 days of equity returns produces good estimates of the volatility implied by the 5-year CDS quotes. Anyway, this view on optimal volatility estimator seems not to be shared by all the analyzed works on Capital Structure Arbitrage. In particular, Bajlum and Larsen (2007) implement the arbitrage strategy calibrating CreditGrades model with the 1,000-day historical volatility, with the 250-day historical volatility and with the option-implied volatility. Their results suggest that historical volatility may severely lag the market and therefore using the option-implied volatility results in superior strategy execution. Their result is partially backed by the finding of Avino and Lazar (2013), who found a strong correlation between the returns of the strategy when the 1,000-day and the 250-day historical volatility are used.[51] In fact, Avino and Lazar (2013) test the role of 1,000-day historical volatility against the 250-day volatility and do not find any added value from the use of a shorter sample period to estimate volatility in equity returns. Finally, Wojtowicz (2014) proposes a model calibration based on the historical volatility implied in the model itself. In fact, the author first computes the market-implied CDS volatility on CreditGrades model and then compute for each company the 1-year moving average volatility based on the past CDS-implied volatility.

[51] Avino & Lazar (2013) found that the correlation between returns of a same strategy under 1,000-day and 250-day historical volatility is extremely high (0.93) during the pre-crisis period, while it was lower than 0.5 during the crisis.

3.4 A GARCH approach to calibrate equity volatility

The choice of the best volatility estimator to calibrate the CreditGrades model appeared to be topic of discussion of most of the works written on Capital Structure Arbitrage. The CreditGrades Technical Document, in fact, advocates that the simple measure of volatility obtained as the daily standard deviation of equity returns during the last 1,000 days produces good estimates of the volatility implied by the 5-year CDS quotes. The document explains that the choice of a long-dated estimator is not surprisingly, since the true asset volatility for a firm is quite stable through time. However, several authors claimed that a volatility measure depending on a so long historical data-series is not able to react timely to sudden changes in market conditions. For an arbitrageur, in fact, the responsiveness of the model to changed market conditions is of paramount importance to determine when to correctly open or close a trade. For this reason, several other volatility measures have been tested. Comparing the results obtained in academia, it appears that, when calibrating the structural model with option-implied volatility, the strategy returns are higher.[52] Moreover, it appears that changing the horizon of historical equity returns to estimate volatilities from 1,000 days to 250 days does not significantly affect strategy returns.

However, the lower liquidity of options respect to equity could represent an obstacle to using option implied volatility to calibrate the structural model.[53] It seems then appealing to analyze if a quite simple to implement volatility estimator as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) could be somehow helpful when used along with CreditGrades model for Capital Structure Arbitrage purposes. Therefore, in the next chapter will be illustrated how a GARCH calibrated CreditGrades impacts on arbitrage returns respect a standard implementation of the strategy using the 1,000-day equity returns volatility. The use of GARCH as volatility estimator appears to be an interesting choice in this context: it is, in fact, a function of long term volatility but it is also dependent on

[52] Bajlum & Larsen (2008).

[53] Finding data on option implied volatility could in fact result to be more difficult than to find historical equity returns volatility. This seems to be confirmed by the fact that Avino & Lazar (2013) decide not to use option implied volatility due their lack of data on it.

short term changes in equity returns.[54] It seems, then, to be an instrument that can mediate between these authors that claim that short term volatility estimators are more attuned to change in market conditions, and these that believe that a long time-series is a better source to determine the real asset volatility.

GARCH was first proposed by Bollerslev in 1986.[55] In GARCH model the equity returns variance is calculated from a long run average variance, from the historical estimation of variance itself and from historical equity return. The most common form is GARCH(1,1), that means that variance on day n is calculate from the most recent observation of equity return and from the most recent estimates of the variance rate. GARCH(1,1) equation can be written as

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

where V_L is the long-run average variance rate, u_{n-1}^2 is the percentage change in stocks'price between day $n-2$ and $n-1$ and σ_{n-1}^2 is the estimates of variance rate in day $n-1$.[56] The more general GARCH(p,q) model calculates σ_n^2 from the most recent p observation of u^2 and the most recent q estimates of the variance rate. The parameters γ, α and β are the weights given to each element of the equation and their sum must equal to 1.

Hence, the equity volatility as estimated by GARCH(1,1) is directly linked to the change in equity value during the two days before the estimation. Therefore, a sudden change in equity value from one day to the other has a considerable effect on the prevision of equity variance the day after. To avoid amplifying this effect when computing the 5 years probability of default with CreditGrades model and then having an extremely volatile prediction of credit spread, the variance rate will be estimated from the most recent estimation of variance rate and the average u^2 during the 30 days before. In this way the previsions of variance rate are expected to be smoothed and more able to produce reasonable probability of default over a period of 5 years.

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[54] For a comparison of GARCH(1,1) with other volatility estimator see Hansen, P. & Lunde, A. (2005). *A Forecast Comparison of Volatility Models: Does Anything Beat a Garch(1,1)?* Journal of Applied Econometrics, 20(7), 873-889.

[55] Bollerslev, T. (1986). *Generalized autoregressive conditional heteroskedasticity*. Journal of Econometrics, 31(3), 307-327.

[56] Hull, J. (2012). *Risk management and financial institutions* (Vol. 733). John Wiley & Sons.

Moreover, I will follow the CreditGrades Technical Document when it suggests using a reference share price and equity volatility to determine an asset volatility and keep it stable for some period of time. The variance estimated trough GARCH at the start of the sample period will therefore be kept stable for a period of 30 days before being updated based on the behavior of the share-price during that 30 days.
The choice to update the variance estimation every 30 days seems reasonable compared to the scope of the sample period will be taken under analysis in this work. However, it is not goal of this research how to best determine the GARCH parameters. What instead is of interest is to determine if GARCH as variance estimating tool has any advantage in better determining the probability of default of firms and consequently to produce better previsions on the fair spread on credit default swaps.

3.5 Credit default swaps

The recurrent presence of credit default swaps on Credit Arbitrage literature suggest a dedicated dissertation of the features of this derivative instrument.
The development of structural models for debt pricing has been, to a great extent, led by the aim to estimate and mathematically reproduce the probability of default for a firm. This default probability has then been used for the pricing of corporate debt. Anyway, corporate bonds' price is affected by a multitude of factors: default probability plays a key role, but cannot explain alone the dynamics affecting corporate bonds' pricing process. Two other important factors affecting corporate bonds' value are, in fact, represented by liquidity risk and interest rate risk.
The trade of the only credit risk has been made possible and saw increasing diffusion during last two decades following the noteworthy growth of credit default swap popularity. Between 2002 and 2007 CDS gross notional amounts outstanding grew from below USD 2 trillion to nearly USD 60 trillion.[57] It therefore became the preferred instruments for capital structure arbitrageur.

3.5.1 Core elements of a CDS contract

Credit default swaps are credit derivative contracts traded over the counter. This means that these contracts are not traded in a regulated market, but their exchange is normed by an agreement between the parts. Generally, the absence of a regulated market for a security implies its lower liquidity. Anyway, CDSs' growing popularity made them quite a liquid financial instrument during last years.[58]
In its simplest form, a credit default swap is a contract between two parts that allows to trade or hedge the risk that an underlying entity defaults. One of the part assumes the role of protection buyer: she pays a periodic premium to be assured against the default of a certain entity. The payments are due until the credit event happens or the contract reaches maturity. The protection seller, instead, receive the payments from the protection buyer but is obliged, in the event of default of the underlying entity, to bear the loss. The entity of the loss is given by the face value of the

[57] Greiner, A., Speyer, B., & Walter, N. (2009). *Credit default swaps: Heading towards a more stable system*. Deutsche Bank Research.
[58]Oehmke & Zawadowski (2016).

underlying security and the recovery rate in the event of default that can be recovered from the reference borrower.

In practice, a CDS resembles an insurance contract against the loss in value of a corporate bond, where one part pays to be assured and the other receives the premium and supports the risk of default.

In figure 3 is reported a stylized diagram, summarizing the mutual payment obligations.

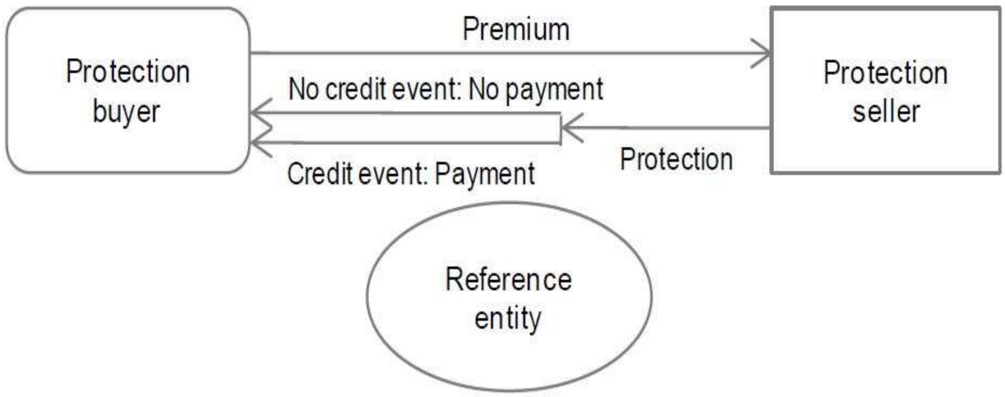

Figure 3 CDS's payment obligations (source Deutsche Bank Research (2009))

When the two parts enter the contract, they agree on a series of indentures: the reference entity, the amount of the premium paid by the protection buyer, the frequency of the payment, the length of the contract, the definition of the credit event and the settlement.

The reference entity is represented by a company or a country. The CDS allows to be hedged against the risk of insolvency or default of a country or a company. The amount of the premium paid is usually expressed by the CDS spread: it is the ratio between the payment, on annual basis, made by the protection buyer and the notional capital of the contract. The notional capital is the amount the protection buyer is being assured on and is represented by the face value of the underlying securities.

The determination of the CDS premium is, primarily, function of the probability of default of the reference entity and the expected recovery rate in the event of default. The CDS premium should, in fact, cover the expected loss of the reference entity. Hence the CDS premium can be expressed as $PD * (1 - RR)$, where PD stands for the probability of default during the life of the contract of the reference entity and RR is the expected recovery rate from the reference borrower in the event of default. Usually, the premium is paid quarterly and the typical length of a contract is five years.[59]

3.5.2 Credit events

The definition of the credit event represents a fundamental point. Looking at a CDS contract as an insurance policy, the credit event represents the explicit contractual definition of the "insured event".

The standard credit events included in CDS contracts reference the 2003 ISDA Credit Derivatives Definitions and supplements.[60] These provide the basic framework for CDS contracts and provide the standard set of definitions and provisions that govern the majority of CDS transactions.[61] ISDA definitions enumerate as credit event the following situations

1. Bankruptcy
2. Obligation Acceleration
3. Obligation Default
4. Failure to Pay
5. Repudiation/Moratorium
6. Restructuring

Obviously, the credit events relevant for a given CDS contract are those explicated in the agreement's indentures. Anyway, for standard North American and European corporates and financial institutions the relevant credit events are bankruptcy, failure to pay and restructuring.

[59] Hull, J. C. (2005). *Fondamenti dei mercati di futures e opzioni*. Pearson Italia Spa.
[60] ISDA is the International Swaps and Derivatives Association. It is a trade organization for participants in the market of over-the-counter derivatives. ISDA works for the stabilization of the OTC derivatives market and the reduction of credit and counterparty risk on these contracts through the development of standard form agreements.
[61] Haworth, H. (2011). *A guide to Credit Events and auctions*. Credit Suisse Research.

Slightly different are the credit events used in contract having has underlying a sovereign obligation: in this case, often bankruptcy is replaced by repudiation/moratorium. In figure 4 are reported the credit events applicable to standard CDS contracts, based on the underlying entity.

	Bankruptcy	Failure to Pay	Restructuring	Repudiation/ Moratorium	Obligation Acceleration
NORTH AMERICAN CORPORATE	X	X	X		
EUROPEAN CORPORATE	X	X	X		
SUBORDINATED EUROPEAN INSURANCE CORPORATE	X	X	X		
EMERGING EUROPEAN CORPORATE	X	X	X	X	X
LATIN AMERICA CORPORATE	X	X	X	X	X
AUSTRALIA CORPORATE	X	X	X		
NEW ZEALAND CORPORATE	X	X	X		
JAPAN CORPORATE	X	X	X		
ASIA CORPORATE	X	X	X		
WESTERN EUROPEAN SOVEREIGN		X	X	X	
LATIN AMERICA SOVEREIGN		X	X	X	X
EMERGING EUROPEAN & MIDDLE EASTERN SOVEREIGN		X	X	X	X
AUSTRALIA SOVEREIGN		X	X	X	
NEW ZEALAND SOVEREIGN		X	X	X	
JAPAN SOVEREIGN		X	X	X	
ASIA SOVEREIGN		X	X	X	

Figure 4 Credit events applicable to standard CDS contract (source: Credit Suisse (2011))

3.5.3 Settlement

The settlement of the contract can assume two forms: physical settlement and cash settlement. The physical settlement is the typical form adopted in CDS contract.[62] In a physical settlement, in the event of default the protection buyer sells the underlying bond to the protection seller receiving the face value of the obligation. This method has the advantage that do not require the determination of defaulted bond price and recovery rate: the CDS seller simply became the bondholder. The market for defaulted bonds could, in fact, be quite thin and it could result difficult for the parts to agree on a residual value. Furthermore, the interest of the two parts are different: the protection buyer will have all the interest in that the recovery is maximized while the protection buyer does not care at all about the residual value

[62] Helwege, J., Maurer, S., Sarkar, A. & Wang, Y. (2009). *Credit default swap auctions and price discovery*. The Journal of Fixed Income, 19(2), 34-42.

of the obligation. The disadvantage of physical settlement come from the fact that often investors assumes naked positions on CDS: this could result on credit default swaps contracts written on a number of corporate's bonds higher than the actual bonds on circulation. This situation, in the event of default of the reference entity would clearly produce a problem for the protection buyers deemed to the physical delivery of the bond.

The cash settlement instead does not require the CDS buyer to deliver the underlying, but obliges the protection seller to pay to the protection buyer the loss given default on the underlying bond. The drawback of this method is that the two parts must agree on the residual value of the bonds. As early mentioned, this could be quite a difficult task if the market for the defaulted bond is illiquid. A possible solution to the problem is represented by the CDS auctions. The CDS auction provides a method for all CDS contracts to be settled at the same recovery for the same bond (or loan). Practically, following a credit event, interested CDS buyers and sellers send a notice to the ISDA prior to a "cut-off" date agreeing to adhere to a "protocol." The protocol amends the existing CDS documentation to allow settlement at a single "final price" for all adhering parties

Once illustrated the basic technical characteristics of credit default swap contracts, it is simpler to understand the success that this financial instrument saw from the beginning of nineties. CDSs, in fact, allow to separately trade or hedge the default risk. This characteristic of CDSs make them attractive both for financial institutions both for speculators.

Financial institutions found in CDSs a useful management tools. Through the use of CDSs, in fact, banks can reduce their concentration risk without reducing the amount of loans towards a given entity. To reduce the risk coming from an excessive exposure to a single counterparty, a bank can, in fact, sells part of the credit risk to another institution with a lower exposition in that direction. Similarly, a bank can gain buying credit risk on entities it is not exposed at all. The reduction of concentration risk, in turn, allows to banks to free regulatory capital for productive investments.

