SCHOOL OF
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Extending the Merton Model

A New Approach to Incorporating Forward-Looking Market Information into Credit Risk Modeling

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Abstract

This thesis contributes to the credit risk literature by analyzing the Merton model's ability to replicate credit default swap (CDS) spreads. Since defaults are rare events, resulting in low statistical power, the method is evaluated by comparing model implied CDS spreads to market ones. The data sample used includes quarterly observations from 2015 to 2024 for 44 firms included in the NASDAQ Composite Index. The primary contribution lies in proposing a new approach for incorporating forward-looking information into credit risk modeling in the form of a VIX weighted volatility measure. While using CDS spreads for the evaluation restricts the sample to firms with active CDS contracts, the approach is broadly applicable and can be used for any publicly listed company. The results suggest that the standard Merton model offers an adequate risk indicator but falls short in replicating the CDS market, since it only produces a limited number of positive spread estimates. The thesis finds no optimal default threshold that consistently improves the replication results. Incorporating VIX weighted volatility in the model increases the number of positive spread estimates, although it remains insufficient in capturing market CDS spreads.

Keywords: Merton model, CDS spreads, Credit risk, VIX weighted volatility, Default probability

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Contents

1 Introduction

Credit risk is the uncertainty surrounding borrowers' ability to meet their debt obligations (Hull, 2023). When assessing corporate credit risk, accurately identifying which firm will default on its debt remains inherently uncertain. However, since default risk is a critical aspect of debt pricing, regulation, and market stability, analysts and researchers use probabilistic evaluations to assess a firm's likelihood of default (Crosbie & Bohn, 2002). To compensate risk averse lenders for bearing risk, firms pay an interest rate beyond the risk-free rate. The difference represents the credit spread, which is proportional to default probability (Crosbie & Bohn, 2002; Amato & Remolona, 2003). If default probability increases, lenders require higher compensation for taking on riskier investments, and the credit spread increases (Vassalou & Xing, 2004).

Among important financial derivatives are credit default swap (CDS) contracts. These contracts provide a real time, market-based measure of perceived credit risk and are designed to protect against credit default risk (Hull, 2023). In its simplest form, a corporate bondholder can hedge the default risk of a bond by purchasing a matching CDS contract from an insurer. The CDS effectively transfers risk to the protection seller in exchange for periodic premium payments. These payments represent the CDS spread of the contract and, therefore, reflect the cost of carrying the risk (Collin-Dufresne et al., 2001; Hull et al., 2004).

While CDS is a market-based measure of default risk, structural models, such as the one developed by Merton (1974), provide a theoretical framework for estimating risk. The model is a foundational cornerstone in the field of credit risk modeling, serving as the basis for both academic research (see e.g. Afik et al., 2016; Bai et al., 2020; Feldhütter & Schaefer, 2018) and industry practice, such as through the widely adopted KMV-Merton extension (Crosbie & Bohn, 2002). By conceptualizing the value of a firm's equity as a European call option on its assets and defining a default scenario in which the value of the firm's assets falls below its debt value at maturity, the model provides a mathematically intuitive framework to understand default risk. From the seminal Merton model, distance to default, probability of default, and implied credit spreads can be derived, each offering valuable insights into firm-specific risk (Gemmill & Marra, 2019; Hull et al., 2004).

Although praised for its ability to provide an ordinal ranking of firms' riskiness (Hull, 2023; Jessen & Lando, 2015; Tudela & Young, 2005), studies have found the model to severely misprice credit risk, with Gemmill & Marra (2019) noting that model implied CDS spreads are often close to zero under normal market conditions. Such results contradict the characteristics of the financial market, where CDS spreads are consistently higher than zero because there otherwise would not be a supply of them. The empirical finding that CDS spreads are wider than what can be explained by expected default losses is known as the credit spread puzzle (Amato & Remolona, 2003; Bai et al., 2020). If structural credit risk models do not fully capture expected losses, it poses a challenge for analysts seeking to model and analyze risk dynamics. The CDS market reached a peak notional value of $61.2 trillion at the end of 2007 and has since faced significant regulatory reforms (Gemmill & Marra, 2019; Gadgil, 2024). Nevertheless, this financial derivative remains an important function, providing liquidity and insurance to the credit market. Based on this, it is interesting to investigate whether the Merton model accurately predicts CDS spreads.

The thesis aims to evaluate how accurately the Merton model's implied CDS spreads align with market CDS spreads during the years 2015-2024. The study further explores whether the model maintains its credibility as a reliable measure of credit risk in diverse market conditions. When implementing the model, a commonly used approach is to assume a maturity of one year (Aretz & Pope, 2013; Vassalou & Xing, 2004). In contrast, this study contributes by using quarterly estimations. It employs a panel data analysis of firms within the NASDAQ Composite Index to assess the model's performance for each year in the sample. This is relevant since the Merton model has certain simplified assumptions, including constant volatility, making it particularly valuable to evaluate the model's performance across different years with varying economic conditions. The sample begins with a period of relatively low equity volatility, followed by the unprecedented disruption of the COVID-19 pandemic with low interest rates, and concludes with the high interest rate environment of recent years.

Firstly, this thesis evaluates the standard Merton model in its ability to replicate market CDS spreads over the full sample and yearly periods. Next, it examines the sensitivity of the default threshold by analyzing whether there exists an optimal choice of the long-term debt weight in the total value of liabilities, which results in the highest replication ability. Finally, this thesis proposes a new approach for incorporating forward-looking information in the model by computing a VIX index weighted equity volatility parameter and evaluating whether it enhances the Merton model's accuracy for replicating CDS spreads. The VIX index measures the market's expectation of volatility over the next 30 days (CBOE, n.d.). By capturing investor's anticipation, it is an appropriate proxy for market uncertainty. The hypothesis is that using the VIX weighted volatility as an input in the Merton model better incorporates risk than using the standard historical volatility measure. As such it is expected to give a better estimate of market risk, here evaluated in the form of CDS spreads. To the author's knowledge, this specific approach has not been explored in this way before and is therefore a valuable addition to the literature.

The thesis is organized as follows. Chapter 2 provides the theoretical framework, focusing on CDS spreads and the Merton model. Chapter 3 presents a review of the literature. Chapter 4 details the dataset and variables used to implement the model. Chapter 5 explains the methodology and implementation. Chapter 6 presents the results, comparing model implied CDS across different specifications and market conditions. Additionally, the chapter includes a discussion of findings and suggestions for further research. Finally, Chapter 7 concludes the thesis.

2 Theoretical Framework

The following chapter begins with an introduction to credit risk and the CDS market and precedes with an overview of the Merton model. Then, a derivation of the Merton model is carried out, and an expression for implied credit spreads is derived.

2.1 Credit Risk and the CDS Market

There are several reasons why financial entities are concerned with credit risk. Given that credit risk has the potential to influence the allocation of capital, the likelihood of insolvency, and the value of assets, entities often aim to monitor and mitigate it (Melicher & Norton, 2017). Credit risk management is also outlined in regulatory requirements that banks must comply with, such as the Basel III framework, which specifies banks' minimum capital requirements (Basel Committee on Banking Supervision, 2011). Hedging is a well-established strategy to lower risk exposure or provide insurance against unfavorable outcomes (Melicher & Norton, 2017). To protect against credit risk, the owner of a risky asset can shift default risk to a third party, which requires a credit spread in exchange for bearing the credit risk. The spread, in turn, reflects the yield differential between the risky bond and a risk-free bond of the same maturity (Hull, 2023)

CDS is a popular measure of spreads and serves as a derivative that allows market participants to hedge corporate bond positions. It allows for credit risk trading, where the agreements are typically negotiated directly between two parties (Hull, 2023). For instance, if an investor or bank holds a corporation's 5-year maturity bond as an asset on its balance sheet, it can buy a 5-year maturity CDS contract from a third party. This third party is considered the seller of the CDS contract. In exchange for periodic payments to the seller, the buyer is protected until the contract reaches maturity or if a credit event occurs (Blanco et al., 2005). [1]

The periodic payments that the buyer makes are known as the CDS spreads. They are measured in basis points (100 bps = 1 percent) and represent a percentage of the notional principal (i.e. the value of the bond that payments are calculated from) (Bharath & Shumway, 2008). The bid spread represents the annual premium a buyer is willing to pay to obtain credit protection, while the ask spread is the premium a seller requires to provide the protection. In the CDS market, market makers (e.g. a large bank) play an important role in providing liquidity by quoting bid and ask prices for CDS contracts simultaneously. If a market maker quotes a 5-year CDS on a firm with a bid of 150 bps and an ask of 160 bps, then the market maker is

[1] In this context, a credit event is identified as a firm defaulting, resulting in the halt of periodic payment.

willing to pay 1.5 percent to purchase protection and 1.6 percent to provide protection. The 10-bps difference between the prices captures the bid-ask spread, which reflects the compensation of the market marker for taking on the risk and providing market liquidity (Hull, 2023). On the occurrence of a credit event, the buyer's loss is compensated by the seller, which is usually the difference between the face value of debt and post default market value of debt.