On the speculators' side, CDSs appeared to carry out several tasks. According to Oehmke and Zawadowski (2016) CDS are preferred by speculators, that on average have shorter trading horizon, when taking positions in the credit market due to their higher liquidity respect to corporate bonds. Moreover, CDSs serve as standardization: the two authors found as net notional CDS amounts are larger for firms having bonds that are fragmented into many issues.

Another advantage of CDSs' trade is that they allow to have a simple access to credit risk market and allow smaller investors to short credit risk more easily, if compared to corporate bonds.[63]

Finally, many authors recognized that CDSs' prices lead the discovery process for credit spread. Blanco, Brennan and Marsh (2005), Norden and Weber (2004) and Zhou (2004) all recognized that in the short run the derivatives market moves ahead of the bond market in price discovery. Further, Norden and Weber found that CDSs seem not to be affected by change in credit ratings. This represent a clue of the rapid responsiveness of CDS to change in companies' creditworthiness.

As a result, CDSs are nowadays a quite diffused instrument in the market of derivatives. It is used both by little investor, that found in this instrument a useful tool for speculative purposes, both by financial institutions, due to its applicability in risk-management strategies.

[63] Blanco, R., Brennan, S. & Marsh, I. (2005). *An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps.* The Journal of Finance, 60(5), 2255-2281.

3.6 Conclusion

This chapter has analyzed the characteristics of the Capital Structure Arbitrage strategy. A review of main literature of the subject have been proposed. Starting from the early works, illustrating the strategy on its "pure" and simple form, the proposed improvements of more recent works have been described. In fact, it appears how the attempts to improve the return of the strategy have been sought in several ways. In particular, what has mostly moved the research on this subject has been the willing to estimate more accurately credit risk and to define an effective equity hedge.

Credit risk evaluation has therefore been tested for, but not limited to, several structural models and different volatility estimators.

The results are in some case not univocal: for instance, it is not clear if Capital Structural Arbitrage is explained by common risk factors or not. What instead appear to be a common result is the riskiness of this arbitrage strategy: all the authors recognized that, even if on an aggregate level the strategy can return attractive Sharpe Ratios, the risk of huge losses on single trades is relevant.

Interestingly, the authors recognized in general to structural models the ability to predict credit spread from market observables, but the choice of the model appears to be of secondary importance. The real gain in terms of predictive capacity appears, in fact, to be linked to the correct estimation of model's parameters.

The fundamental role that parameters setting appeared to have in models' predictive ability suggested to deepen the role of those parameters in CreditGrades model. As variously reported before, CreditGrades represents the benchmark model in credit risk valuation. Therefore, it seemed useful to propose a more depth analysis of the model. Furthermore, the dual vision in academia on the best calibration of equity volatility in the model, that is the historical standard deviation of equity returns versus the option implied volatility, suggested to propose a volatility measure that can conciliate the historical data on equity volatility with the recent movements of share price. The calibration of CreditGrades model through the of GARCH as volatility estimator seems to be a choice that can conciliate these two visions: the first one that advocate the necessity to have a volatility value reflecting a log series of historical price, the other that prefers a volatility measure able to be more attuned to sudden change in market conditions. GARCH model, in fact, predicts the equity variance starting from the historical data, but incorporating also information from recent change in equity value.

The effects of the introduction of GARCH in Capital Structure Arbitrage will be therefore illustrated in the next chapter.

Finally, the features of the CDSs have been presented. These are instruments that allow to trade the sole credit risk, thus represent the best choice for an arbitrageur interested in implementing a Credit Arbitrage. They, in fact, have the advantage, respect to corporate bonds, to do not be affected by other risks, such as interest rate risk. Furthermore, CDSs appeared to be preferred by short term investors thanks to their higher liquidity.

At the end of this chapter the mechanism and the variable that determine the profitability of Capital Structure Arbitrage are clear. The importance attributed by previous literature to some parameters of the model, such as the definition of an appropriate equity hedge or an effective volatility estimator, is therefore been justified.

In the next chapter, the profitability of the arbitrage strategy during the period 2015-2017 will be inquired through a simulation on historical data. The back-testing will also be useful to understand if GARCH model can add a significant advantage, in terms of returns and Sharp ratio, when Capital Structure Arbitrage is implemented.

4 Capital Structure Arbitrage profitability and the effects of GARCH

4.1 Introduction

The aim of this chapter is to answer two main questions: is Capital Structure Arbitrage an investment strategy still profitable? Can a GARCH calibrated CreditGrades model offer any advantage for an investor implementing the Capital Structure Arbitrage?

To try giving an answer to these questions, a simulation of the implementation of Capital Structure Arbitrage is proposed. The back-testing is performed on a sample of twenty big listed companies, having liquid credit default swaps traded in the market. The strategy has been performed both using the CreditGrades model calibrated as suggested by the CreditGrades Technical Document both using the GARCH model as volatility estimator.

The chapter starts with a description of data used in the simulation. Assumptions made are reported along with sources of data.

Then the case study of Berkshire Hathaway is presented. The procedure detailed for the conglomerate company is explicative of the general procedure adopted for all companies in the sample. I report the rules that govern the enter and exit signals for each trade as well as the assumptions on notional capital and margin account, that influence the trading returns. Charts plotting market and model spreads are presented.

Once delineated the procedure used for the simulation, I illustrate the results obtained for the whole sample. The relations between model and market spread are analyzed, as well as the effects of GARCH. The general results of the strategy during the period are reported, along with its riskiness.

Finally, an observation on the role of leverage in the model is proposed. The effect of market leverage, in fact, appeared to influence heavily the ability of the model to predict market CDS spreads.

4.2 Data collection

In order to perform the back-testing of the arbitrage strategy, data about daily stock-prices and CDS spread for the companies in the sample are required. To this end, the companies that have been encompassed in the sample are big, listed companies having liquid credit default swaps traded in the market. In particular, the sample is composed by the 20 highest capitalization companies in the world having CDS spread historical data available.[64] The ranking of companies by market capitalization is reported by the "Global Top 100 Companies by market capitalization" document released by PricewaterhouseCoopers on March 2017.[65]

The CDS dataset used is provided by Bloomberg. The database, in turn, gets data on CDS spread from Markit Group. This is also the source of data on CDS spread used by most of the works on Capital Structure Arbitrage mentioned in previous chapter.[66]

The CDS spread used are the daily composite spreads on five-year CDS contracts on selected obligors with currencies denominated in US dollars. The CDS spread historical data goes from August 2015 to August 2017.

The information on equity price has been obtained from Bloomberg. The historical data-set of share prices covers a longer period, since at the starting of the sample period it is required to have evidence of standard deviation of previous 1,000-day equity returns.

The information on companies' debt level are gathered from quarterly balance sheets, that have been obtained from Bloomberg.

Finally, the risk-free interest rate has been set equal to the yield of five-year constant maturity Treasury bonds. Daily data on Treasury bonds are also from Bloomberg.

The simulation of the trading strategy has been performed for each company starting from 1st of August 2015 to 31th of August 2017. Where data on CDS spread or stock prices were not available, trades have not been opened nor closed, in order to avoid bias in the simulation.

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64 The companies in the sample are, in order of market capitalization, the following: Berkshire Hathaway, Jhonson&Jhonson, JPMogan, Wells Fargo, AT&T, Bank of America, Procter&Gamble, Anheuser-Busch InBev, Royal Dutch Shell, Walmart, Pfizer, Verizon, Walt Disney, Comcast, Toyota, Home Depot, CISCO, Citigroup, IBM, UnitedHealth.

65 PricewaterhouseCoopers (2017). *Global Top 100 Companies by Market Capitalisation*.

66 See, for istance, Yu (2006).

The sample considered is therefore composed by 9,716 daily CDS spreads, along with the correspondent share price, on 20 obligors.

4.3 Strategy implementation: the case of Berkshire Hathaway

In this section, the data case of Berkshire Hathaway will be presented to illustrate the general procedure applied to all the companies in the sample. Berkshire Hathaway is an American multinational conglomerate company, with stakes in several industries. Its capital structure is characterized by a moderate leverage: at the start of the sample period (22 September 2015) the D/E ratio of the company was 1.17.

The trading analysis in this work, how explained, isolates the period from 31 August 2015 to 31 August 2017. Where the CDS spread was not available from the beginning of the sample, the starting point of the strategy has been postponed consequently.

The first step, once collected the data needed, has been to compute the theoretical spread. As anticipated in the previous chapter the strategy has been performed calibrating the structural model chosen both with the 1,000-day equity volatility both with the volatility measure given by the GARCH model.

The GARCH(1,1) measure of volatility have been computed from the historical stock price data-series of the company, consisting of more than 1,000 daily observation. The GARCH(1,1) parameters have been estimated iteratively through the maximum likelihood method procedure. The first variance rate in the GARCH calibrated model is set equal to the standard CreditGrades model calibrated with the 1,000-day volatility, to have a common point of departure. Then the volatility has been updated using the estimated parameters. To smooth the previsions on volatility obtained by GARCH(1,1) and do not let to a single day change in stock price have a huge influence over the five-year default probability prediction, each volatility estimation is taken stable for 30 days and then updated on the basis of the variance of equity returns during the 30 days before. This choice is also justified by CreditGrades Technical Document, which reports that often makes sense to use a reference share price and equity volatility to determine an asset volatility and then keep it stable for a certain period of time.[67]

[67] Finger (2002).

The daily volatility used for the standard model implementation, instead, has been obtained has the standard deviation of equity stock price returns continually compounded.

In figure 5 are visible the time-series for the two volatility estimators. How one could have expected, GARCH estimated volatility is much less stable during the sample period.

The other inputs the CreditGrades model requires, as previously shown, are the equity price S, the debt per share D, the mean global recovery rate $\overline{L}$, the standard deviation of the global recovery rate λ, the bond specific recovery rate R and the risk-free interest rate. The assumptions on these values are borrowed from Yu (2006). Specifically, D is obtained as the ratio between total liabilities and common shares outstanding. The value of D every day is computed from the most recent quarterly balance sheet, to avoid look-ahead bias. It means that, for instance, the value of D registered on January first comes from the balance sheet referring to the period ending 31 December of the year before, while the value of D registered for the 31 December come from the balance sheet referring to the trimester ending 30 September of the same year.

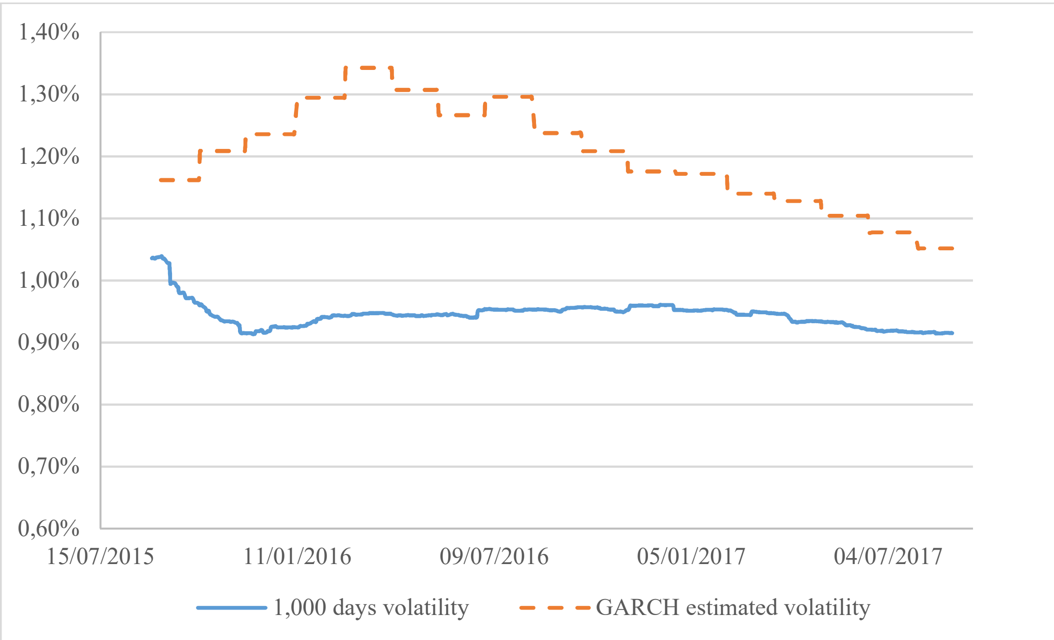

Figure 5 Time-series of 1,000-day equity volatilitie and GARCH predicted volatilities

The risk-free rate, as anticipated, is assumed to be equal to the five-year constant maturity Treasury yield. The mean global recovery rate and the bond specific recovery rate are assumed to be respectively 0.3 and 0.5. The CreditGrades Technical Document motivates the above choice of λ. The same document also suggests a value for $\bar{L}$ and takes the value of R from a JPMorgan database. Anyway, the procedure that have been here adopted is the same reported in the previously reported works on Capital Structure Arbitrage: value of R is set equal to 0.5, following Yu (2006), while $\bar{L}$ is determined by data on CDS spread observed in the market. In fact, to determine the value of $\bar{L}$ that, for each company, will be used to set the model, the first ten day before the starting of the back-testing period are used to fit the level of $\bar{L}$ in such a way that, the sum of the squared differences between the market CDS spread and the model spread results to be minimized. The value of $\bar{L}$ so determined for Berkshire Hathaway is 0.99 when the model is calibrated with 1,000-day historical volatility while it is 0.95 when the model is calibrated with GARCH predicted variance rate.

In figure 6 are shown the market CDS spread with the standard CreditGrades model spread and the market CDS spread with the GARCH calibrated CreditGrades model spread. The spread produced by CreditGrades when the 1,000-day volatility are used appears to be very similar to the spread produced when GARCH is used. Anyway, GARCH seems to have the advantage to produce, during all the period, spreads closer to the market ones. In fact, the average deviation of model spread from market spread when GARCH is used goes from 19.8 bp tp 16.1 bp. Moreover, GARCH calibrated model spreads seems to better anticipate market movements during the initial period, when the market spread actually spikes up.

In figure 7 are visible the movement of equity price during the same period. It does appear that the behavior of CDS market spreads and share prices are negatively associate. The jump in CDS spread during first months of the sample period is, in fact, anticipated by a fall in share price.

It also appears that, in both the models, the model spreads are more stable than the market ones. For instance, during the seven days from 4 February 2016 to 11 February 2016 the market CDS spread goes from 107 bp to 151 bp, while in the same period the model spread moves from 67 bp to 69bp when using the 1,000-day volatility and remain stable at 74 bp when calibrated with GARCH.

These sharp movements of CDS spreads, that are not justified by other market observable are exactly the trading opportunities that the arbitrageurs look for.