CDS captures the perceived credit risk by the market for a given firm. Therefore, it does not necessarily correspond to the firm's actual creditworthiness, as it is the market's perception of the firm's ability to meet its obligations. Thus, it is important to keep in mind that the observed CDS spreads are defined by the market, and as such, there are potential gaps between pricing and underlying risk, creating opportunities for flawed contracts (Hull, 2023). When CDS spread increases, it signals a higher perceived credit risk by market participants, who demand greater compensation for bearing the potential default risk of the entity in question, widening the credit spreads (Melicher & Norton, 2017). The reverse is true if a position becomes less risky, with economic upturns characterized by optimistic investors and narrowing spreads.

CDS were first introduced by J.P. Morgan in the early 1990s and started to grow as they became widely traded instruments in over-the-counter markets (Hull, 2023). [2] The Bank for International Settlements' (BIS) first observation of issued CDS in 2004, was approximately $6 trillion. The market peaked at $61.2 trillion at the end of 2007 and a decade later they declined to $9.4 trillion (Aldasoro & Ehlers, 2018). In response to regulators' concern that CDSs contributed to systemic risk, post global financial crisis regulatory reforms mandated the central clearing of standardized CDS contracts and introduced margin and collateral requirements to mitigate counterparty risk (IMF, 2010). While more complex credit derivatives stopped being issued following the crisis, regular CDSs, with a relatively easier structure, continued to be actively traded on the market (Hull, 2023). CDS instruments remain an important tool within the U.S. financial system, particularly for large corporations with liquid debt markets and for managing bank credit portfolios through risk mitigation and regulatory capital relief.

[2] Over-the-counter markets are decentralized markets where financial instruments are traded directly between two parties without a central exchange or broker.

2.2 The Merton Model

In the seminal 1974 paper, Merton introduces a structural model for credit risk, which has since become the basis for other models in the field (e.g. Moody's KMV-Merton extension). The Merton model estimates the probability that a firm will default by looking at a its balance sheet, namely its assets and liabilities. Here, a firm defaults when the value of its total debt to be repaid exceeds the value of total assets, at the time debt maturity. Looking at a firm's balance sheet, a firm's assets today A_0 equal the combined value of the debt D_0 and equity E_0 today.

$$A_0 = D_0 + E_0 \tag{2.1}$$

For the model to hold, certain assumptions are identified. First, the model assumes that debt is structured as a zero-coupon bond with a fixed maturity time of T and a nominal value of K. Moreover, the firm is not able to issue new debt or equity until time T, at which time the firm is liquidated.

By interpreting the firm's equity as a long call option of the firm's assets, the model allows for the widely used Black-Scholes option pricing model to be applied (Black & Scholes, 1973). The Black-Scholes model determines the fair value of European options, which are contractual agreements that derive their value from the performance of an underlying asset. The financial derivative grants the buyer the right but not the obligation to buy or sell the underlying asset at the strike price. European options can only be exercised at a specified expiration date (Melicher & Norton, 2017).

In the Merton model, the equity holder's payoff of the call option is defined as

$$E_T = \max[A_T - K, 0] \tag{2.2}$$

There are only two possible scenarios identified, namely, that the firm can either meet its obligations or default on its debt at the specified time T. The second scenario of the firm defaulting only occurs if the assets are lower than the nominal value of the zero coupon bond (i.e. if $A_T < K_T$), this means that the value of equity is zero. Meanwhile, in the first scenario, assets are greater than the amount of debt principal and interest to be paid (i.e. $A_T > K_T$). If, at T, the firm's asset value exceeds its liabilities, equity holders exercise their option and claim the remaining value $A_T - K$.

Since the Merton model builds upon the Black-Scholes option pricing framework, by treating equity as a call option on the firm's assets, it inherits certain assumptions from it.

In the option pricing model, the main assumptions are as follows:

1. The underlying asset S is the stock price. S follows a Geometric Brownian Motion (GBM) stochastic process.
2. The market is frictionless, with no transaction costs or taxes.
3. There are no dividends on the underlying asset S
4. The call option matures are time T, has strike price K, and can only be exercised at maturity.
5. The risk-free interest rate r, growth rate μ, and stock return volatility σ are known and constant.

Building on the work of Black and Scholes (1973), Merton (1974) suggests that the firm's asset value A should exhibit similar dynamics as those of a single stock S. As such the value of a firm's underlying asset follows a GBM process

$$\mathrm{d}A = \mu_A A\mathrm{d}t + \sigma_A A\epsilon\sqrt{\mathrm{d}t} \tag{2.3}$$

where μ_A and σ_A are the expected return and standard deviation of asset returns, respectively, and $\epsilon \sim \Phi(0,1)$. Additionally, the logarithmic value of A_T follows a normal distribution of

$$\ln A_T \sim \Phi(\ln A_0 + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T \,, \sigma_A\sqrt{T}) \tag{2.4}$$

Equity value is assumed to follow the same dynamics as asset value (i.e. a GBM)

$$\mathrm{d}E = \mu_E E\mathrm{d}t + \sigma_E E\epsilon\sqrt{\mathrm{d}t} \tag{2.5}$$

Using Ito's formula, an expression of how equity follows a stochastic process in relation to assets can be obtained

$$\mathrm{d}E = \left(\frac{\partial E}{\partial t} + \mu_A A\frac{\partial E}{\partial A} + \frac{1}{2}\sigma_A^2 A^2\frac{\partial^2 E}{\partial A^2}\right)\mathrm{d}t + \sigma_A A\frac{\partial E}{\partial t}\epsilon\sqrt{\mathrm{d}t} \tag{2.6}$$

Based on the framework in Black and Scholes (1973) and Merton (1974), the market value of equity is defined as

$$E_0 = A_0\mathrm{N}(\mathrm{d}_1) - Ke^{-rT}N(d_2) \tag{2.7}$$

where N() is the standard normal cumulative distribution function and r is the risk-free rate. Equations 2.6 and 2.7 are especially important for the practical implementation of the Merton model, as later described in Chapter 5.

Moreover, d_1 and d_2 are defined as

$$\mathrm{d}_1 = \frac{\left(\ln\frac{A_0}{K}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{2.8}$$

$$\mathrm{d}_2 = \frac{\left(\ln\frac{A_0}{K}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{2.9}$$

By transformation of equation (2.8) and (2.9) above, one obtains

$$\mathrm{d}_1 = \frac{\left(\ln\frac{A_0 e^{rT}}{K}\right)}{\sigma_A\sqrt{T}} + \frac{\sigma_A\sqrt{T}}{2} \tag{2.10}$$

$$\mathrm{d}_2 = \mathrm{d}_1 - \sigma_A\sqrt{T} \tag{2.11}$$

Leverage capturers the firm's ability to meet its debt obligations and it is defined as

$$L = \frac{Ke^{-rT}}{A_0} \tag{2.12}$$

Equation (2.12) allows for the simplification of equation (2.7) and (2.10)

$$E_0 = A_0[N(d_1) - LN(d_2)] \tag{2.13}$$

$$d_1 = \frac{-\ln(L)}{\sigma_A\sqrt{T}} + \frac{\sigma_A\sqrt{T}}{2} \tag{2.14}$$

From equation (2.1) the value of debt is known to be $D_0 = A_0 - E_0$, combining this with the expression for the value of equity in equation (2.13) gives

$$D_0 = A_0 - A_0[N(d_1) - LN(d_2)] = A_0[1 - N(d_1) + LN(d_2)]$$
$$= A_0[N(-d_1) + LN(d_2)] \tag{2.15}$$

since $1 - N(d_1) = N(-d_1)$. Note that the market value of debt is the present value of the nominal value of debt,

$$D_0 = Ke^{-Ty} \tag{2.16}$$

where y is defined as the yield to maturity of the credit risky debt.

Further, the yield to maturity can be obtained by combining the two equations for the value of debt (2.15 and 2.16), dividing by Ke^{-rT} and inserting the formula for leverage

$$Ke^{-Ty} = A_0[N(-d_1) + LN(d_2)]$$

$$\Leftrightarrow \; y = r - \frac{1}{T}\ln\left(\frac{N(-d_1)}{L} + N(d_2)\right) \tag{2.17}$$

The Merton model implied credit spread (s) is defined as the difference between the yield to maturity and risk-free rate, as such

$$s = y - r = -\frac{1}{T}\ln\left(\frac{N(-d_1)}{L} + N(d_2)\right) \tag{2.18}$$

The credit spread depends on the asset volatility (σ_A), leverage (L) and maturity (T). This derivation of the implied credit spread is similar to the one portrayed in Gemmill and Marra (2019) and Hull et al. (2004). It requires no specific assumptions about the recovery rate (i.e. the proportion of the amount lent that can be recovered in case of default), since it is implicitly implied in equation 2.18.

3 Literature Review

The following chapter discusses alternative credit risk methods, and highlights the Merton model's strengths and limitations based on previous findings. The review also covers the model's sensitivity parameters and model specification. This establishes the foundation of this thesis research objectives.