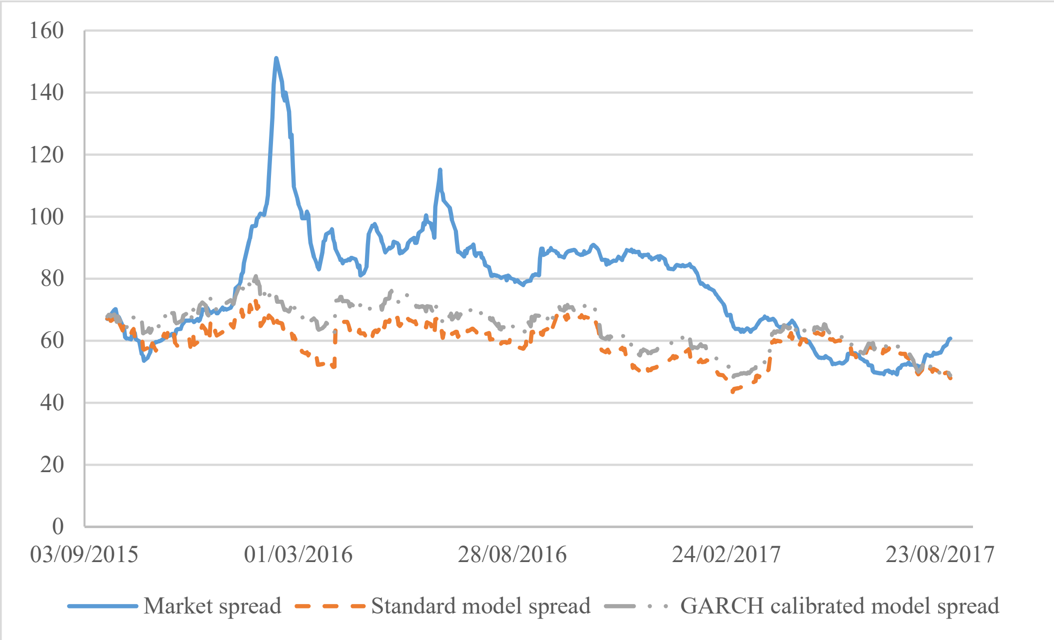

Figure 6 Time-series of market and model CDS spreads of Berkshire Hathaway

Figure 7 Time-series of stocks prices of Berkshire Hathaway

To understand if these trading opportunities would have been actually profitable, the trading strategy is simulated. The first day of the sample period available for trading is 22 September 2015. Data on CDS spreads, in fact, are not available, for the company in question during the period from 31 August 2015 to 8 September

2015. The first ten days of observable CDS spread are then used to estimate the value of $\overline{L}$. Consequently, the first day useful for trading is 22 September.
Then, for each of the 491 daily spreads in the sample I check whether the market spread and the model spread differs by more than a predefined trading trigger. The chosen trading trigger is 0.5.[68] It means that when $c_t > 1.5c_t^*$, where c_t is market spread and c_t^* is model spread, a short position on CDS is assumed, along with a short position on equity as a hedge. Instead, when $c_t^* > 1.5c_t$ a long position on CDS is assumed while shares are bought as a hedge.
These positions are held open until convergence of model and market spread or when a prespecified period of time is reached. In particular, I close down open trades after 90 open-market days, if convergence does not occur before.[69]
When the model suggests entering in a trade I assume a position in CDS for a notional amount of $100. I also assume a position in stocks computed through delta hedging in the moment the trade is opened, and keep it stable for the whole trade.
To compute return for each trade an initial capital of $50 is assumed. It basically corresponds to put $50 on a margin account. Generally, in academia, the amount of initial capital is set equal to one tenth or to half of the notional capital. I chose to use the lower level of leverage to avoid fostering even more strategy returns' volatility.
The equity hedge, as anticipated, is defined using delta hedging. Namely, when the enter signal is triggered, in that day I compute the ratio between the percentage change in model predicted CDS spread when stock price rises of $1 and the percentage change in share price when the price rises of $1. This ratio is a measure of how CDS spread reacts to a change in equity price. The delta value so computed is then multiplied for the notional amount of CDSs' position.

[68] The trading-trigger values generally used to perform the back-testing in academia are 0.5, 1 and 2. The decision to use a value of 0.5 comes from the willingness to exploit the highest number of trading opportunity and to have a more significant sample of trades to compare the two strategies analysed. For effect of trading trigger on strategy return see, among the others, Yu (2006).
[69] The decision to choose 90 days as maximum period for a trade to stay open comes from previous works. In general, leaving a trade the possibility to stay open longer have positive effects on strategy returns. For this reason, I chose to mediate between the two trading period limits commonly used of 30 and 180 days. The goal is to have more possibilities to enter in a trade during the sample period.

The value of the CDS contract when the trade is closed is computed following the procedure commonly used in previous studies on Capital Structure Arbitrage, explained in previous chapters. The first trade, when the model is calibrated with 1,000-day volatility, is on 29 January 2016, when market spread is 100.99 bp and the model predicted spread is 64.75 bp. Is therefore assumed a short position in CDS and $6.13 of shares are sold.

The GARCH calibrated model, instead, suggest waiting until 5 February 2016 to enter the trade, when the market spread is 112.79 bp and model spread is 74.99 bp. Similarly, a short position in CDS is assumed and $5.49 of stocks are shorted.

Both the trades are closed when the time limit is reached, because convergence does not happen during the 90 days period.

In the first case, the gain on CDS leg of the trade amount to $0.52, because the spread moved from 100.99 bp to 91.56 bp.[70] On the equity side, instead, a loss of $0.53 is registered since the value of the stocks shorted passed from $6.13 to $6.66. The holding period return of the trade results then to be basically zero, having the loss on equity hedge completely off-set the gain on CDSs.

In the second case, when GARCH is used, a gain of $0.96 is registered on CDSs. CDS spread, in fact, passes from 112.79 bp to 97.89 bp. On the other side, the stocks produce a loss of $0.62: at initiation $5.49 of shares are shorted and at closing $6.11 of shares are bought back. The holding period return in this case is 0.68%, that correspond to an annualized return of 2.75%.

Hence, for this single trade the use of GARCH seems to have been positive, having the model suggested a better moment to start the strategy.

During the whole sample period three trades have been performed, both with the standard strategy implementation both when GARCH is used. The standard strategy

[70] Computation of returns on CDS position is performed following the common procedure in academia, described in this work in section 3.2.2. In particular, the formula used to compute the change in value of a CDS position held from time 0 to t is an approximation of $\pi(t,T) = [c(t,T) - c(0,T)] \int_t^T P(t,s)q_t(s)ds$, where $c(t,T)$ is approximated by $c(t,T+t)$ to avoid problem in finding secondary market quotes on an existing contract. Then the formula used to compute CDS returns is $\pi(0,T) = (c(0,T) - c)\int_0^T e^{-rs}q(s)ds = \frac{c(0,T)-c}{r}\left[q(0) - q(T)e^{-rT} - e^{r\xi}\big(G(T+\xi) - G(T)\big)\right]$, where c is the CDS spread of the contract when it was first initiated and $c(0,T)$ is a function of equity price as suggested by CreditGrades model. Basically, once the contract is initiated the equation computes the change in value of the CDS by extracting the survival probability implied in the new market spread. Further explanation on the computation of CDS returns can be found in Yu (2006) and Bajlum & Larsen (2007).

implementation led to an average holding period return of 0.86%, that corresponds to an annualized 3.5% returns, and a Sharpe ratio of 0.64. The GARCH calibrated strategy, instead, produced an average holding period return of 2.0%, that corresponds to an 8.52% on an annual basis, and a Sharpe ratio of 1.33.

Results from Berkshire Hathaway seems to suggest a marked increase in strategy performance when a faster responsive volatility estimator is used. They also suggest that, when GARCH is used, the strategy returns attractive Sharpe ratios.

In the next section, in order to understand if results here found are valid also for other obligors, the back-testing is reproduced for a larger sample of companies.

4.4 General results for individual trades

In this section are reported the aggregated results from the trading strategy replicated for all the obligors in the sample. Aggregating all the simulations, the sample is composed by 9,716 daily CDS spread.

Considering the plain Capital Structure Arbitrage, the days of open-trade are 7,504. Instead, when GARCH is introduced, the open-trade days are 6,969.

The lower number of open-trade days when GARCH calibrate model is used, reflects a lower number of trades entered into. Calibrating model with GARCH led to 86 trades, while the 1,000-day volatility calibrated model produced 91 trades. The lower number of trade entered into and the total number of open-trade days seem to be explained by the fact that when GARCH is used into the model the average deviation from model spread and market spread decrease. In fact, in seventeen cases out of twenty the GARCH calibrated model produced lower average deviation between the two spreads during the sample period.

Before going through the general trading returns, it is useful to understand how and if the CreditGrades model has been able to predict market CDS spreads. It also is worth noting how model spread time-series, when GARCH and when 1,000-day volatility are used, differ. In particular, when looking at how well the structural model have been able to predict model CDS spread, three different patterns can be noticed. The first one is when model spread and market spread are closely related. This is, for instance, the case of Citigroup and Toyota, that are shown, respectively, in figure 8 and 9. For these companies, model spread and market spread remain substantially close during the whole sample period and when they occasionally diverge, they end to converge again.

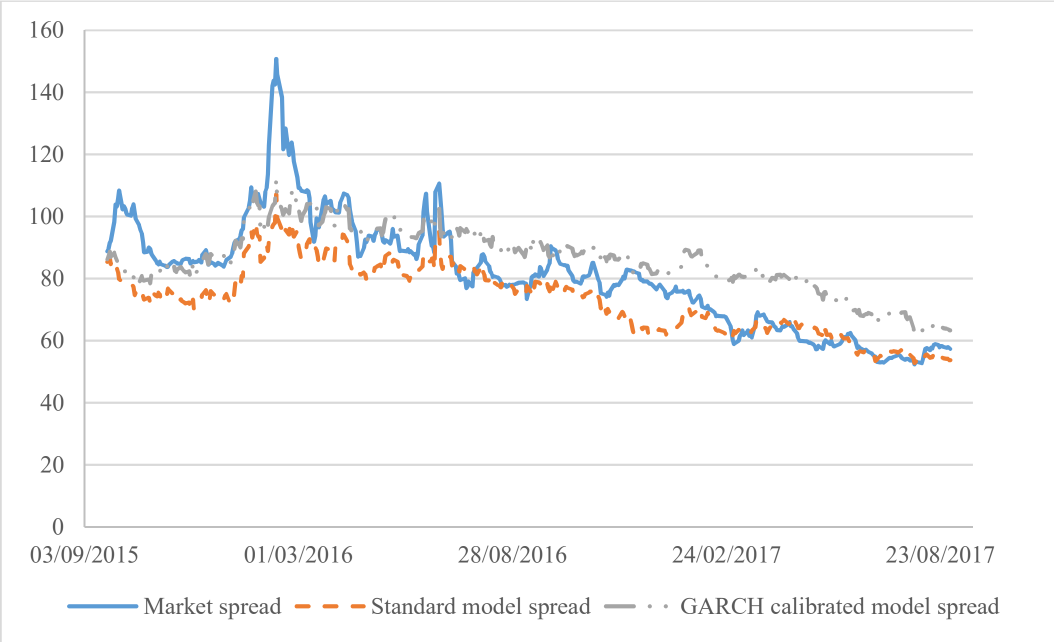

Figure 8 Time-series of market and model CDS spreads of Citigroup

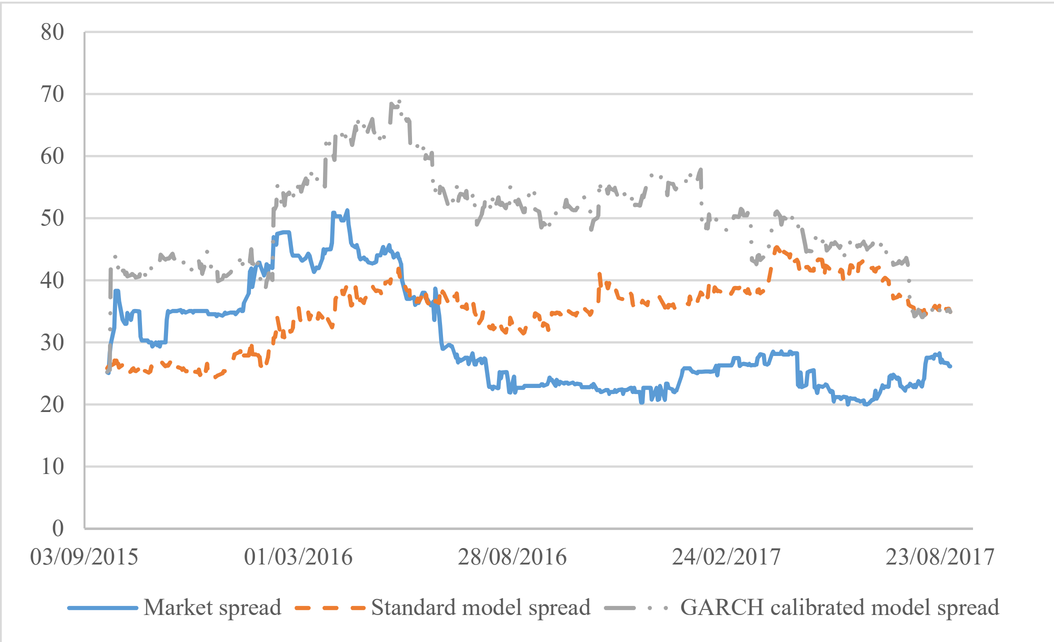

Figure 9 Time-series of market and model CDS spreads of Toyota

The second observed situation is when market spread and model spread appears to be close only during part of the sample, diverging more or less sharply for the rest of the period. This is the case of Anheuser-Busch InBev or UnitedHealth, for instance. The case of Anheuser-Busch InBev, visible in figure 10, shows how the model has been able to predict spreads reasonably close to the market only starting from June 2016.

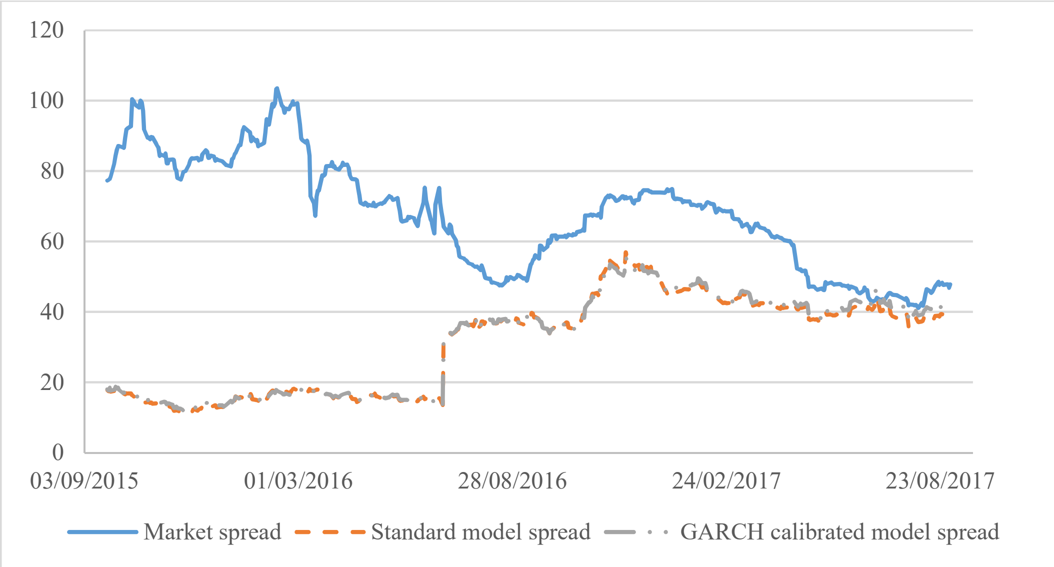

Figure 10 Time-series of market and model CDS spreads of Anheuser-Busch InBev

Similar, but specular, the case of UnitedHealth, where the model seems to be somehow meaningful only during first months of the sample period. Market and model spreads time-series of UnitedHealth are visible in figure 11.

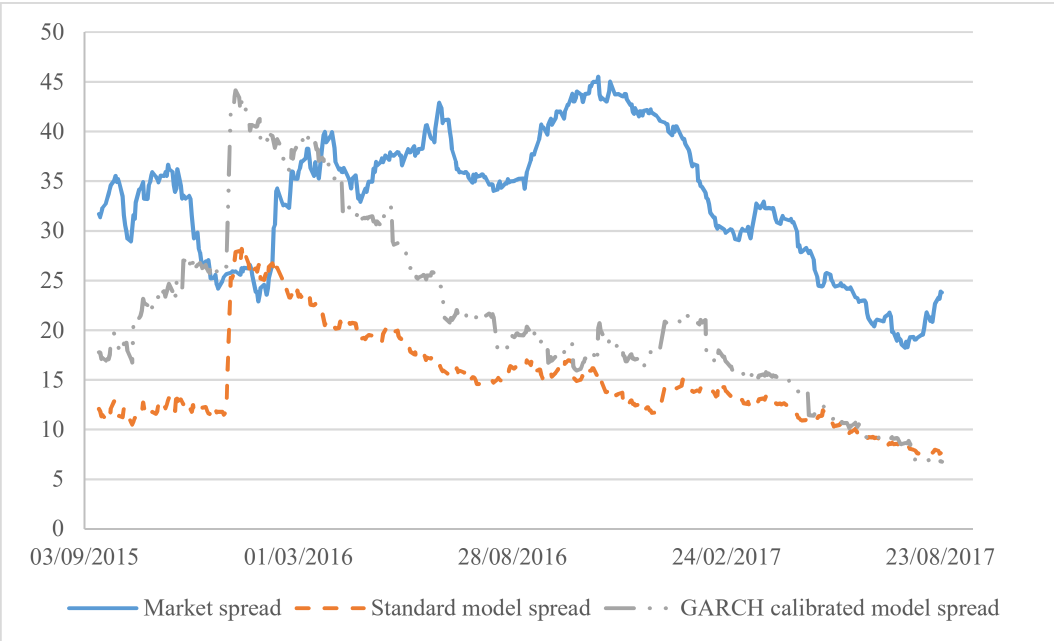

Figure 11 Time-series of market and model CDS spreads of UnitedHealth

The third case is represented by some firms, for which the model spread and the market spread time series do not converge during all the sample period. Often, for these companies, spread time-series are parallel and settled at different levels, being the market one several times higher than the predicted spread series.

It is the case, among others, of Walmart, that is visible in figure 12. For this companies, the two spread-series seem to depend from different variables. This observation, then, leaves as most likely explanation the model ineffectiveness.

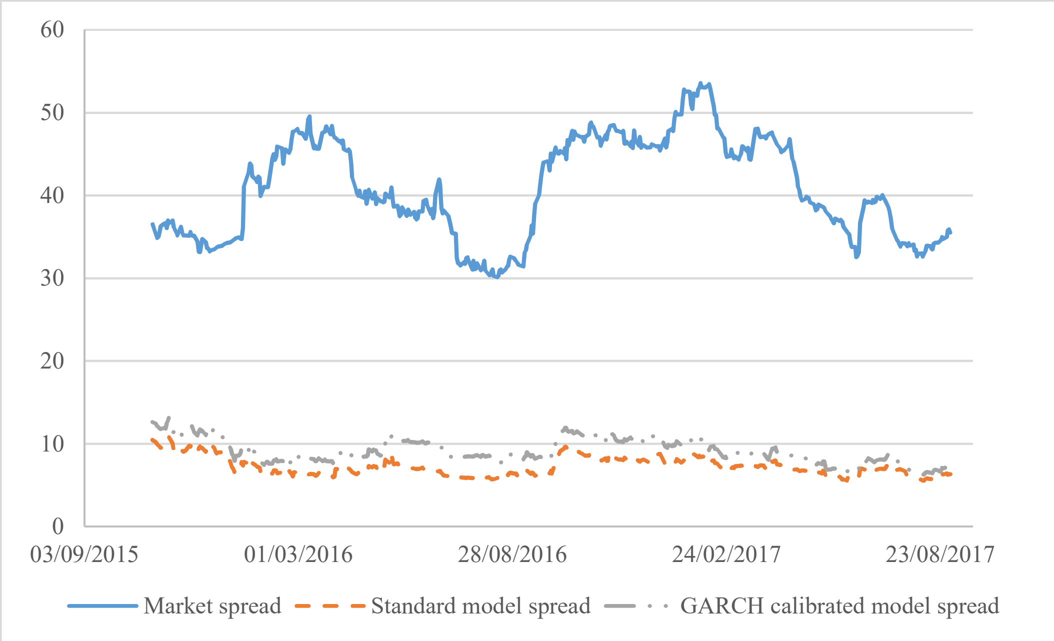

Figure 12 Time-series of market and model CDS spreads of Walmart

Turning to how the use of GARCH as volatility estimator impacted on CDS spread prevision, again three different conditions can be observed. The first one common situation is when the two spread-series are close, but GARCH seems to predict spreads that are closer to those then realized in the market. This is the case, for instance, of Bank of America and Royal Dutch Shell, visible respectively in figure 13 and 14. In these cases, GARCH improves the CreditGrades predictive ability and increase the arbitrage returns. It is also worth noting that in some cases, when GARCH is used, the number of trades for certain obligors goes to zero. This happens because the trade enter signal is never triggered, being the model and market spread close during all the sample period.

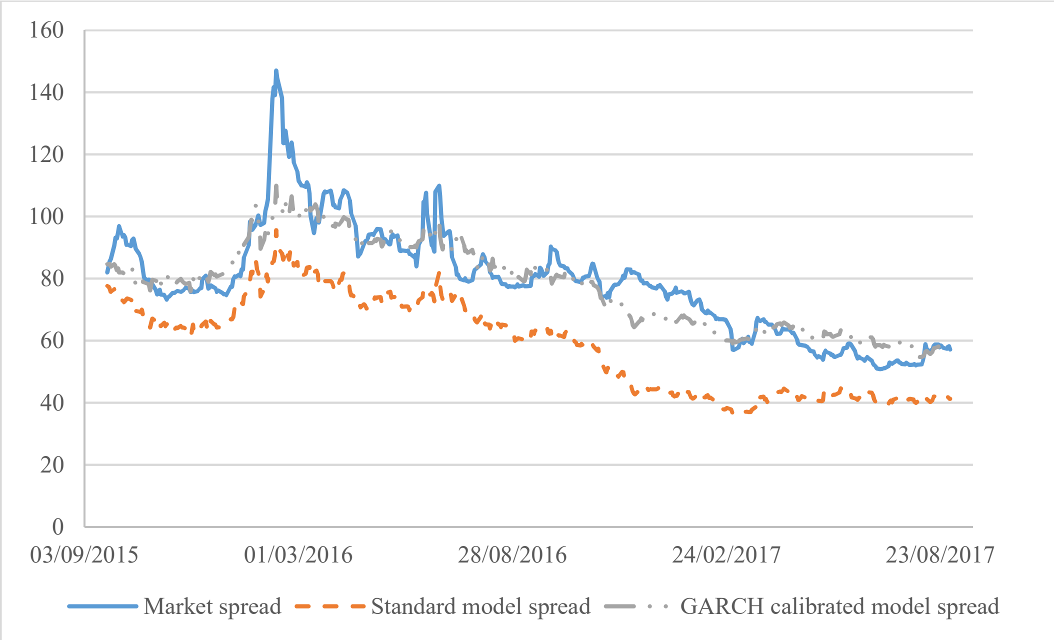

Figure 13 Time-series of market and model CDS spreads of Bank of America

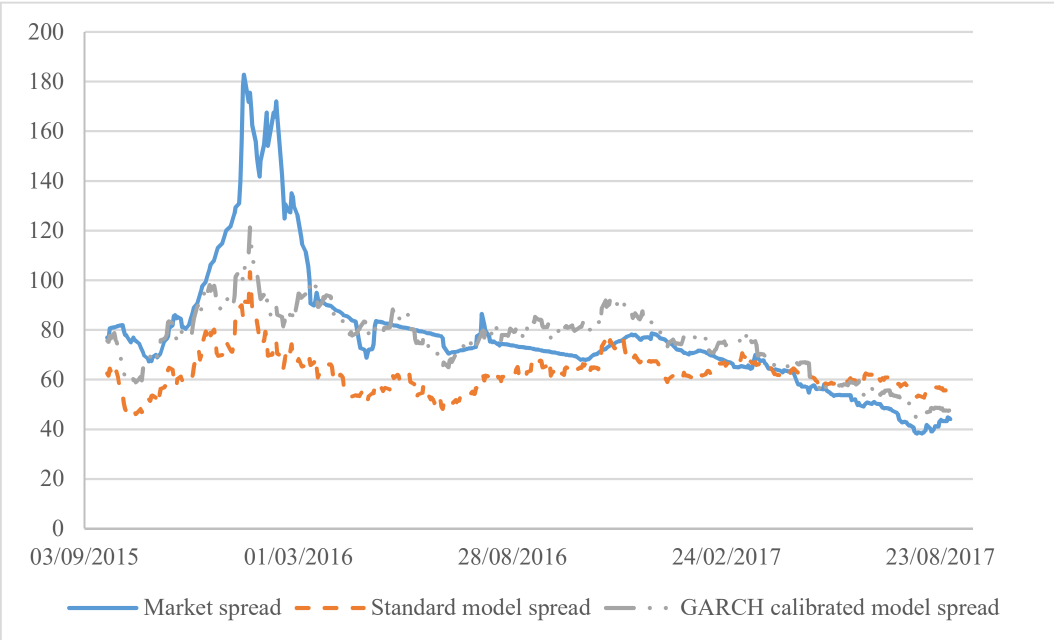

Figure 14 Time-series of market and model CDS spreads of Royal Dutch Shell

A second situation is represented by model spread series that seems to do not be much affected by the change in volatility estimator implemented. This is the case of Verizon and IBM, visible in the following figures. For these companies, the use of GARCH in predicting CDS spreads substantially did not lead to any improvement in term of strategy returns.

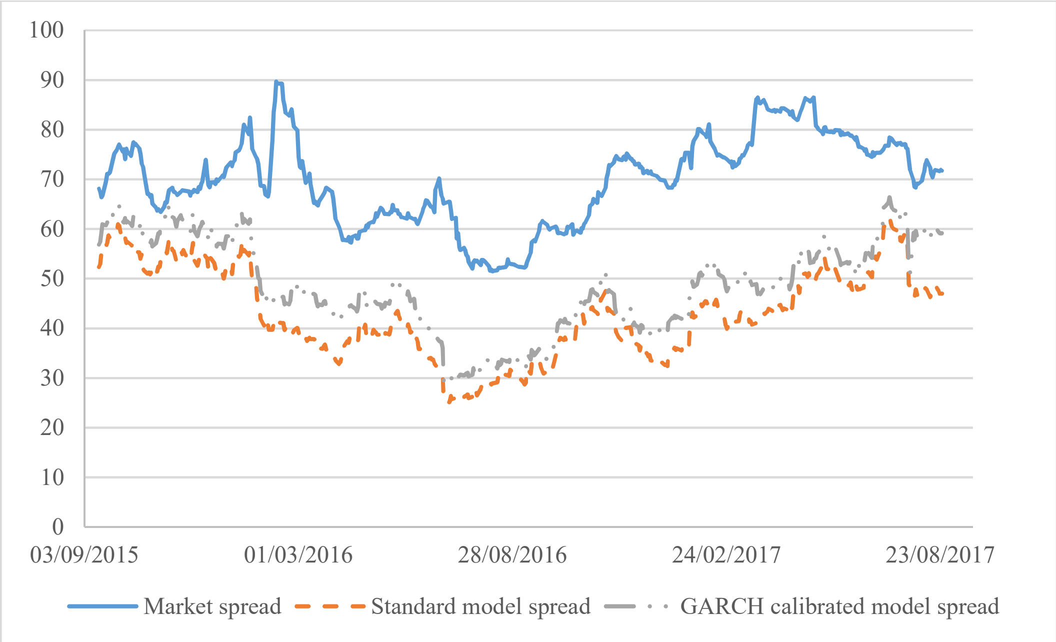

Figure 15 Time-series of market and model CDS spreads of Verizon

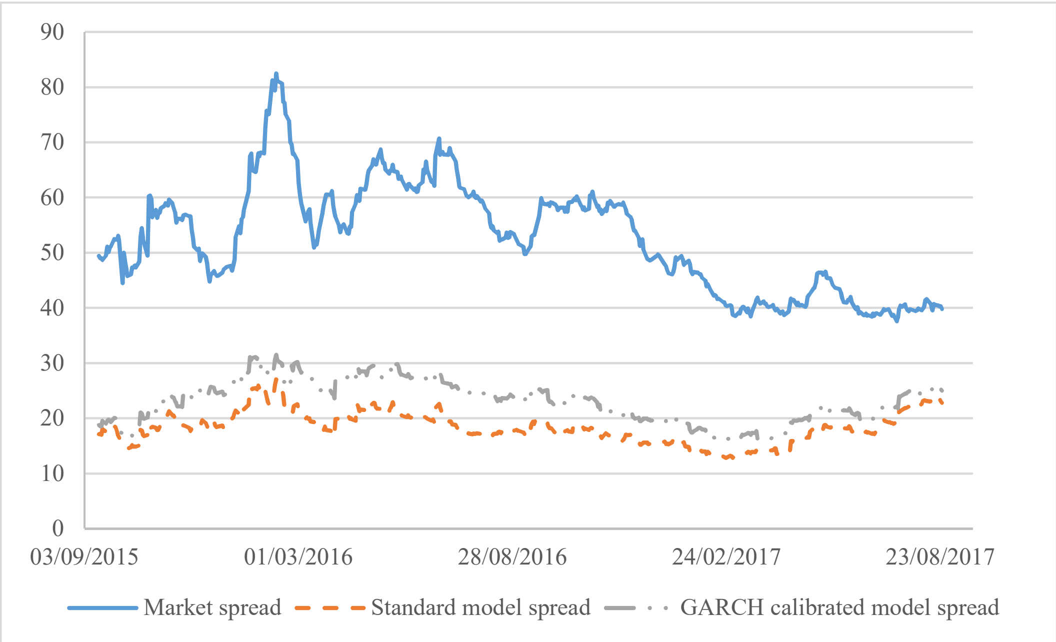

Figure 16 Time-series of market and model CDS spreads of IBM

The last case is represented, instead, by a poorer performance of CreditGrades model, when GARCH is used as volatility estimator. These are the cases of Wells Fargo and Toyota. The loss in predictive capacity appears, in these two cases, both looking at the spread time-series both at the trading returns.

In figure 17 the model and market spread for Wells Fargo are illustrated. The loss in accuracy of GARCH calibrated model is evident.