3.1 Models and Methods for Estimating Credit Risk

Among the methodologies used to assess credit risk are accounting-based approaches, which use accounting derived variables to predict corporate financial distress. These include Altman's Z-score discriminant analysis (Altman, 1968) and Ohlson's conditional logit model (Ohlson, 1980), both of which rely on periodically updated, backward-looking information. Additionally, credit rating agencies offer standardized assessments of a borrower's creditworthiness. However, they tend to follow a through-the-cycle approach with the aim of maintaining rating stability. As such, they only respond to fluctuations if they are expected to impact long term creditworthiness (Hull, 2023). Callen et al. (2007) find that credit ratings often lag behind CDS spreads. The stickiness of credit ratings reduces their applicability for credit risk assessment in short term volatile market conditions.

By incorporating market-based inputs, the Merton model has been found to outperform accounting models, providing more information about default probabilities (Hillegeist et al., 2004). Previous literature evaluating the Merton model has highlighted its effectiveness in ordinally ranking firms based on their likelihood of experiencing financial distress (Afik et al., 2016; Jessen & Lando, 2015; Tudela & Young, 2005). This supports the notion that the model serves as a valuable indicator of a firm's relative riskiness compared to others. However, the application of the model is limited to publicly traded firms since the necessary inputs are typically only observable for them. In this context, it should be emphasized that the model relies on the premise that markets are efficient and well-informed, as pointed out by Bharath and Shumway (2008). Meanwhile, Hillegeist et al. (2004) stress that markets may not always efficiently incorporate all publicly available information related to default risk, a potential shortcoming.

Research on the Merton model's predictive power includes both the foundational structural version and several extensions, one well-known being the KMV-Merton (Crosbie & Bohn, 2002). Moreover, when applying the Merton model, different specifications have been used to solve the estimated asset value and asset volatility, which are otherwise unobservable.

The textbook approach does this by solving two nonlinear equations simultaneously (see e.g. Eom et al., 2004; Hillegeist et al., 2004; Campbell et al., 2008). Meanwhile, the single equation approach includes simplified assumptions, such as setting asset volatility equal to historical equity volatility (see the naïve model in Bharath & Shumway, 2008), and the alternative iterative method uses equity value to infer a time series of daily assets (see e.g. Aretz & Pope, 2013; Campbell et al., 2008; Vassalou & Xing, 2002).

3.2 Merton Model Assumptions and Parameter Sensitivity

The standard Merton model simplifies the firm's debt structure. By differentiating between short-term and long-term debt, the KMV-Merton is argued to provide a more realistic measure of default risk (Crosbie & Bohn, 2002). Several papers have followed the approach, choosing the book value of debt to be comprised of short-term debt plus half the long-term debt, to adequately capture the financing constraints of firms (Aretz & Pope, 2013; Bharath & Shumway, 2008; Vassalou & Xing, 2004). Afik et al. (2016) examine the predictive power of the Merton model using seven different weights of long-term debt. When they apply the single equation method the results are similar to the KMV approach, with them finding an optimal long-term debt of weight of 0.5. In contrast, when they use the two equation Merton model, the optimal weight is found to be 0.1.

Furthermore, the standard Merton application commonly uses historical equity volatility as the input for the equity volatility. Meanwhile, it has been highlighted that incorporating forward-looking information can enhance model accuracy (Bharath & Shumway, 2008). Hull et al. (2004) find that an option-based implementation to the traditional calibration improves the accuracy of estimating CDS. Using option implied volatility rather than historical data may lead to tail risk being better incorporated. However, scarce firm data on option-implied volatility limits its practical use (Afik et al., 2016).

While the outputs derived from the Merton model are economically intuitive and relatively simple in their formulation, their validity rests on the framework's assumptions, as outlined in Section 2.2, and hence may not hold under alternative asset dynamics (Duffie & Singleton, 2003). Heavily relying on its theoretical framework, the model has been criticized for not adequately capturing sudden and severe market disruptions. In fact, empirical evidence has found wider tails than those captured under the normal distribution assumption, leading to an underestimation of default probabilities (Crosbie & Bohn, 2002). Several papers investigate alternative dynamics since they are valuable when traditional models fail to capture the characteristics of asset prices. These include incorporating stochastic volatility (see Heston, 1993) and jump processes (see e.g. Jessen & Lando, 2015; Bai et al., 2020). Collin-Dufresne et al. (2001) observe implied volatility smiles, suggesting that markets anticipate return distributions with fatter tails and non-constant volatility. This finding contradicts the assumptions of the Black Scholes model. Additionally, Jessen and Lando (2015) find that when there are substantial jumps in asset value, the model is less reliable in its ability to rank the default risk of firms.

The Merton method seems to underestimate credit spreads relative to market levels, particularly for safer firms or shorter maturities (Bai et al., 2020). Moreover, Amato and Remolona (2003), suggest that investors require extra compensation to bear the risk of rare but extreme losses. This non-diversifiable risk helps explain why credit spreads are higher than traditional models predict. The credit spread puzzle may thus partly stems from the Merton model's inability to capture the skewed nature of real-world default events. Bai et al. (2020) explicitly model firm asset values using a jump-diffusion process, allowing for continuous price changes (as in the standard Black-Scholes framework) as well as sudden, discrete jumps. They find that assigning discrete price jumps helps explain the puzzle, highlighting the potential of volatility-based extensions to the model.

3.3 Relevance and Hypothesis Development

From the previous discussion, it is evident that the primary strength of the standard Merton model is not in its ability to price credit risk accurately. Despite its limitations, the model remains theoretically insightful and serves as an appropriate baseline for this thesis. This baseline allows for an extension to include a forward-looking volatility measure, which can be broadly applied to public firms. Although option-implied volatility has been shown to improve the model's accuracy, its application is restricted by data availability, as it is only observable for firms with actively traded options (Afik et al., 2016). In contrast, the VIX index, which captures the market's expectations of the S&P 500, offers a compelling alternative forward-looking market risk indicator. Incorporating a VIX-based volatility weight into the Merton model raises the question of whether including forward-looking information more broadly is a possible extension that increases the model's accuracy.

Moreover, when estimating corporate default probabilities, the value of liabilities is a valuable sensitivity parameter (Crosbie & Bohn, 2002; Afik et al., 2016). While the primary objective of this thesis is to assess how the VIX weighted volatility influences model accuracy, it also examines the model's sensitivity to the optimal weight of long-term debt. Building on these considerations, this thesis pursues an evaluation through three objectives: assessing the standard Merton model's ability to replicate market CDS spreads across different market conditions, evaluating the model's sensitivity to varying default thresholds, and lastly testing whether a VIX weighted volatility enhances CDS spread replication. From these three objectives, the following hypotheses are formulated:

> *Hypothesis 1*: The standard Merton model provides an appropriate risk indicator but severely underestimates CDS spreads.
>
> *Hypothesis 2*: An optimal weight of long-term debt exists that most accurately replicates market CDS spreads.
>
> *Hypothesis 3*: Incorporating forward-looking information in the form of VIX weighted volatility improves the model's ability to capture market credit risk.

By examining predictive accuracy and parameter sensitivity, this thesis aims to contribute to the evaluation of the Merton model and its practical applicability.

4 Data

The following chapter outlines the data used for the model evaluation and how the data was transformed. Covering firms from 17 different industries, the period spans from the 1st of January 2015, to the 31st of December 2024. All data was obtained using the Capital IQ Excel Plug-in provided by S&P Global Market Intelligence (2025), with the exception of the CBOE Volatility Index (VIX), which was retrieved from the Federal Reserve Bank of St. Louis (FRED) (2025).

The dataset consists of firms included in the NASDAQ Composite Index. The selection of the broad index is methodologically justified on two grounds. Firstly, it encompasses diverse US industries, thereby mitigating potential sector-specific biases. Secondly, it maximizes the sample size, originally encompassing over 3,000 US-based and international companies (Nasdaq, n.d.). Quarterly observations were chosen, as they serve as the lowest common frequency across key variables. While higher frequency data, such as monthly or weekly, potentially offers more variation, such data is unobservable for the variables needed when implementing the Merton model. For instance, firm-level debt composition is only reported on a quarterly basis.

Five-year CDS contracts were selected to evaluate the model's ability to estimate credit risk, as they represent the most commonly traded and liquid maturity in the CDS market (Hull, 2023; Aldasoro & Ehlers, 2018). Moreover, the mid-spread was used, as it reflects the average between the bid and ask quotes. Using solely listed firms with available five-year CDS contracts, as of 2024, the initial dataset was reduced to a preliminary sample of 90 firms. To ensure consistency and data completeness, the sample was further restricted to only US-based firms with CDS spread data over the entire observation period. Following this refinement, the final sample comprised 44 firms. See Appendix A for the list of companies. With 40 quarterly observations per firm, the resulting panel dataset contains 1,760 unique observations (44 firms × 40 quarters).

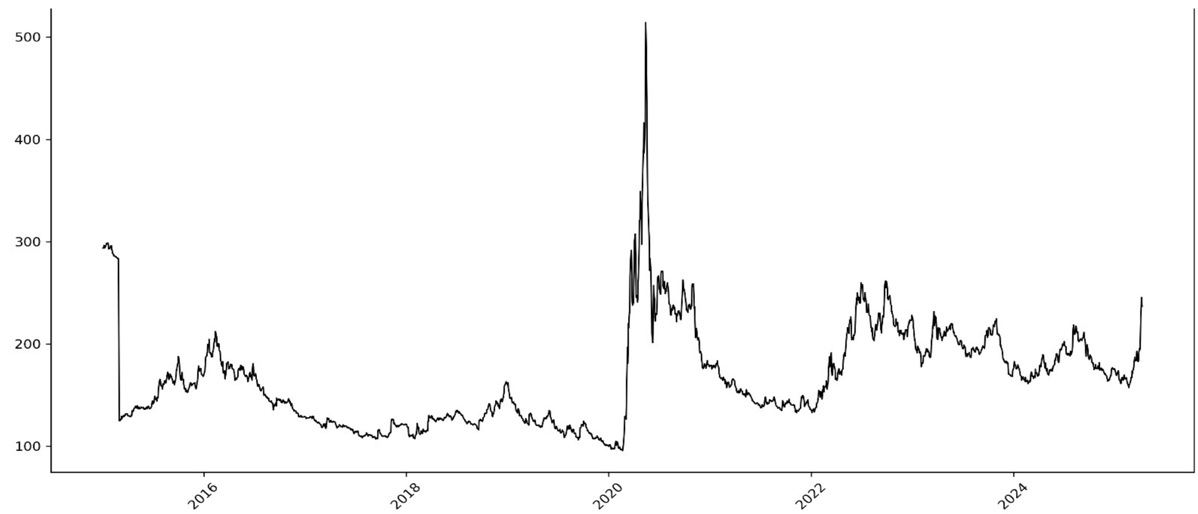

Figure 4.1: Daily average market CDS spread (mid) in bps for the chosen 44 companies 2015-2024. (Source: S&P Global Market Intelligence (2025) & authors calculations)

Figure 4.1. depicts the daily CDS mid spreads for the ten-year period. Following a sharp drop in early 2015, CDS spreads remained relatively stable until 2019, fluctuating between 100 and 200 bps with no significant spikes. This indicates a period of relatively low perceived credit risk. In early 2020, a sharp surge exceeding 500 bps is observed, corresponding with the onset of the COVID-19 pandemic, triggering a sudden increase in credit risk expectations. During 2021 and 2022, spreads gradually declined from pandemic highs. In 2022, a noticeable upward trend reemerges, following tightening monetary policy and broader macroeconomic stress.

As input in the Merton model, daily observations of market capitalization (as a proxy for equity value) were collected and aggregated into quarterly averages. Moreover, the daily share price was collected to estimate historical equity volatility. Retaining solely companies that have been actively listed for at least 10 years on the NASDAQ, volatility was calculated for firms with continuous trading data. Using solely trading days (approximately 250 days yearly), each firm's log returns were computed, as they are time-additive and considered appropriate for statistical modeling. Lastly, volatility was converted to a quarterly frequency to match the frequency of other model inputs.

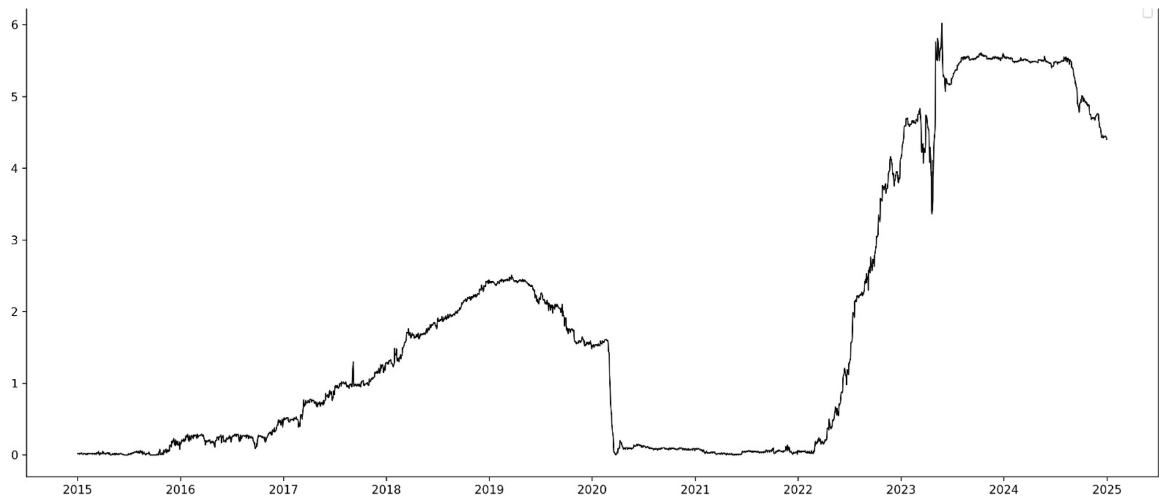

Figure 4.2: Daily 1-month US Treasury Bill rate 2015-2024 in percent. (Source: S&P Global Market Intelligence (2025) & authors calculations)

The 1-month US treasury bill rates were collected as a proxy for the risk-free rate. These were transformed in a similar manner to the equity value. As seen in Figure 4.2 the rate rises gradually from 2015 to 2019, then drops sharply to nearly zero during the COVID-19 pandemic, followed by a dramatic spike starting in 2022. These shifts across time enable an interesting analysis of the Merton model's performance under varying market conditions.

While the Merton model is fundamentally market-based, it incorporates accounting data in the form of firm debt. Quarterly balance sheet data was collected to estimate this, with current liabilities serving as a proxy for short-term debt (to be paid within one year) and long-term liabilities representing debt with maturities exceeding one year.

Finally, the VIX index was used to compute a new weight for equity volatility. The index is based on S&P 500 option prices and serves as a forward-looking indicator of investor sentiment and anticipated market risk (FRED, 2025). A majority of the firms used in the analysis are constituents of the S&P 500, making it an appropriate forward-looking weight in the sample. A higher VIX suggests increased uncertainty in the market, while a lower VIX indicates greater confidence and stability.

5 Methodology and Implementation

This chapter outlines the methodology for evaluating and testing the hypotheses. Specifically, it describes the econometric regression technique and error measurement approach used to evaluate the Merton model and to compare the theoretically implied CDS spreads to the market ones.

5.1 Merton Model Implementation and Optimization

As discussed in the literature review, certain assumptions of the model may not hold in real world application. Despite this, the Merton model still provides a structural framework to estimate the unobserved parameters with a closed form solution. Specifically, the empirical implementation of the model requires estimates of a firm's asset value (A_0), asset volatility (σ_A) and expected asset return (μ_A).

In practice, the expected asset return is often assumed to grow in parallel (i.e. same growth rate) with the risk-free rate (see e.g. Afik et al., 2016; Bai et al., 2020). This implies that the default probability is risk neutral. Typically μ_A is higher than r, since risk averse investors need to be compensated (Hull, 2023). In this thesis the expected asset return is set equal to the risk free rate (i.e. $\mu_A = r$). This choice is based on Afik et al. (2016) findings that using the risk-free rate as the expected asset return outperforms other tested assumptions for the two-equation model. Starting from the Black-Scholes formula, as presented in Chapter 2, the market price of equity is

$$E_0 = A_0 \mathrm{N}(d_1) - Ke^{-rT} N(d_1) \tag{5.1}$$

The market value of equity is known for publicly traded firms. The practical implementation of the Merton model involves reversing equation (5.1) and solving for A_0 and σ_A. Since there are two unknowns, a second equation is needed. Jones, Mason & Rosenfeld (1984) made a significant contribution to the field with their empirical application of the Merton model. Using Ito's formula, they provide the following equation for the instantaneous (i.e. should hold all the time) standard deviation of equity

$$\sigma_E = \sigma_A \frac{A}{E} \frac{\partial E}{\partial A} \tag{5.2}$$

The equation above can be transformed to the following equality

$$\sigma_E E_0 = \sigma_A A_0 N(d_1\ ) \tag{5.3}$$

This thesis employs the textbook approach of solving two non-linear equations simultaneously (Eom et al., 2004; Hillegeist et al., 2004; Campbell et al., 2008). Thus, the practical implementation of the Merton model here involves solving for A_0 and σ_A using equations (5.1) and (5.3). Successfully estimating the unknowns requires restating the equations in a form that is suitable for simultaneous numerical solving. The following expressions of the two equations are computed

$$f_1 = A_0\,\mathrm{N}(d_1) - Ke^{-rT}\mathrm{N}(d_2) - E_0 \tag{5.4}$$

$$f_2 = \frac{A_0}{\mathrm{E}_0}\mathrm{N}(d_1)\sigma_A - \sigma_E \tag{5.5}$$

and A and σ_A are solved for $f_1 = 0$ and $f_2 = 0$.