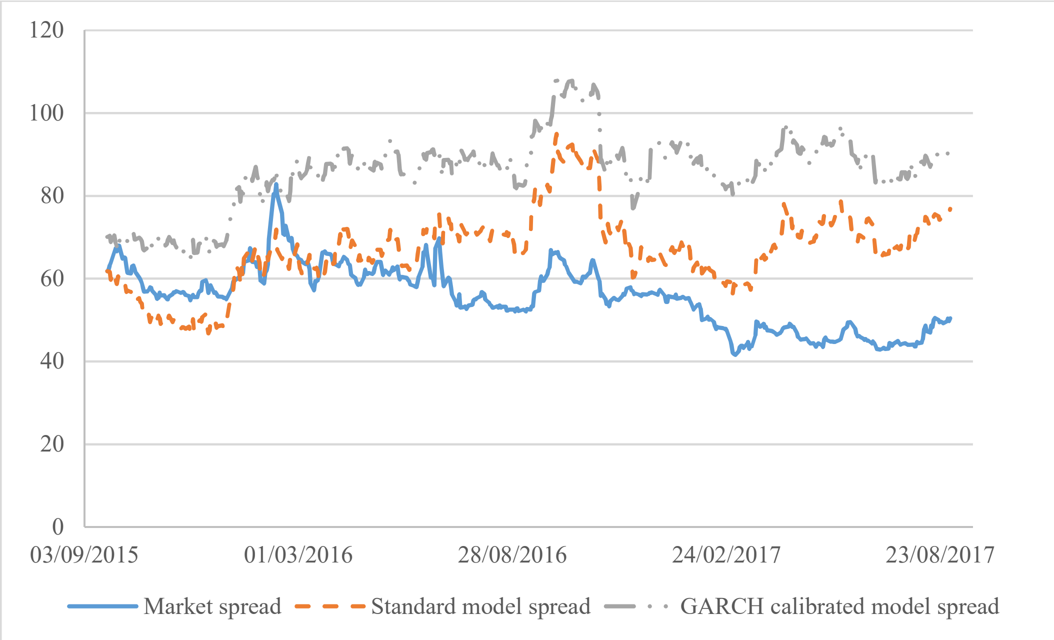

Figure 17 Time-series of market and model CDS spreads of Wells Fargo

Once the different behaviors of model and market CDS spreads have been illustrated, it results interesting to see how, on aggregated level, they impacted on the Capital Structure Arbitrage returns.

In particular, when the standard Capital Structure Arbitrage is implemented, the average holding period return is 0.35%, that corresponds to a 1.51% annualized return. Considering that during the sample period the average annual risk-free rate has been 1.55%, the Sharpe ratio registered by the strategy would have been negative.

When the volatility in the model is estimated through a GARCH, the average holding period return results to be 0.88%, that corresponds to a 10.38% on an annualized basis. The Sharpe ratio over the sample period of the strategy, in this case, would then have been 0.48.[71]

Looking at the annual return distributions of the two simulated strategy, reported in figure 18 and 19, two observations can be done. The first is that the positive returns of Capital Structure Arbitrage are explained by few high returns. In both the strategies, in fact, most of the trades register annualized returns in the interval between -2.5% and 0%.

[71] The average annualized return has been obtained averaging the annualized return on each single trade.

The second observation is that the overall better performance produced using GARCH as volatility estimator is not explained by constant improved performances over the whole sample. Rather, it is explained by few large returns. Comparing the two distributions of return, in fact, it appears that the proportion of trades in each interval of returns is basically the same, and are the values in the tails that do the difference.

The standard Capital Structure Arbitrage produced a minimum annualized return of -37.53%, while the worst annualized return for the other strategy is just -16.66%. On the righthand side of the distribution, the standard strategy implementation registers a maximum annualized return of 51.61% while, when GARCH is plugged into the CreditGrades, the maximum annualized return is 162.20%.

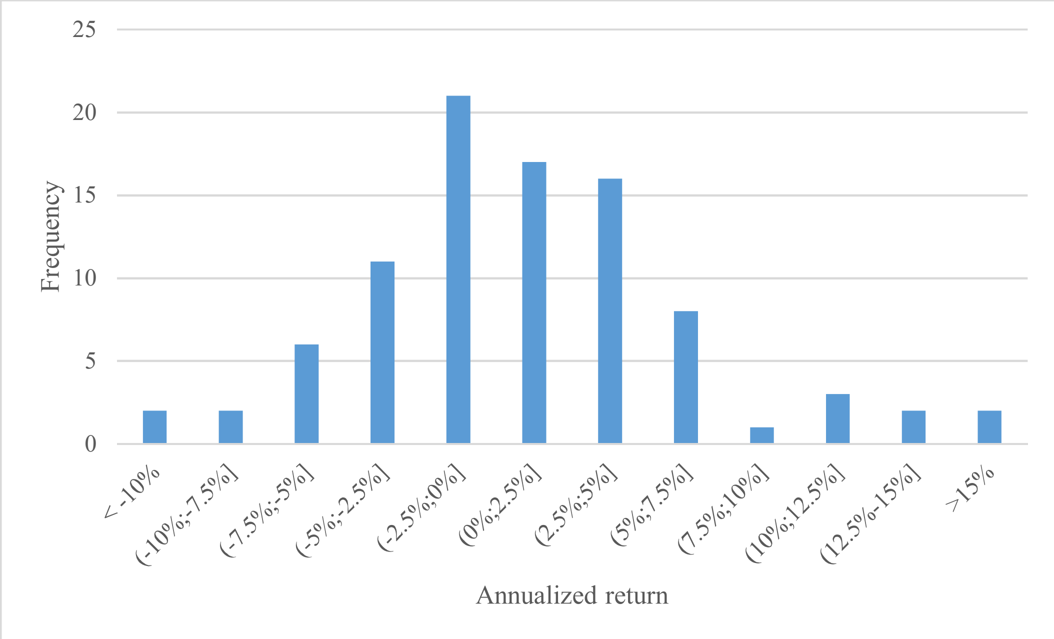

Figure 18 Distribution of annualized return for standard strategy

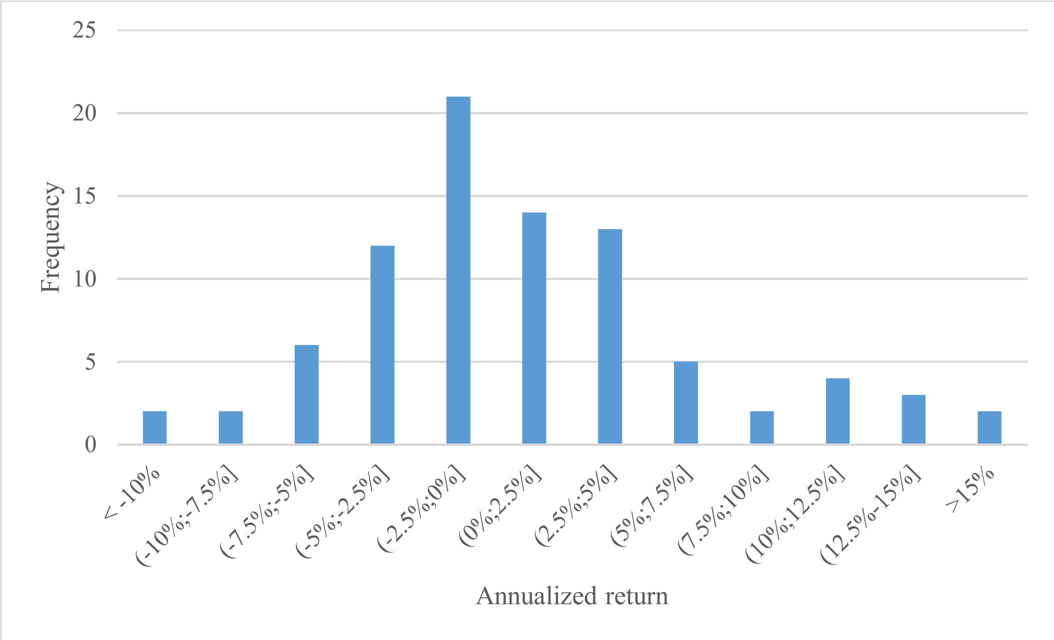

Figure 19 Distribution of annualized return of the strategy when GARCH is used

While the dependence of the positive returns of Capital Structure Arbitrage on few, highly profitable, trades was something found also by most of the previous works, the role of leverage of obligors in model effectiveness is a topic that seems not have been covered.

Instead, a marked difference between the market leverage and the book values leverage seems to have a huge influence on the ability of CreditGrades model to predict market CDS spread and consequently to allow a profitable implementation of the arbitrage.

Hence, a more depth analysis of the effect of leverage on predictability of CDS spread is presented in next section.

4.5 Observations on the role of leverage

Looking at those companies for which the use of CreditGrades turned out to be completely ineffective, it appears how in general these are the companies having a low level of leverage, but, at the same time, a consistent level of debt if compared to book value of equity.

In particular, plotting the average holding period return for each company, along with their price to book ratio at the start of the sample, it appears how, for higher values of P/B the returns are generally lower. The price to book ratio in this context serves as measure of the difference between the market value leverage and the book value leverage. In fact, since CreditGrades compute firm's leverage from its debt face value and its equity market value, a P/B ratio that is different from 1 means that the market leverage is different from the book value leverage.

From figure 20 this appears more clearly: for firm having a price to book ratio higher than 2, the average strategy returns are generally lower and often negative.

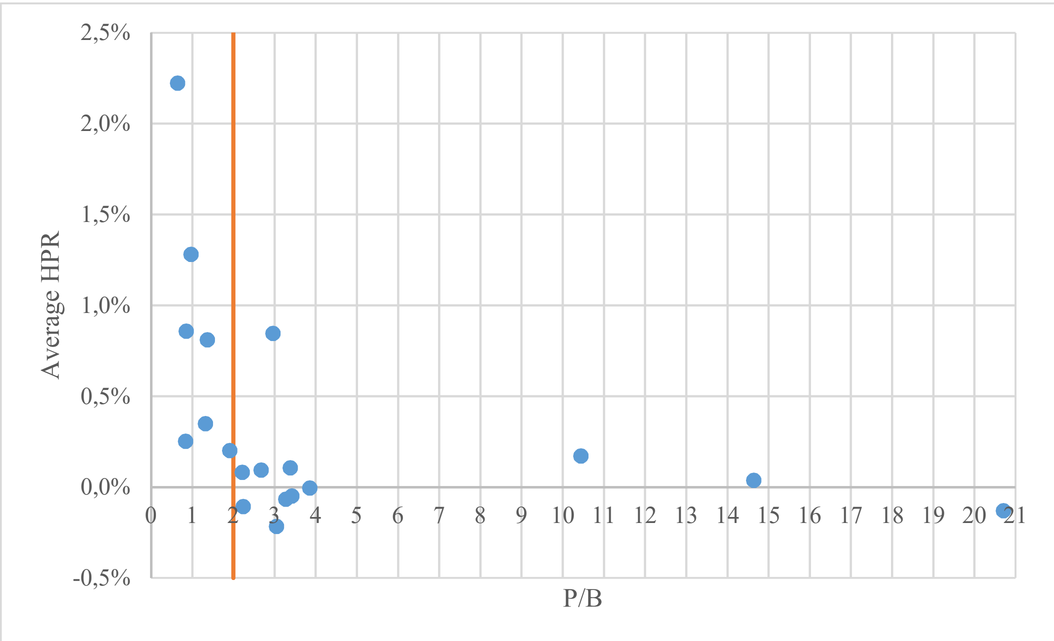

Figure 20 Average HPR and P/B relation

This finding suggests that market operators rely, to a certain extent, on the book value of equity when estimating default probability for a company. They, in fact, appear to be hugely influenced by the proportion of debt face value and book value of equity. The only market leverage, then, seems not to be able to explain alone the CDS spreads and a crucial role appears to be played by company book values.

In order to test the validity of this hypothesis, I computed again the CDS spreads for the firms in the sample using, as leverage measure, debt per share and book value of equity per share, instead of the ratio between debt per share and stock price. The results show that, when book values are used, the CDS spread predicted by the model is much more stable during time. This was an expected result, since the equity value is updated once every trimester. Of more interest is the effect of this new model calibration on firms for which the standard model implementation was not able to produce reasonable CDS spread previsions. In figure 21, 22 and 23 are reported respectively the cases of Walmart, Johnson&Johnson and Procter&Gamble. In all these cases, when equity book value is plugged in the model the model produced spreads improve sensibly in terms of predictive ability.