As outlined in Chapter 4, the data spans over 10 years for 4 quarters for 44 different firms, meaning that this system of equations has to be solved 1,760 times in order to find the optimal values for A_0 and σ_A, for each of the firm observations. To perform this optimization, a popular quasi-Newton algorithm known as the BFGS method is applied. The method is suitable for solving non-linear optimization problems without restrictions (Nocedal & Wright, 2006). The minimization starts with an initial guess for A_0 and σ_A. In this analysis, the initial guess for the firm's asset value is set equal to its liabilities (i.e. $A_0 = D_0 + E_0$). For the asset volatility, the initial guess is that it is equal to equity volatility (i.e. $\sigma_A = \sigma_E$). These initial guesses differ for every observation and as such they are updated for every computation, making them nonuniform. The BFGS method iteratively creates an estimate of the Hessian matrix to find a local minimum of the following objective function

$$f(A_0, \sigma_A) = \sqrt{(f_1)^2 + (f_2)^2} \tag{5.6}$$

The optimization results provide estimated values for both A_0 and σ_A. [3]

5.2 Variable Computation

Following the KMV-Merton, the weight of long-term debt, k, is set to 0.5 in the preceding analysis (with the exception of the sensitivity analysis). As discussed in Chapter 3, the KMV-Merton approach is argued to provide a more realistic measure of default risk and to appropriately capture firms' financing constraints (Aretz & Pope, 2013; Vassalou & Xing, 2004).

[3] For additional insight, a comprehensive derivation of the BFGS method can be found in chapter 6.1 of Nocedal & Wright (2006).

The value of debt is described as follows

$$Value\ of\ Debt\ (K) = Short\ term\ Debt + k \times Long\ term\ Debt \tag{5.7}$$

For the calculation of the volatility weights, the last observation within each quarter is used (VIX_{last}) and then divided by the average of the quarter (VIX_{avg}). This ratio is applied as a weighting factor to historical equity volatility σ_E, thereby incorporating forward-looking information. If the ratio is above one, the market expects relatively higher future volatility. The new volatility estimate σ_{VIX} is expressed in the following way

$$\sigma_{VIX} = \sigma_E \times \frac{VIX_{last}}{VIX_{avg}} \tag{5.8}$$

The estimated values of A_0 and σ_A from the optimization enable the calculation of three relevant risk measures, namely implied CDS spreads, distance to default (DD), and probability of default (PD). The implied CDS spreads are calculated using equation 2.18 and plugging in the relevant parameters. The resulting CDS spreads are then multiplied by 10,000 in order to get them in bps. Expanding on the foundations of the Merton model, Crosbie & Bohn (2002) formalize the distance to default risk measure and the corresponding probability of default. The distance to default is the number of standard deviations that a firm's asset value is from default and is defined as

$$DD = \frac{\ln\left(\frac{A_0}{K}\right) + \left(r_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{5.9}$$

Within the Merton model, the stochastic component of a firm's asset returns is assumed to follow a normal distribution. The probability of default is expressed using the cumulative normal distribution and is computed directly from the distance to default measure

$$PD = N(-DD) \tag{5.10}$$

The distance to default and probability of default equations offer insight into how sensitive default risk is to changes in the model's parameters. Notably, a lower rate of asset return (μ_A), a higher variability of the asset value (σ_A) and a higher leverage all increase the probability of default, ceteris paribus. An increase in the distance to default intuitively implies a decrease in the default probability, and vice versa.

5.3 Evaluation Methodology

To address the hypotheses of this thesis, the following simple linear regression model will be used to evaluate how well the implied CDS spreads replicate the market observed CDS spreads

$$CDS_T^{market} = \beta_0 + \beta_1 CDS_T^{implied} + \epsilon_T \tag{5.11}$$

where CDS_T^{market} and $CDS_T^{implied}$ are the dependent and independent variables, respectively. β_0 is the intercept, β_1 the slope parameter and ϵ_T is the error term (Wooldridge, 2019; Campbell et al., 2008). [4] Two additional evaluation measures will be used, namely the mean absolute error (MAE) and mean absolute percentage error (MAPE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| CDS_T^{market} - CDS_T^{implied} \right| \tag{5.12}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{\left| CDS_T^{market} - CDS_T^{implied} \right|}{CDS_T^{market}} \times 100 \tag{5.13}$$

The MAE is an average of the absolute prediction errors in bps and the MAPE represents the absolute errors as a percentage of the observed market CDS (Wooldridge, 2019). Lower values of these two measures indicate a better model fit and the MAPE is insightful when comparing different levels of CDS.

[4] It is important to note that here a simple linear model is being used to assess the ability of a structural model's output to replicate a market variable. If one is interested in explaining the many determinants of the observed market CDS spreads then a more complex regression models may be appropriate. However this is not the focus of this thesis.

6 Results and Discussion

In the upcoming chapter, the results of the analysis will be presented. The chapter starts by showing the estimations from the standard Merton model and compares them to the market observed CDS over the different periods. Following is a sensitivity analysis of varying the default threshold of the model aimed at checking if the replication ability of the implied CDS spreads improves for a specific debt level. Next, the results derived from incorporating the VIX is evaluated. The chapter concludes with a general discussion of the findings and potential extensions for further research.

6.1 Standard Merton Model

The optimization and theoretical calibration of the implied CDS spreads only produced 227 positive values, while 1,533 observations (a vast majority of the sample) yielded zero or marginally negative values. This imbalance demonstrates that there is a clear limitation in the models ability to effectively estimate CDS spreads, since they are always positive in the real world. This result is consistent with Gemmill & Marra (2019), who point out that the standard approach of estimating CDS spreads through the Merton model yields spreads close to zero. In order to better evaluate the models ability to explain market CDS spreads, the evaluation outlined in Chapter 5 is solely carried out for the positive values.

Table 6.1.1 presents the result of the regression of the positive implied CDS spreads on the market ones, using the linear model outlined in Section 5.3.[5] The regression is performed on the full time periods as well as for individual years to be able to assess the model's ability to replicate the market CDS in varying market conditions.

[5] Table B.1 in the Appendix displays the same analysis for the full 1,760 observations (i.e. including zero's and marginally negative implied CDS spread values). These are omitted from the main results of the thesis since zeros or negative values do not in practice occur in the financial market.

Table 6.1.1: Results of analysis using implied CDS spreads from the standard Merton model and market CDS spreads.

Period	β_0	β_1	R²	MAE	MAPE	N
Full	73.5378*** (6.9367)	0.2281 (0.8829)	0.0000	73.4362	99.76%	227
2015	137.9391 (119.7846)	-3274674497.0415 (3106515492.3364)	0.1338	103.7425	100.00%	4
2016	65.3887*** (16.9120)	85.0852 (423.1425)	0.0012	66.4586	99.93%	28
2017	41.0856*** (7.6430)	45.0753 (56.4307)	0.0311	43.5676	99.87%	20
2018	31.9710*** (6.0304)	235.3517*** (53.2437)	0.2105	39.6754	99.92%	28
2019	36.1399*** (4.7121)	153.7098** (74.3520)	0.1708	42.7633	99.90%	28
2020	123.0887*** (33.6279)	-3.9457 (2.6917)	0.0029	120.0630	98.97%	38
2021	7.0454*** (0.8521)	379.0067*** (43.3538)	0.7926	8.2837	99.98%	6
2022	98.0695*** (25.8506)	364.4562 (324.5359)	0.0258	108.1389	99.93%	25
2023	95.2237*** (19.9754)	88.4355 (240.3292)	0.0046	98.3698	99.95%	22
2024	51.5896*** (12.7885)	193.6299 (156.1760)	0.0587	61.9597	99.89%	28

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Note: Implied CDS spreads are computed using half of the long term debt (i.e. $k = 0.5$). Solely positive estimates of implied CDS spreads are included in the analysis. For regression, dependent variable is market CDS spreads and independent variable is implied CDS spreads.

The results show that the standard implied CDS spreads derived from the Merton model are not able to replicate the market spreads. When examining the full time period, the implied spreads have no significant effect on market ones and the explanatory power of the linear model is none (i.e. $R^2 = 0$). The MAE and MAPE are also notably high, meaning that the model is a bad fit. The MAE signifies that the average absolute prediction error is 73.4362 bps and the MAPE shows that the model's predictions of CDS spreads deviates from the market CDS by 99.76%, on average. The explanatory power of the model is quite low for most of the years and the coefficient for the implied CDS is only statistically significant in 2018, 2019 and 2021. It is important to recognize that the observation count has been significantly reduced since only positive estimates are included. As such the results across the different time periods should be interpreted with caution. Additionally, a Wald test is carried out to examine if the implied CDS spreads match the market ones and the hypothesis is rejected in all time periods. [6] This rejection further indicates that the two CDS measures deviate from each other, suggesting that there may be other factors that contribute to the market CDS spreads.

[6] The joint hypothesis of the Wald test is $\beta_0 = 0$ and $\beta_1 = 1$. It is rejected in all time periods since the associated p-values are below 0.05

The theoretical foundation that the Merton model relies on suggests that a higher distance to default implies lower CDS spreads. Although the model is unable to replicate the market, it is still insightful to evaluate the distance to default estimates and their relation to market CDS spreads. Table 6.1.2 shows the results of a regression similar to the one in Table 6.1.1, however, now the distance to default is the independent variable. Note that when estimating the asset volatility from the optimization, some estimates were very low (practically zero). Since asset volatility is in the denominator of the distance to default formula, these low values make the distance to default measure explode to unreasonably high values. To account for this, the outliers with a distance to default above the 99th percentile are dropped.

Table 6.1.2: Results of analysis using distance to default from the standard Merton model and market CDS spreads.

Period	β_0	β_1	R^2	N
Full	54.9877*** (5.6649)	-0.4940*** (0.1884)	0.0407	1742
2015	97.5576*** (24.6768)	-1.6996*** (0.5622)	0.0641	173
2016	65.8684*** (8.5125)	-0.8506*** (0.2025)	0.1247	175
2017	43.8806*** (3.9966)	-0.4051*** (0.0773)	0.1077	170
2018	42.9319*** (4.0785)	-0.4102*** (0.0892)	0.0654	174
2019	42.9610*** (3.8539)	-0.4487*** (0.0826)	0.1009	172
2020	96.7753*** (19.2284)	-2.3259*** (0.7026)	0.0658	176
2021	65.9808*** (8.1537)	-0.9632*** (0.1995)	0.1277	175
2022	81.8917*** (12.2773)	-1.3941*** (0.4184)	0.0826	176
2023	53.4931*** (4.3596)	-0.1718*** (0.0503)	0.0345	175
2024	67.6655*** (9.3179)	-0.8241*** (0.2359)	0.0611	176

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1
Note: Distance to default estimates are computed using half of the long term debt (i.e. $k = 0.5$). Outliers in the 99th percentile of distance to default estimates are dropped (18 observations in total).

The results from Table 6.1.2 show that the coefficient of the distance to default variable is statistically significant in all time periods. All of the coefficients are negative meaning, that a decrease in the distance to default (i.e., a higher probability of default) will increase the market CDS spread, and vice versa. This result supports the theoretical relationship between the two variables since theory predicts that a lower distance to default should lead to higher CDS spreads. The explanatory power of the regression models over the time periods is still quite low, meaning that default risk influences CDS spreads only to a certain degree. It is especially interesting to highlight the year 2020, when COVID-19 started. The coefficient on the distance to default is the highest there out of all the years (-2.3259), meaning that a decrease in the distance to default in 2020 would increase the CDS spread more compared to the other years. Interestingly, the relationship seems to hold through all of the years, even with their varying market conditions and the exceptionally high volatility in 2020.

6.1.1 Varying weight of long-term debt

As discussed in Chapter 3, the predictive power of the Merton model can depend on the optimal choice of the long-term debt weight in the total debt input. In order to explore the sensitivity of the weight, an analysis is carried out where the Merton is estimated using varying values of k. These values are defined as a sequence from 0.1 to 1 increasing by an increment of 0.1 each time, meaning that ten new variations of each estimated variable are computed. The estimated parameters of implied CDS spreads and distance to default with the varying k's were evaluated in the same approach as defined in Section 6.1. No consistent level of k was found to provide the highest model explanatory power or lowest error measure over all periods. For illustration purposes, Table B.2 and B.3 in the Appendix show the results for which k's provide the highest explanatory power for each variable. [7] It is notable that lower values (0.1 to 0.4) of k were found to provide slightly more explanatory power compared to higher ones. For the implied CDS spreads, the difference in R^2 compared to the KMV-Merton approach of k = 0.5 was small. Moreover, the lower values of k provided even less positive spread observations. Overall, no strong evidence was found to support the hypothesis that there exists a k which is best suited for the predictive power within the context of this thesis.

6.2 VIX Weighted Merton Model

Table B.4 in the Appendix presents the regression results of the implied CDS spreads calculated with the VIX weighted volatility as an input in the Merton model. It has the same specifications as Table 6.1.1 and the only difference is the use of the VIX weighed volatility. The result from the model is that this way of calculating the implied CDS spreads does not significantly increase the replication ability. However, a valuable insight is that the number of positive implied CDS spreads has grown to 484, while they were only 227 in the standard Merton model. This is a particularly interesting result since it indicates that the Merton model with VIX weighted equity volatility is able to better produce positive implied CDS spreads. Regarding the evaluation

[7] Since the full results of this specific analysis are lengthy and do not provide additional insight beyond showing that no overarching optimal k exists, they are omitted for the Appendix.

metrics, the VIX weighted approach is not found to consistently produce better R^2 nor MAE compared to the standard Merton. However, MAPE is lower for all years with exception to the volatile year of 2020. The explanatory power is still low, and the error measurements relatively high, indicating that incorporating VIX weighted volatility still falls short of capturing market behavior.

Table B.5 in the Appendix replicates Table 6.1.2 using the VIX weighted distance to default as the dependent variable. Although showing similar R^2 findings, the coefficients of the distance to default variable in the regression are statistically significant in all time periods and more negative compared to the standard Merton. Interestingly, this implies that a decrease in the distance to default will increase the market CDS spread more relative to the standard Merton.

6.3 Model Comparison and Findings

The following section provides a detailed discussion and comparison of the two models employed and addresses the characteristics of included firms. Here, the aim is to highlight the results alignment with and deviations from existing literature while also offering further insights into potential explanations for the observed findings. The comparison begins with Table 6.3.1, which presents a comparison of the three different CDS values. In the table, *market* refers to the observed spreads on the market, *standard* represents the implied spreads from the standard Merton model and lastly *VIX* refers to the version of the model that incorporates a VIX-based weight.

Table 6.3.1: Comparison of market CDS spreads and implied CDS spreads computed using standard Merton model and VIX adjusted one.

Period	Group	CDS				Volatility		N
		Avg	Min	Max	Std	σ_A	σ_E	
Full	Market	41.52	2.99	1200.61	61.55			1760
	Standard	0.13	0.00	15.16	1.11	0.14	0.23	227
	VIX	15.07	0.00	3134.90	161.55	0.31	0.50	482
2015	Market	43.39	3.91	1200.61	99.26			176
	Standard	0.00	0.00	0.00	0.00	0.11	0.22	4
	VIX	0.42	0.00	10.30	1.92	0.19	0.49	29
2016	Market	40.49	4.67	329.35	44.87			176
	Standard	0.01	0.00	0.13	0.03	0.13	0.19	28
	VIX	0.47	0.00	16.23	2.67	0.19	0.36	37
2017	Market	29.46	5.64	125.59	27.39			176
	Standard	0.06	0.00	0.50	0.12	0.10	0.14	20
	VIX	0.03	0.00	0.37	0.07	0.19	0.28	45
2018	Market	31.73	4.26	149.36	29.50			176
	Standard	0.03	0.00	0.20	0.06	0.13	0.16	28
	VIX	0.08	0.00	1.16	0.18	0.28	0.40	57
2019	Market	30.14	4.51	129.74	26.75			176
	Standard	0.04	0.00	0.19	0.06	0.14	0.16	28
	VIX	0.08	0.00	0.69	0.16	0.24	0.33	53
2020	Market	56.15	2.99	892.59	105.44			176
	Standard	0.61	0.00	15.16	2.68	0.22	0.46	38
	VIX	86.76	0.00	3134.90	383.15	0.65	1.05	83
2021	Market	37.44	4.96	267.23	41.62			176
	Standard	0.00	0.00	0.02	0.01	0.10	0.18	6
	VIX	0.43	0.00	11.85	2.24	0.20	0.49	28
2022	Market	50.91	5.12	354.29	58.98			176
	Standard	0.03	0.00	0.17	0.05	0.12	0.22	25
	VIX	0.05	0.00	0.79	0.15	0.24	0.45	51
2023	Market	50.05	3.35	290.55	54.91			176
	Standard	0.04	0.00	0.26	0.06	0.14	0.20	22
	VIX	0.10	0.00	2.08	0.32	0.23	0.33	47
2024	Market	45.44	3.11	324.73	61.16			176
	Merton	0.05	0.00	0.24	0.06	0.13	0.20	28
	VIX	0.10	0.00	1.77	0.28	0.30	0.42	52

Note: Solely positive estimates of implied CDS spreads and distance to default are included in the analysis.

Both the standard model and the VIX-adjusted version are not able to estimate market CDS spreads. In almost all cases, they underestimate market spreads, despite the theoretical expectation that credit risk should be reflected in the prices. Although the difference is small, the average CDS spread predicted by the VIX model is higher in all years, except for 2017. This suggests a slight improvement by incorporating forward-looking information.

Incorporating VIX increases estimated volatility compared to using only historical volatility, which partly explains why the VIX-based model produces more positive CDS values across all periods (higher volatility implies higher risk).