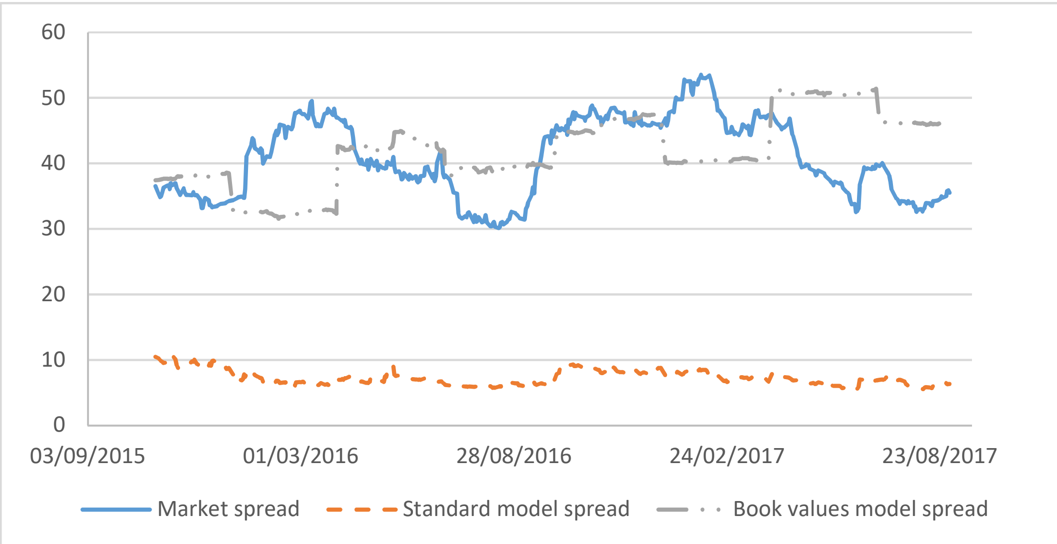

Figure 21 Time-series of market and model CDS spreads of Walmart

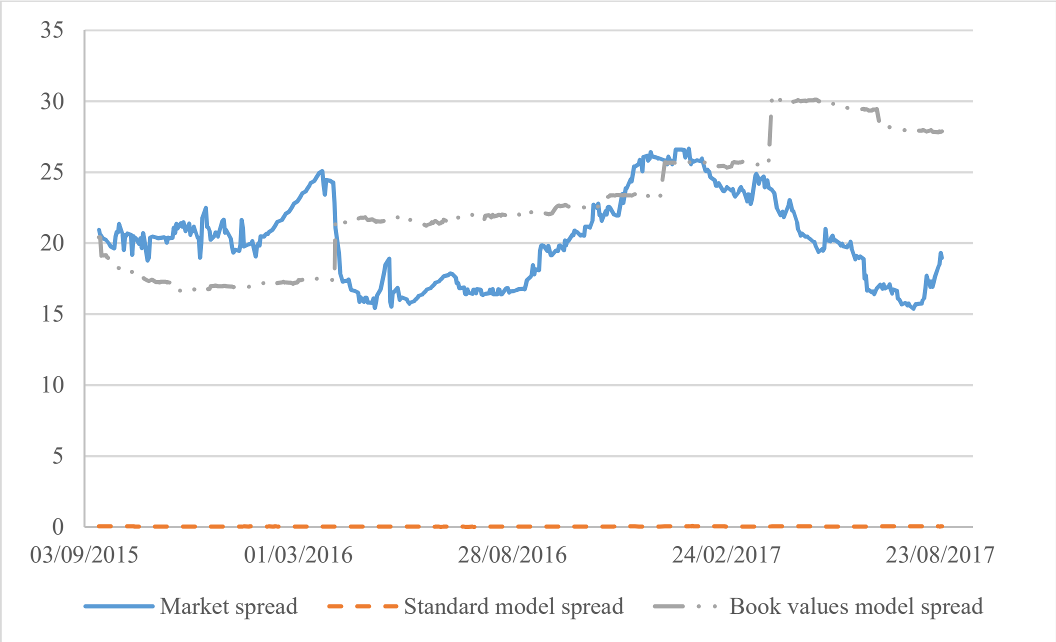

Figure 22 Time-series of market and model CDS spreads of Jhonson&Jhonson

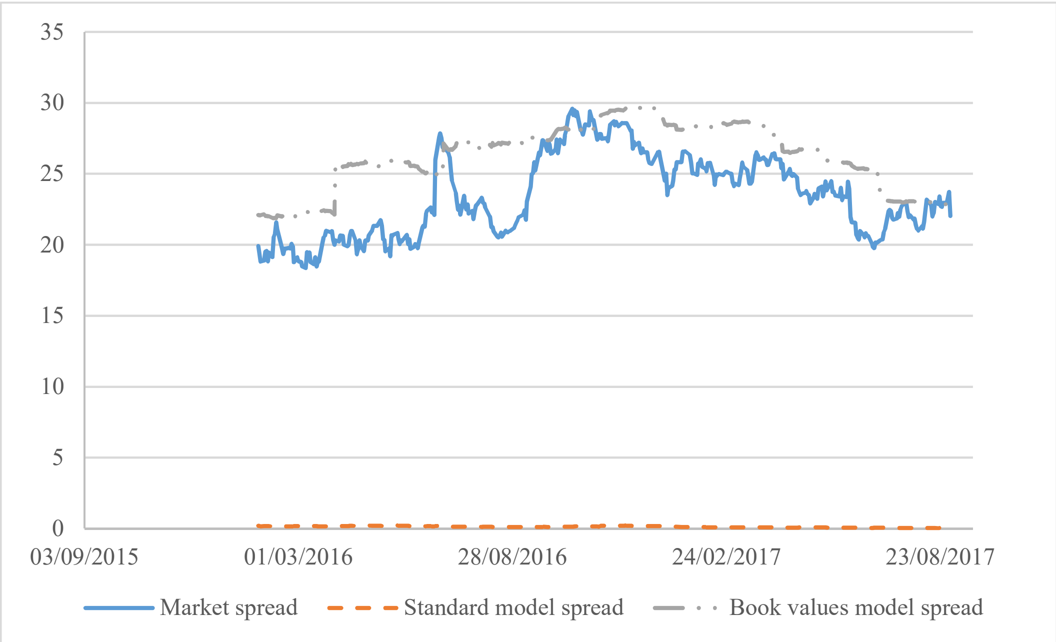

Figure 23 Time-series of market and model CDS spreads of Procter&Gamble

It is also interesting to note that for those companies for which standard CreditGrades was able to produce good estimate of CDS spread, the book values model still appears to be somehow effective.

This is the case, for instance, of Toyota and Citigroup, shown below.

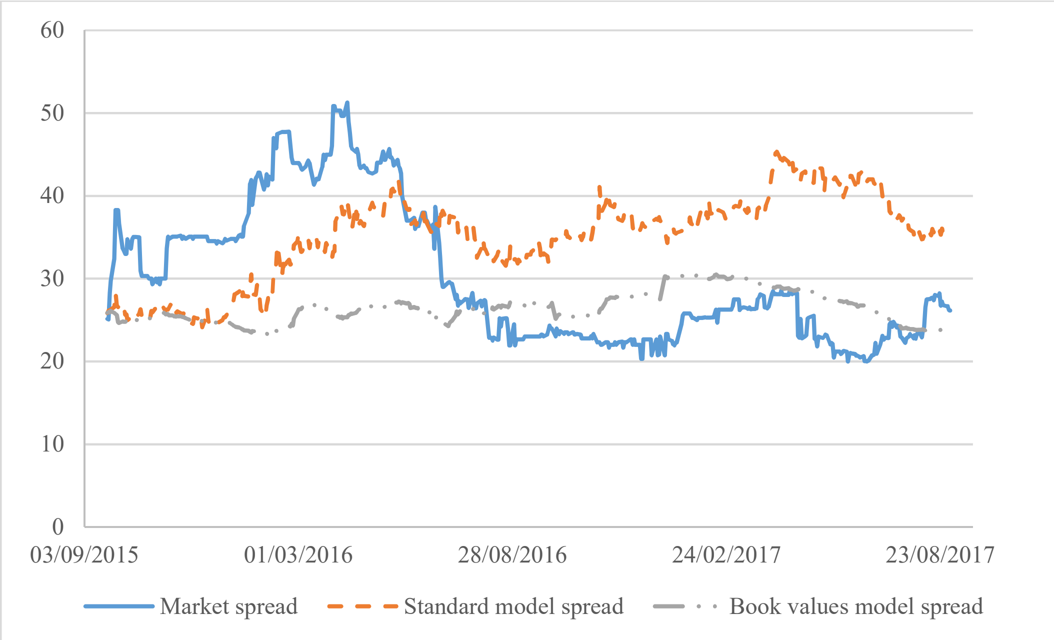

Figure 24 Time-series of market and model CDS spreads of Toyota

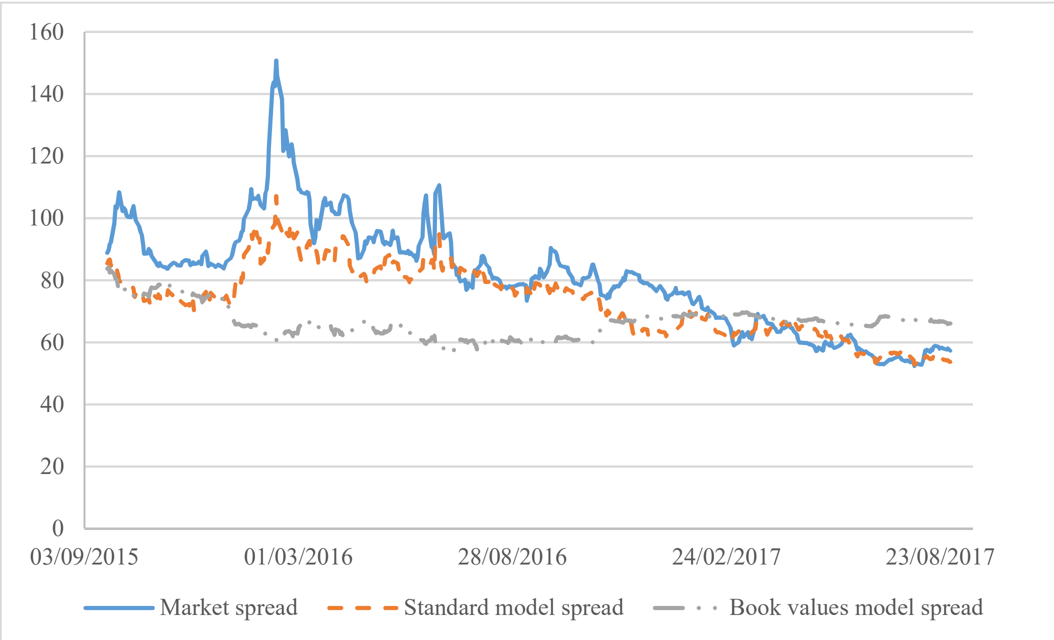

Figure 25 Time-series of market and model CDS spreads of Citigroup

Anyway, for some other companies the model spread so predicted did not produced significative credit spread.

Summing it up, it appears that the hypothesis that the book value leverage plays a role in the market perception of firms' default probability is confirmed. Plugging the book values of equity in the model produced CDS spread that in general appears to be close to the realized spreads. In particular, for those companies where market leverage and book value leverage differ more, the use of book values in calibrating the predictive model produced a clear improvement in terms of spreads predicted.

4.6 Conclusion

At the end of this chapter, it is possible to give an answer to the questions about the profitability of Capital Structure Arbitrage and about the effects of GARCH on its implementation.
Having regard to the profitability of Capital Structure Arbitrage, it appears that the Sharpe ratios produced by the investment strategy are not attractive. In fact, in both the simulations proposed, the Sharpe ratio resulted to be less than 0.5. These findings, in part, confirms the findings of previous studies that recognized to the arbitrage high returns, but with an extreme volatility. Some single trades resulted to be extremely profitable, but when returns are aggregated and adjusted for risk, this investment strategy loses any attractivity.
The strategy implemented in the classic way, calibrating volatility with the 1,000-day equity returns standard deviation, output an average annualized return of 1.51%, with a maximum annualized return of 51.61% and a maximum loss of 37.53% on annual basis. When the GARCH(1,1) is introduced to calibrate the equity volatility, the average annualized return resulted to be 10.38%, with a maximum annual return of 162.20% and a minimum of -16.66%. Anyway, the latter offered higher returns on average at a price of higher returns volatility. The volatility in returns of first strategy, in the simulation, in fact, is 8.56%, versus a standard deviation of returns equal to 18.35% when GARCH is used. Hence, it appears how, even though with the right calibration the returns of the strategy can appear attractive, when also riskiness is considered, Capital Structure Arbitrage do not longer seem to be a good deal.
Determined that the strategy does not appear to offer adequate remuneration for its riskiness, it must be recognized that the introduction of GARCH led to some improvements. When GARCH(1,1) is plugged into the structural model, the number of trades over the whole sample decrease, as consequence of model spreads closer to market spreads. The trading trigger, in fact, suggested to enter into 91 trades when 1,000-day volatility is used and into 86 trades when GARCH is used. Moreover, GARCH helped to reduce strategy drawdown: the maximum loss registered when GARCH calibrated model is used is, in fact, lower. Finally, the

Sharpe ratio, even if not attractive, is anyway considerably higher in the GARCH calibrated strategy. The use of GARCH as volatility estimator linked to historical volatility, but as well attuned to sudden change in market conditions, seemed to have led to significative improvement in strategy execution.

To conclude, an observation on the role of leverage has been proposed. By looking at the results of the simulation, in fact, appeared how, for some firms, the spread produced by the model was steadily far below the market spread. I hypothesize that the constant model underprediction is due to the huge difference, for these obligors, between the market leverage, that is used by the model as input, and the leverage as appears by balance sheet. To test the validity of this hypothesis, the model spread has been computed again using, instead of the share price, the book value of equity. Results seems to confirm the hypothesis suggested. For those obligors for which CreditGrades was not able to predict CDS spread close to market, the introduction of book values led to more plausible spreads. Anyway, the use of book-value of equity instead of its market price led to a much less reactive spread time-series, since the equity value was updated only once every three months.

Hence, it appears that market operators rely hugely on the book-value firms' leverage when determining the probability of default for a company. Anyway, book-value leverage appears not to be able, by itself, to produce good estimation of CDS spread when plugged in the model. This is due to its lack in reactivity to changed market conditions.

5 Conclusion

The aim of the research carried out in this work was to develop an organic discussion of Capital Structure Arbitrage. This investment strategy knew some popularity starting from early 2000, even though its implementation was confined to biggest financial operators, due to the high financial knowledge required for its implementation. For this reason, the literature on the subject is not so extensive and a work of research and comparison of the literature on Capital Structure Arbitrage seemed of interest. In particular, this work wants to give an answer to two main questions: is Capital Structure Arbitrage still profitable? And, if yes, can it be improved by a better calibrated structural model?

To this end, the work starts by reporting the main subject of capital structure theories and structural models for debt pricing. In particular, a review of the most common theories on the effect of capital structure and on the optimal level of debt has been proposed. Then, an historical overview of the evolution through the last thirty years of the more relevant structural models is reported. The crucial role played by a correct estimation of default probability on CDS pricing and, as a consequence, on the implementation of the strategy, suggested to focus on the basic assumption of these models and how they have been changed and improved, through the years, to respond to flaws of precedent models. The first model, developed by Merton in 1974, in fact, defined the core assumptions of all the following models, but has the commonly recognized problem to underestimate market CDS spreads. The models that followed all tried to solve this flaw. In particular, two are the assumptions added by later works that appeared to have a certain success in literature, since they have generally been adopted henceforth. The first one has been introduced by Black and Cox (1976), that hypothesized the possibility of early default. It means that firm defaults the first time its asset value hits the default triggering point and not only if asset value is under default level at maturity. The second improvement that appeared to have had a certain success have been introduced by Zhou (1997). The author introduced a jump process of firm's value. The firm's asset value, in Zhou, can hit the default barrier unexpectedly, jumping suddenly under the default level.

We have seen that all structural models share a large or smaller part of assumptions and that no one appeared to be definitely effective. For this reason, various models sharing the same framework, but changing parameters and assumptions have been produced. In most of the cases differences among models are represented by a different calibration of these four parameters: the asset value dynamics, the dynamic of risk-free rate, the determination of default barrier and the definition of the firm's recovery rate.

The conclusion that can be drawn from this comparative analysis is that several authors struggled to produce and improve yet present structural model to precisely estimate default probability of firms. In general, the evolution of structural model led to more complicate models and complex parameters calibration. However, at the end it seemed that the most successful model has been the one able to combine the relevant features developed in academia with simplicity, as a form of transparency. CreditGrades model, in fact, appears to be the one that most success has been in the practice and that will also be used in this work to implement the arbitrage strategy.

The research went on analyzing the mechanism that govern the Capital Structure Arbitrage. Available literature about the investment strategy has been compared, to show the differences in implementation suggested by various authors. In general, academic research found that the arbitrage strategy can generate attractive risk adjusted returns, even if riskiness of single trades is relevant. Moreover, it appeared how all the authors used the CreditGrades model to look for market's anomalies and earn positive returns by implementing the strategy. The results obtained by authors are not univocal: for instance, it is not clear if Capital Structural Arbitrage is explained by common risk factors or not. What instead appear to be a common result is the riskiness of this arbitrage strategy: all the authors recognized that the risk of huge losses on single trades is relevant. Also, the fundamental role of a correct calibration of model parameters appeared to be a conviction of all the authors.

Therefore, it has been interesting to note how the calibration of equity volatility in the structural model has been one of the main topic of discussion on academia. Authors, in fact, has two opposite opinions on the subject: part of them believe that a long historical time-series of equity return is the best estimator of equity volatility, while other believe that shorter time-series or option implied volatility are better predictor since more reactive to sudden change in market conditions. A third hypothesis has been therefore proposed, that is the use of GARCH as volatility estimator able to mediate between these two visions. GARCH, in fact, relies both on a long-run stable volatility both on equity value movements in the short-run. The effectiveness of GARCH, when plugged into CreditGrades, have been tested in the last chapter of this thesis.

To conclude this work, in fact, a simulation of the investment strategy has been performed as if it was implemented from August 2015 to August 2017.

The results of the back-testing exercise show that during the sample period the arbitrage strategy did not produce attractive risk-adjusted return. Findings also confirms what found in literature about arbitrage returns distribution: the overall return of the strategy is mainly led by few, huge returns. At aggregate level, in fact both the plain Capital Structure Arbitrage and the GARCH calibrated strategy produced positive returns, but when volatility of returns is considered it appears how the strategies have not been able to offer compensation for the risk born. This also clearly appear looking at the distribution of returns. In both the cases, in fact, almost the half of trades ended with a negative return. Hence, an average positive return is explained by high values in the right side of the distribution.

Finally, observing the results obtained, with both the calibration measure adopted, it appeared how the role of leverage seems to play a crucial role in the predictive ability of CreditGrades model. In fact, the CreditGrades model use as input to compute default probability also the leverage of firm in question. Then, the model produced low level of CDS spread for firms having low level of market leverage. Instead the market seemed not to agree to the model prediction. In fact, for these firms the market CDS spreads were far away from predicted spreads. I then hypothesized that the anomalies of these firms were due to the fact that the book-value leverage of these firms departs hugely from the market value leverage. To test the validity of the hypothesis, the simulation has been repeated using, instead of the equity market value, the book value of equity. Results confirms the hypothesis. The book-value leverage seems to explain the unreasonable spread produced by the model for some firms.

To sum up, the goal of this thesis has been to offer an overview on Capital Structural Arbitrage and on structural models. The interest was to understand better this peculiar investment strategy and to understand its link to company default probability estimation. The results obtained suggest that, during recent years, the CDS market has been able to price quite efficiently the swaps and no much room is left for arbitrageurs.

At the same time, the use of GARCH model as equity volatility predictor led to a better strategy execution, suggesting that future research on default estimator models should focus on the role of generalized autoregressive conditional heteroscedasticity as a tool in explaining companies' default probability.

Lastly, the role of book leverage in market perception of default probability is a topic never treated before, but that, from this work, appears to have a strong influence on CDS spreads observed in the market. The exact role of book-values leverage on default probability market perception and how to include it into more sophisticated structural models is left has matter of future research.

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Department of Business and Management

Chair of Advanced Corporate Finance

The profitability of Capital Structure Arbitrage from 2015 to 2017: evidence on volatility estimator and companies' leverage

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Contents

Summary

Chapter 1: Introduction

The topic of this thesis will be the investment strategy known as Capital Structure Arbitrage and the predictive models the strategy relies on.

Capital Structure Arbitrage prescribes to trade one security against another security issued by the same firm. A common way to implement the arbitrage is to trade the debt against the equity of a given firm. Generally, it is implemented trading stocks and CDSs.

The willingness to deepen the knowledge on this arbitrage strategy comes from the scarcity of academic research on the subject and the will to deepen the knowledge on models for default probability estimation. In fact, a correct implementation of the Capital Structure Arbitrage requires, as input, a correct and timely estimation of default probability of companies through time. The success of Capital Structure Arbitrage is therefore strictly linked to the effectiveness of these predictive models.

In particular, this work will enquire if Capital Structure Arbitrage is still a profitable investment strategy and if there is, eventually, room for improvement in strategy execution. The last found paper written on the subject, in fact, dates back to 2014 and it concludes that the profitability of the strategy seems to be linked to specific time periods.[1] Moreover, the Capital Structure Arbitrage profitability could have been explained, in past years, by a low liquidity of credit default swap market. In this regard, Cserna and Imbierowicz (2008) found that the average returns of the strategy appear to decline over time and argue that the phenomenon could be explained by an increased efficiency of the credit default swap market.

At the same time, several authors remarked the importance of model's parameters setting to have acceptable CDS spread previsions.[2] In particular, the parameter that has mostly been subject of study is the equity volatility.[3]

Hence, I will start the discussion with a literature review on debt riskiness and capital structure decisions. To follow, an historical digression on structural models is reported. Then, the features of Capital Structure Arbitrage are analyzed. The

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[1] Wojtowicz, M. (2014). *Capital Structure Arbitrage Revisited*. Duisenberg School of Finance - Tinbergen Institute Discussion Paper; Working Paper.

[2] See, for instance, Bajlum & Larsen (2008).

[3] See Bajlum & Larsen (2008), Avino & Lazar (2013) and Wojtowicz (2014).

investment strategy will be dissected and the various approaches reported in academia will be compared, along with the result obtained by various authors. An innovative approach to volatility calibration will also be proposed.

Finally, the results of a simulation of the analyzed strategy is proposed. The simulation is performed through a back-testing of the arbitrage in the period from August 2015 to August 2017. The aim of the strategy back-testing is to understand if Capital Structure Arbitrage is still able to produce attractive returns and if the introduction of GARCH as volatility estimator can have a positive effect on strategy effectiveness.

Interestingly, the strategy simulation shed light on a feature of the used structural models, that was not mentioned in any of previous works on the matter. In particular, leverage seems to play a fundamental role on the ability of the model to predict market spreads. A possible explanation of the phenomenon is proposed and tested.

Chapter 2: Capital structure and debt riskiness

The implementation of an arbitrage on firms' capital structure requires that debt and equity are not priced consistently. Debt and equity are the two components of the capital structure of every firm and their characteristics, in terms of riskiness and value, are linked to the same entity, that is the assets of the firm.

The effect of different shapes of capital structure on assets' value has raised debates in academia. Many research papers on the effects of capital structure composition on the firm's value and the determination of an optimal leverage ratio has been produced during last decades. No one produced a definitive answer. On the contrary, different theories arose, testifying how the capital structure valuation of firms is still topic under discussion. In particular, the three main theories on the subject, considered in this work, are the irrelevance of capital structure, proposed by Modigliani & Miller (1958), the Trade-off theory, and the Pecking order theory.

Turning to structural models of corporate debt pricing, these models have been developed to formally link firm's asset value and the value of its capital structure components. The need to have a clear understanding and a theoretical term of comparison of the implication of a given level of leverage on the value of asset and consequently on the value of the component of its capital structure has been addressed creating models able to include the expectations that a firm will suffer from financial distress.

The theory on credit risk modelling owes its birth to the works of Black & Scholes (1973) and Merton (1974). They first model the dynamics of firm value following a standard Brownian motion and apply the option pricing technique to debt valuation, recognizing that equity's value behavior can be assimilated to a European call option on firm's assets. In this way, Merton model can produce a term structure of risky interest rate. Later, Black & Cox (1976) introduced the possibility of an early default. Modeling the equity as a European option, in Merton model default is possible only upon maturity. Black and Cox, instead, introduce an absorbing barrier, allowing the firm to enter default prior to maturity if its asset value hits this barrier any time up until maturity. Geske (1977) introduces the hypothesis of bonds of different maturities and different coupon rates. Moreover, Geske uses a system of compound options to compute bonds' value. Kim, Ramaswamy & Sundaresan (1993) change part of the assumptions introduced by Merton, maintaining the possibility of early default, as in Black & Cox (1976). They, in fact, assumes the risk-free interest rate to be a stochastic variable. Moreover, they focus on the firm defaulting on its coupon obligation, rather than on default caused by assets' value falling beyond the threshold. Longstaff & Schwartz (1995) maintain the floating interest rates introduced by Kim, Ramaswamy & Sundaresan (1993), proposing a closed-form valuation expression for risky coupon bonds as well as risky floating-rate debt. Furthermore, default, here, is triggered the first time assets' value touch a certain lower threshold, that is not necessarily linked to the debt face value. This definition of financial distress is consistent with both the net worth default both with the cash-flow based default. The work of Leland & Toft (1996) drops the assumptions of stochastic risk-free rates. An important innovation introduced by the authors is the determination of bankruptcy endogenously in the model. Moreover, the authors, state that their work is the first that focuses on optimal capital structure, making explicit reference to the trade-off theory accounting equation. Zhou (1997) makes a radical change in the assumption on asset value process. In his model, the value of the firm follows a jump diffusion process, rather than the plan diffusion process. The jump component implies that the recovery rate is endogenously generated in the model. With the jump specification, in fact, in the event of default the residual value of the firm could be anywhere between the default threshold and zero. The default in Zhou is determined, as in Black and Cox and following models, by the first time the value of the firm hits the default barrier. The default barrier determination is borrowed by Longstaff & Schwartz (1995). Briys & Varenne (1997), aiming at improving the definition of threshold level proposed of Longstaff & Schwartz, propose to set the default barrier at the level of the discounted value, at risk-free rate, of the face-value of debt at maturity. They insert the assumption of stochastic risk-free rate, which in turn determines that also the default barrier is stochastic. Fan and Sundaresan (2000) provides a framework for debt renegotiation where bargaining power of share-holders and debt-holders can be varied. They consider the effect of taxes, as in Leland and Toft (1996), assumes that the zero-rate curve is flat and the threshold barrier is endogenously determined. They, in addition, impose that assets sale for dividend payment are prohibited. CreditGrades (2002) introduces the uncertainty in default barrier. The default barrier is here determined as the average recovery rate on debt times the debt value. The recovery rate considered is stochastic and hence also the default barrier is stochastic in the model. Another differentiating aspect of CreditGrades, respect to previous models, is the focus on valuation of credit spread rather than on default probability. The risk-free rate here is assumed constant. Two more recent models, proposed by Cremers, Driessen and Maenhout (2008) and Zhang, Zhou and Zhu (2009), both follows Zhou (1997) in the definition of asset value dynamic. Both the models propose, then, sophistication of the jump components estimation.

It appears how the evolution of structural models passed through the modification and elaboration of certain parameters, while the core framework remained the same. In particular, the factors that mainly determine the differences among models are the dynamic of asset value, the dynamic of risk-free rate, the determination of the default barrier and the determination of the recovery rate.

This chapter went through two main topics: the capital structure theories and the structural models' evolution. The theme that links these topics is the credit risk. Credit risk represent a core element in identifying opportunities of Capital Structure

Arbitrage. This is the reason why a diffused discussion of the interrelation between capital structure, asset volatility, debt pricing and credit risk has been proposed.

Chapter 3: Capital Structure Arbitrage

This chapter will go through the mechanism of Capital Structure Arbitrage investment strategy. This peculiar strategy relies on the debt pricing models that have been illustrated in the previous chapter. As a matter of fact, this strategy bets on the fact that, in the medium term the market value of debt and equity of a given entity will reach an equilibrium level and this equilibrium level is determined by the structural model chosen by the arbitrageur. In particular, structural models are fed with equity market value and volatility and debt face value to obtain a probability of default for the firm. Default probability, in turn, allows to predict a fair credit spread on company's credit default swaps.

The position in stocks and CDSs the investor should assume is determined by the fact that the actual spread is higher than the theoretical one or that the opposite is true. If the theoretical spread results to be higher than the observed one, it follows that the CDSs are undervalued or that the CDS spread is right and stocks' volatility is undervalued and consequently stocks are expensive. In fact, if we believe that the model and market spread will converge, we expect one of the two happening: or the model spread will decrease or the market spread will increase. The model spread decreases if the equity volatility decreases, and hence the stocks'price increases. If the equity valuation, instead is correct, the market spread will increase. The correct way to exploit the individuated opportunity will therefore be to buy credit protection and hedge the position by buying stocks. On the contrary, if the CDSs are overpriced or the stocks are undervalued (as effect of an overvalued equity volatility), then the correct way to implement the arbitrage is to sell credit protection and sell short stocks as a hedge.

The subsequent movements of the CDSs and equity price after the arbitrageur has implemented the trading strategies can be summarized in the following three situations:

1. Both credit spreads and stock price rise or both decrease. This is a case of convergence. The arbitrageur profits from both positions.

2. CDS spread and equity price moves in the opposite directions. The arbitrageur suffers loss on one side while earnings in the other. Depending on the exposure, the investor will report an overall profit or a loss.
3. Both credit spreads and stock price rise or both decrease, in the opposite direction respect to what the arbitrageur expected. This a sure case of divergence. The investor suffers losses from both positions.

Academia agree on the fact that the Capital Structure Arbitrage is an investment strategy that historically produced attractive Sharpe ratios, even if the riskiness on each single trade is high. Point in common to most of the authors is a huge attention to parameters used to calibrate the structural model chosen, rather than on the choice model itself. Particular focus has been set on equity volatility calibration.

The structural model that is more widely adopted in literature is CreditGrades model. The large adoption of this model has been explained by the fact that CreditGrades is considered a standard in credit risk valuation among professionals. The standard estimation of volatility suggested by CreditGrades Technical Document (2000) is the 1000-day equity return standard deviation. Several authors argued that, in this way, the model is not able to react to sudden changes in market conditions. For this reason, various other hypothesis of calibration has been proposed in literature.

The use of a GARCH estimated volatility, then, seems to be useful to have a volatility measure linked to the long term standard deviation, but also attuned to short term market movements. In GARCH model the equity returns variance is calculated from a long run average variance, from the historical estimation of variance itself and from historical equity return.

In the fourth chapter, the profitability of the arbitrage strategy during the period 2015-2017 is inquired through a simulation on historical data. The back-testing will also be useful to understand if GARCH(1,1) model can add a significant advantage, in terms of returns and Sharp ratio, when Capital Structure Arbitrage is implemented.

Chapter 4: Capital Structure Arbitrage profitability and the effects of GARCH

The aim of this chapter is to answer two main questions: is Capital Structure Arbitrage an investment strategy still profitable? Can a GARCH calibrated CreditGrades model offer any advantage for an investor implementing the Capital Structure Arbitrage?

To try giving an answer to these questions, a simulation of the implementation of Capital Structure Arbitrage is proposed. The back-testing is performed on a sample of twenty big listed companies, having liquid credit default swaps traded in the market. The strategy has been performed both using the CreditGrades model calibrated as suggested by the CreditGrades Technical Document, both using the GARCH model as volatility estimator.

The trading analysis in this work isolates the period from August 31, 2015 to August 31, 2017. The first step, once collected the data needed, has been to compute the theoretical spread.

The GARCH(1,1) measure of volatility have been computed from the historical stock price data-series of the company. The GARCH(1,1) parameters have been estimated iteratively through the maximum likelihood method procedure. To smooth the previsions on volatility obtained by GARCH(1,1), each volatility estimation is taken stable for 30 days and then updated on the basis of the variance of equity returns during the 30 days before. This choice is also justified by CreditGrades Technical Document. The daily volatility used for the standard model implementation, instead, has been obtained has the standard deviation of equity stock price returns continually compounded.

The other inputs the CreditGrades model requires are the equity price S, the debt per share D, the mean global recovery rate $\overline{L}$, the standard deviation of the global recovery rate λ, the bond specific recovery rate R and the risk-free interest rate r. The assumptions on these values are borrowed from Yu (2006). Specifically, D is obtained as the ratio between total liabilities and common shares outstanding. The value of D every day is computed from the most recent quarterly balance sheet, to avoid look-ahead bias. The risk-free rate is assumed to be equal to the five-year constant maturity Treasury yield. The mean global recovery rate and the bond specific recovery rate are assumed to be respectively 0.3 and 0.5. The CreditGrades Technical Document motivates the above choice of λ. The same document also suggests a value for $\bar{L}$ and takes the value of R from a JPMorgan database. However, the procedure that has been adopted here is the same reported in the previously works on Capital Structure Arbitrage: value of R is set equal to 0.5, following Yu (2006), while $\bar{L}$ is determined by data on CDS spread observed in the market.

In figure 1, the comparison between model and market spreads of Berkshire Hathaway.