Furthermore, since all firms in the sample have been listed on the NASDAQ for at least 10 years, they may be too stable for the model to effectively capture significant credit risk. As the model deems the firms to be very safe, it consequently produces exceptionally low default probabilities (practically zero probability of default), which in turn explains the extremely low implied CDS spreads. This is supported by Bai et al. (2020) as they find safe firms to limit the model's ability to produce positive implied CDS spreads. This argument is also supported by the leverage distribution of the sample (shown in Figure C.1 in the Appendix). The sample's leverage distribution shows that most firms operate at moderate to low leverage levels, which aligns well with the results of low CDS spreads and low probabilities of default. The leverage ratio is a determinant of default risk, with lower leverage indicating lower risk.

The year 2020 produced the highest number of positive CDS values (83 in total)**,** coinciding with the highest observed volatility in the sample. In that year, the model estimates the firms to be less safe, increasing the probability of default which, increases the implied CDS spreads. Although the average CDS values were elevated in 2020, this was largely driven by specific quarters where market risk spiked**,** leading to sharp increases in predicted CDS spreads. While the VIX-adjusted model captured more positive CDS values overall, it also appeared to be sensitive to extreme market conditions**.** In particular, during periods of very high estimated default probabilities, the VIX model generated CDS spreads far exceeding those actually observed in the market**,** suggesting a potential overreaction to volatility. Ultimately, the VIX approach seems to be extreme on both sides of the spectrum. When volatility is low it produces CDS spreads close to zero and when the volatility is very high the model severely overestimates the market CDS spreads.

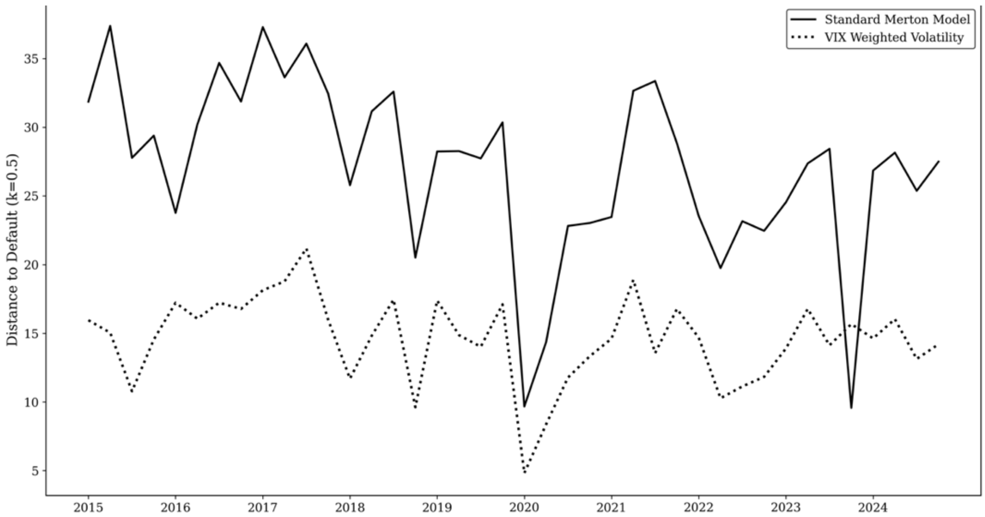

Figure 6.1: Average distance to default for standard Merton model and VIX model 2015-2024 with the 99th percentile dropped (Source: S&P Global Market Intelligence (2025) & authors calculations).

Figure 6.1 visually supports the discussion above, i.e. that higher volatility periods produce lower distance to default and that the standard model estimates firms to be more safe compared to the VIX. Notably, the standard model produces much higher distance to default than the VIX weighted one for most of the years (the end of 2023 is the exception). This, to some extent, explains the higher average of spread values with the VIX model estimates.

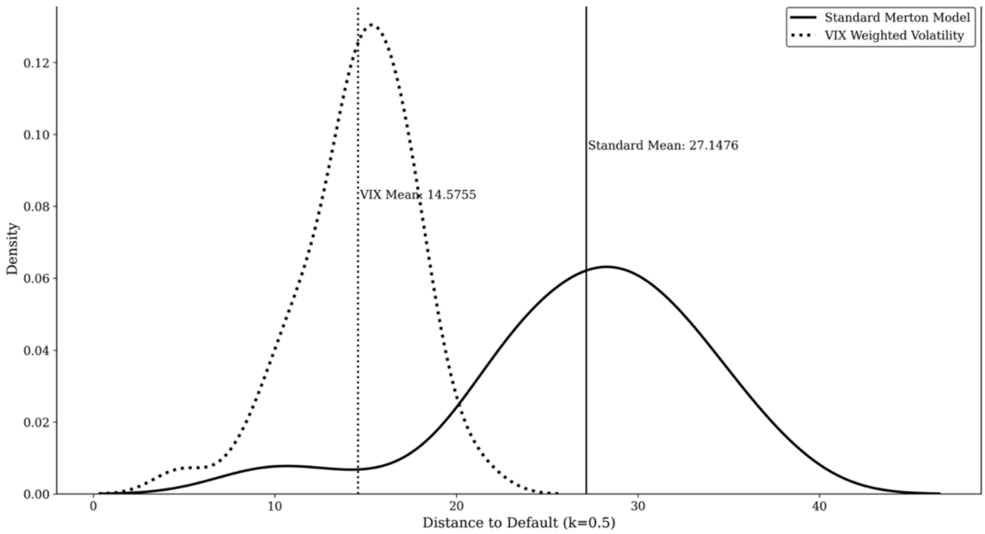

Figure 6.2: Density distribution of distance to default for standard Merton model and VIX model 2015-2024 with the 99th percentile dropped (Source: S&P Global Market Intelligence (2025), FRED (2025) & authors calculations).

Figure 6.2 compares the density of the distance to default for each approach and highlights that the standard deviation from default is much larger for the standard model compared to the VIX weighted volatility one. This indicates that the standard Merton model produces a safer risk measurement than the alternative model does. The VIX weighted volatility captures lower distance to default, resulting in more positive implied CDS spreads that aligns somewhat better with the CDS market spreads.

The significant distance to default coefficients (found in Sections 6.1 and 6.2) illustrate that the risk measure follows market CDS spreads. These findings are consistent with prior research, demonstrating that the model, despite underestimating risk in absolute terms, captures the relative riskiness of firms. While theory suggests that expected losses should be priced in, CDS spreads seem to also reflect tail risks. These rare but severe losses are not fully captured by the models**.** Additional factors such as systemic risk, risk premia, or market sentiment may contribute to higher market spreads.

6.4 Extensions and Further Research

While the VIX weighted input does not accurately estimate market CDS spreads in absolute terms, it produces positive implied spreads for a subset of the firms. Given that previous studies (Jessen & Lando, 2015; Tudela & Young, 2005), primarily assessed models' ranking ability, a natural extension would be to evaluate whether the order of positive implied CDS spreads corresponds to the order of actual market CDS prices (highest to lowest). The VIX weighted approach could also be applied to evaluate the models ranking ability of defaulted firms. Both evaluations would assess whether incorporating the VIX weight enhances the model's ranking ability in a similar manner to what firm-specific option-implied volatilities have been found to do. Additionally, the data sample is limited to companies with CDS contracts available throughout the entire period. A potential extension could involve restricting the analysis to more recent years, during which CDS spread data is available for more companies.

Moreover, as the bond yield spread should approximately equal the CDS spread, researchers have previously applied the Merton model to estimate bond yield spreads (Hull, 2023). Thus, another valuable addition could be to evaluate the new volatility measure on the bond yield spread, as there is generally more bond yield data available than CDS spread data.

Lastly, the results of this thesis, specifically the severe underpricing of CDS spreads in the Merton framework, indicate that there may be other important aspects to successfully replicate market-observed CDS spreads. Upon further examination of the sample, excess kurtosis (>3) in the log return distribution is observed, indicating heavy tails. This result persists even after adjusting for outliers (with the kurtosis decreasing to 1.7368), which notably deviates from normality (Wooldridge, 2019).

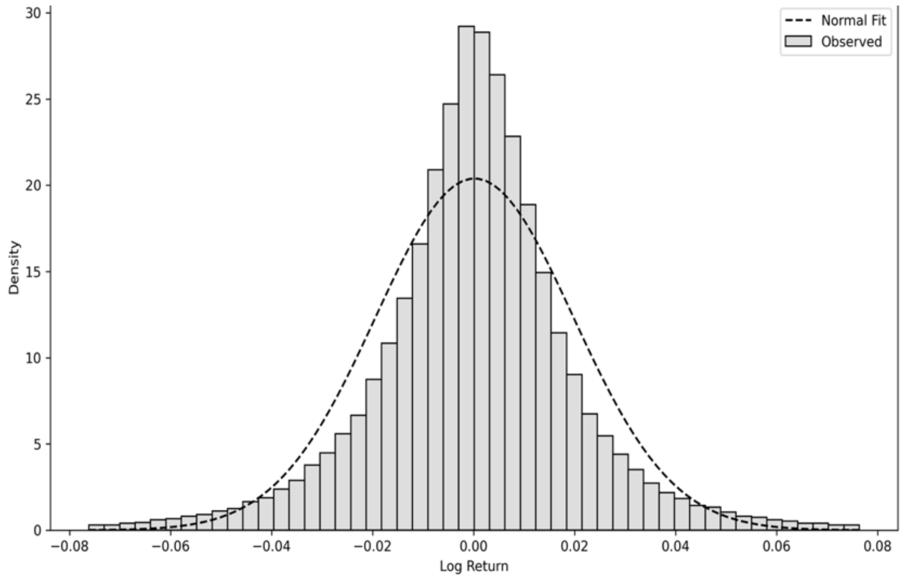

Figure 6.3: Distribution of log stock returns, outlier adjusted. Histogram of observed distribution, with a distribution fit (dashed line) (Source: Capital IQ (2025) & authors calculations).