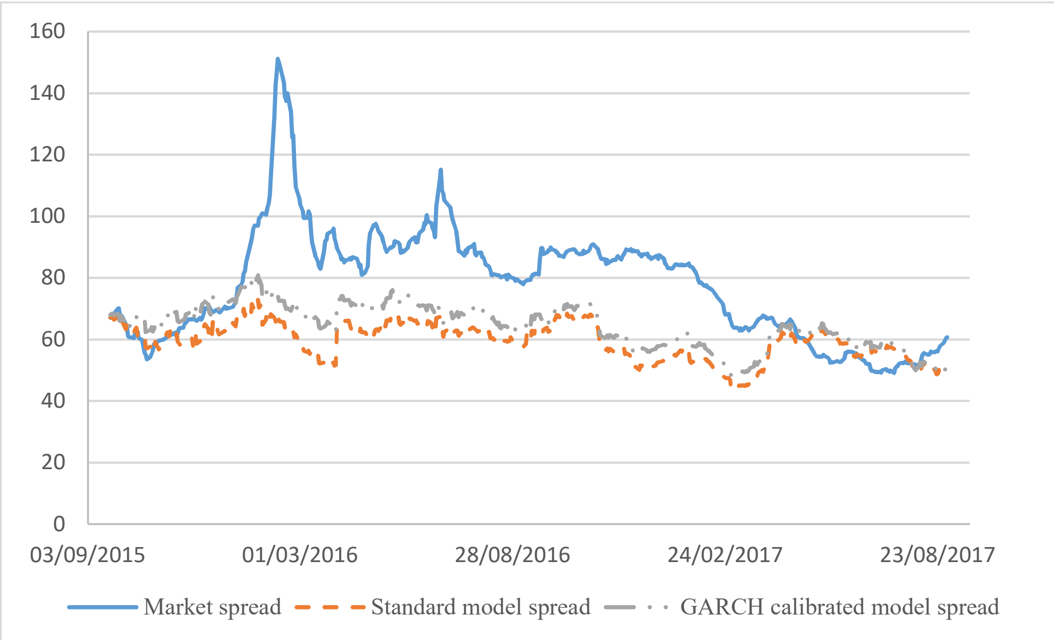

Figure 26 Time-series of market and model CDS spreads of Berkshire Hathaway

By the figure, the spread produced by CreditGrades when the 1,000-day volatility are used appears to be very similar to the spread produced when GARCH is used. However, GARCH seems to have the advantage of producing, during the all period, spreads closer to the market ones. In fact, the average deviation of model spread from market spread when GARCH is used goes from 19.8 bp tp 16.1 bp. Moreover, GARCH calibrated model spreads seems to better anticipate market movements during the initial period, when the market spread actually spikes up. It also appears that, in both the models, the spreads are more stable than the market ones. Sharp movements of CDS spreads, that are not justified by other market observable inputs, are exactly the trading opportunities that the arbitrageurs look for.

Once obtained the model spreads, the trading strategy has been simulated. I check whether the market spread and the model spread differs by more than a predefined trading trigger. The chosen trading trigger is 0.5. These positions are held open until convergence of model and market spread or after a prespecified period of time. In particular, I close down open trades after 90 open-market days, if convergence does not occur before. When the model suggests entering in a trade I assume a position in CDS for a notional amount of $100. I also assume a position in stocks computed through delta hedging in the moment the trade is opened, and keep it stable for the whole trade. To compute return for each trade an initial capital of $50 is assumed. The equity hedge is computed through delta hedging.

Aggregating all the simulations, the sample is composed by 9,716 daily CDS spread. Considering the plain Capital Structure Arbitrage, the days of open-trade are 7,504. Instead, when GARCH is introduced, the open-trade days are 6,969.

The lower number of open-trade days when GARCH calibrate model is used, reflects a lower number of trades entered into. Calibrating model with GARCH led to 86 trades, while the 1,000-day volatility calibrated model produced 91 trades.

In particular, when the standard Capital Structure Arbitrage is implemented, the average holding period return is 0.35%, that corresponds to a 1.51% annualized return. Considering that during the sample period the average annual risk-free rate has been 1.55%, the Sharpe ratio registered by the strategy would have been negative.

When the volatility in the model is estimated through a GARCH, the average holding period return results to be 0.88%, that corresponds to a 10.38% on an annualized basis. The Sharpe ratio over the sample period of the strategy, in this case, would then have been 0.48.[4]

It is also of interest to report that in 17 cases out of 20, when GARCH(1,1) is substituted to 1,000-day equity volatility, the average deviation between model and market spread is lower.

Looking at the annual return distributions of the two simulated strategies, reported in figures 2 and 3, two observations can be made. The first is that the positive returns

[4] The average annualized return has been obtained averaging the annualized return on each single trade.

of Capital Structure Arbitrage are explained by few high returns. In both the strategies, in fact, most of the trades register annualized returns in the interval between -2.5% and 0%.

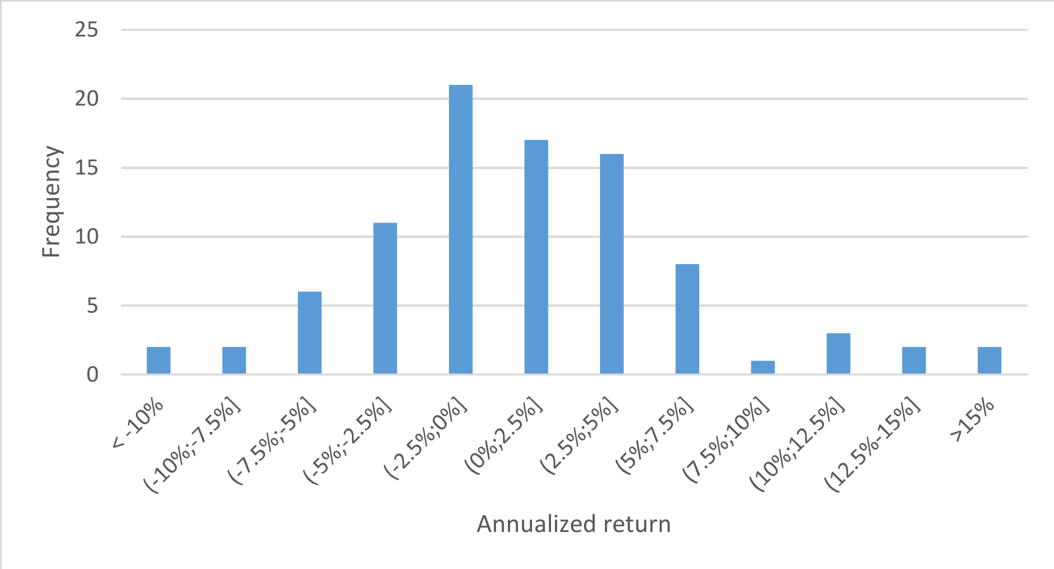

Figure 27 Distribution of annualized return for standard strategy

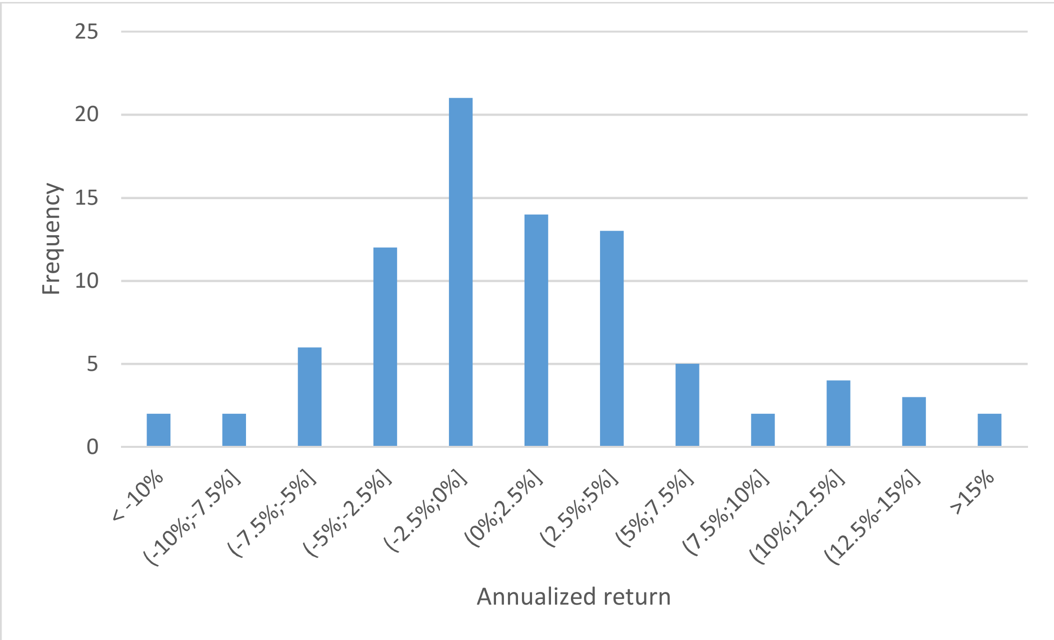

Figure 28 Distribution of annualized return of the strategy when GARCH is used

The second observation is that the overall better performance produced using GARCH as volatility estimator is not explained by constant improved performances over the whole sample. Rather, it is explained by few large returns. Comparing the two distributions of return, in fact, it appears that the proportion of trades in each interval of returns is basically the same, and are the values in the tails that do the difference.

The standard Capital Structure Arbitrage produced a minimum annualized return of -37.53%, while the worst annualized return for the other strategy is just -16.66%. On the righthand side of the distribution, the standard strategy implementation registers a maximum annualized return of 51.61% while, when GARCH is plugged into the CreditGrades, the maximum annualized return is 162.20%

Looking at those companies for which the use of CreditGrades turned out to be completely ineffective, it appears how in general these are the companies having a low level of leverage, but, at the same time, a consistent level of debt if compared to book value of equity.

In particular, plotting the average holding period return for each company, along with their price to book ratio at the start of the sample, it appears how, for higher values of P/B the returns are generally lower. The price to book ratio in this context serves as measure of the difference between the market value leverage and the book value leverage. In fact, since CreditGrades compute firm's leverage from its debt face value and its equity market value, a P/B ratio that is different from 1 means that the market leverage is different from the book value leverage.

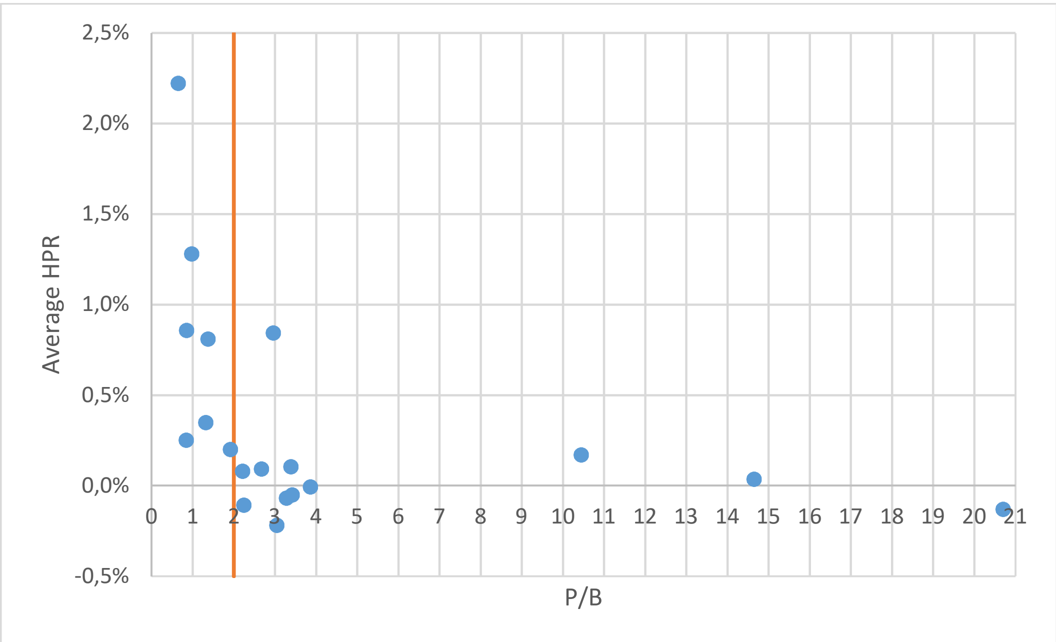

Figure 29 Average HPR and P/B relation

From figure 4, this appears more clearly: for firms having a price to book ratio higher than 2, the average strategy returns are generally lower and often negative. This finding suggests that market operators rely, to a certain extent, on the book value of equity when estimating default probability for a company. They, in fact, appear to be hugely influenced by the proportion of debt face value respect to book value of equity. The only market leverage, then, seems not to be able to explain alone the CDS spreads and a crucial role appears to be played by company book values.

In order to test the validity of this hypothesis, I computed again the CDS spreads for the firms in the sample using, as leverage measure, debt per share and book value of equity per share, instead of the ratio between debt per share and stock price. In those cases where the spread predicted in the explained manner was unnaturally low, when equity book value is plugged in the model, the latter improve sensibly in terms of predictive ability. This is the case, for instance, of Walmart, reported in figure 5.

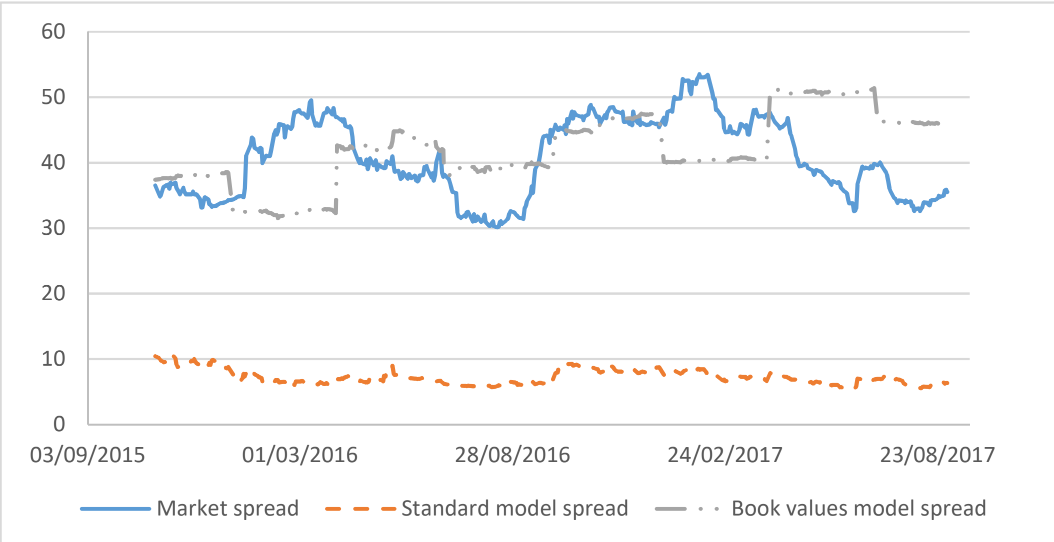

Figure 30 Time-series of market and model CDS spreads of Walmart

Summing it up, it appears that the hypothesis that the book value leverage plays a role in the market perception of firms' default probability is confirmed. Plugging the book values of equity in the model produced CDS spread that in general appears to be close to the realized spreads. In particular, for those companies where market leverage and book value leverage differ more, the use of book

values in calibrating the predictive model produced a clear improvement in terms of spreads predicted, if compared to spread predicted by market leverage.
Hence, it appears that market operators rely hugely on the book-value firms' leverage when determining the probability of default for a company. Anyway, book-value leverage appears not to be able, by itself, to produce good estimation of CDS spread when plugged in the model. This is due to its lack in reactivity to changed market conditions.

Chapter 5: Conclusion

To sum up, the goal of this thesis has been to offer an overview on Capital Structural Arbitrage and on structural models. The interest was to understand better this particular investment strategy and to understand its link to company default probability estimation. The results obtained suggest that, during recent years, the CDS market has been able to price quite efficiently the swaps and not much room is left for arbitrageurs.
At the same time, the use of GARCH model as equity volatility predictor led to a better strategy execution, suggesting that future research on default estimator models should focus on the role of generalized autoregressive conditional heteroscedasticity as a tool in explaining companies' default probability.
Lastly, the role of book leverage in market perception of default probability is a topic never treated before, but that, from this work, appears to have a strong influence on CDS spreads observed in the market. The exact role of book-values leverage on default probability market perception and how to include it into more sophisticated structural models is left as matter of future research.

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