This finding challenges the assumption of normally distributed returns, which underpins the Merton model. Consequently, assumptions within the Merton framework, such as constant volatility and lognormal asset dynamics, may be overly restrictive in capturing key characteristics of financial markets and in accurately estimating implied CDS spreads. The result aligns with Crosbie & Bohn (2002), pointing out empirical evidence of wider tails, which lead to an underestimation of default probabilities. Further research could explore alternative models that relax these assumptions, such as Heston (1993), which allows for stochastic volatility, Bai et al. (2020) allowing for discrete value jumps or Duan (1995), which relaxes constant volatility via a GARCH-based approach. Such extensions may enhance the empirical performance of credit risk models and provide a more market realistic CDS spreads.

7 Conclusion

The purpose of this thesis is to investigate the Merton models ability to replicate CDS spreads. It also explores whether the model's risk measure (distance to default) follows market perceived risk (market CDS). This is achieved by first estimating CDS spreads through a standard Merton, followed by a sensitivity analysis of the optimal choice of default threshold. Additionally, an estimation is conducted by incorporating forward-looking information into the credit risk model, here in the form of the well-known VIX index. All estimations are computed quarterly for the 44 companies over 2015–2024.

The main finding of this thesis is that the Merton model fails to produce CDS spreads that correspond to the market CDS spreads. The implied spreads have values close to zero and this finding is in line with previous ones in the field. Although the VIX weighted model produces small CDS spreads, they are in most cases larger than those from the standard approach. This indicates that using a forward-looking volatility measure may be better suited at capturing CDS spreads than historical volatility does, as it tends to reflect higher perceived risk, reducing firms' distance to default. Despite this, a more refined method is needed to incorporate the forward looking volatility, since very high volatility causes implied CDS spreads to rise to unrealistically large values.

Moreover, a sensitivity analysis of the optimal value of debt was performed to examine how the default threshold affects the model's estimation accuracy. Although lower values of long-term debt weight tended to yield a slightly higher explanatory power compared to the KMV-Merton approach, these lower values also resulted in fewer positive credit spreads. No optimal long-term weight of debt was found. Overall, the assessment indicated that the model's performance is not highly sensitive to the default threshold, suggesting that other factors play a more significant role in influencing the model's accuracy.

It is important to emphasize that although the absolute level of risk is not accurately estimated, the distance to default follows market risk in a manner consistent with theory. This underscores that, despite its limitations, the Merton model remains a useful indicator of credit risk, even during periods of unprecedented volatility. Furthermore, this thesis contributes to the literature by introducing a VIX weighted volatility measure, which, to the authors knowledge, has not been explored before. It is notable that this approach is broadly applicable and can be extended to evaluate any publicly traded company. While the approach requires further refinement, it offers a promising direction for future research on incorporating forward-looking information into structural credit risk models.

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Appendix

A List of Companies

No.	Company Name	Industry by Sector
1	JetBlue Airways Corporation	Industrials
2	Amkor Technology, Inc.	Information Technology
3	Automatic Data Processing, Inc.	Industrials
4	American Electric Power Company, Inc.	Utilities
5	Texas Instruments Incorporated	Information Technology
6	American Airlines Group Inc.	Industrials
7	Advanced Micro Devices, Inc.	Information Technology
8	APA Corporation	Energy
9	Comcast Corporation	Communication Services
10	Amazon.com, Inc.	Consumer Discretionary
11	Cisco Systems, Inc.	Information Technology
12	The E.W. Scripps Company	Communication Services
13	Intel Corporation	Information Technology
14	Intuit Inc.	Information Technology
15	Microsoft Corporation	Information Technology
16	Amgen Inc.	Health Care
17	Apple Inc.	Information Technology
18	Applied Materials, Inc.	Information Technology
19	Avnet, Inc.	Information Technology
20	The Campbell's Company	Consumer Staples
21	Expedia Group, Inc.	Consumer Discretionary
22	Navient Corporation	Financials
23	Avis Budget Group, Inc.	Industrials
24	Flex Ltd.	Information Technology
25	The Goodyear Tire & Rubber Company	Consumer Discretionary
26	Paramount Global	Communication Services
27	Hasbro, Inc.	Consumer Discretionary
28	Viatris Inc.	Health Care
29	Newell Brands Inc.	Consumer Discretionary
30	Exelon Corporation	Utilities
31	United Airlines Holdings, Inc.	Industrials
32	Marriott International, Inc.	Consumer Discretionary
33	Mattel, Inc.	Consumer Discretionary
34	Alliant Energy Corporation	Utilities
35	The ODP Corporation	Consumer Discretionary
36	PepsiCo, Inc.	Consumer Staples
37	PENN Entertainment, Inc.	Consumer Discretionary
38	Service Properties Trust	Real Estate
39	Plains All American Pipeline, L.P.	Energy
40	Sinclair, Inc.	Communication Services
41	Xcel Energy Inc.	Utilities
42	Mondelez International, Inc.	Consumer Staples
43	Regency Centers Corporation	Real Estate
44	Costco Wholesale Corporation	Consumer Staples

B Tables

Table B.1: Results of analysis using implied CDS spreads from the standard Merton model and market CDS spreads.

Period	β_0	β_1	R^2	MAE	MAPE	N
Full	41.5346*** (1.4694)	0.0004 (0.0005)	0.0000	81.4072	335.00%	1760
2015	43.4651*** (7.5234)	-297324452.5220 (934240728.4701)	0.0001	43.3945	100.00%	176
2016	39.7548*** (3.3645)	363.5799 (404.6813)	0.0120	40.4888	99.99%	176
2017	28.9058*** (2.0605)	86.9491 (62.7881)	0.0185	29.4558	99.99%	176
2018	31.8542*** (2.2388)	0.0018*** (0.0002)	0.0034	102.2252	869.88%	176
2019	28.6659*** (2.0446)	213.7977*** (63.2465)	0.0521	30.1342	99.98%	176
2020	55.9303*** (7.9993)	1.6306** (0.7929)	0.0004	56.0136	99.78%	176
2021	37.5667*** (3.1617)	-1173.9632*** (160.8670)	0.0017	37.4355	100.00%	176
2022	47.5619*** (4.1987)	850.7869*** (283.5261)	0.0823	50.9061	99.99%	176
2023	49.6421*** (4.1849)	-0.0034 (0.0023)	0.0037	170.8024	282.51%	176
2024	45.6175*** (4.6468)	0.0008*** (0.0001)	0.0014	253.2160	1497.92%	176

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Note: Implied CDS spreads are computed using half of the long term debt (i.e. $k = 0.5$). All estimates of implied CDS spreads are included in the analysis.

Table B.2: Optimal choice of k for highest explanatory power. Results of analysis using implied CDS spreads from the standard Merton model and market CDS spreads.

Period	Optimal k	β_0	β_1	R^2	MAE	MAPE	N
Full	0.1	80.7077*** (8.9437)	4.8718 (19.7996)	0. 0004	67.1180	275.79%	169
2015	0.6	127.4162 (86.3288)	-1881290346.7675 (2484418327.2736)	0. 1605	90.4155	350.57%	5
2016	1.0	69.8202*** (15.0126)	-546.7213 (484.0827)	0. 0408	57.2034	274.31%	32
2017	0.3	35.1826*** (7.7077)	716.0349** (288.4806)	0. 3056	22.0769	104.22%	16
2018	0.1	34.6383*** (5.3699)	132.8414** (50.1301)	0. 2806	19.2935	122.66%	20
2019	0.2	42.8228*** (5.6559)	262.2026** (91.2465)	0. 3710	14.8905	54.04%	16
2020	0.1	159.2515*** (46.1326)	-21.0451 (41.1917)	0. 0103	149.5807	471.95%	27
2021	0.2	6.6050*** (0.8277)	558.5206** (131.0153)	0. 8583	0.9743	14.01%	5
2022	0.1	83.8645*** (26.1656)	569.2951* (300.9624)	0. 1658	82.6771	387.27%	20
2023	0.1	75.4074*** (15.3730)	579.2296** (214.7210)	0. 2879	48.8138	118.37%	20
2024	0.1	54.0670*** (10.2556)	314.4054** (142.9979)	0. 1947	61.9597	97.14%	22

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Note: Implied CDS spreads are computed using half of the long term debt (i.e. $k = 0.5$). Solely positive estimates of implied CDS spreads are included in the analysis.

Table B.3: Optimal choice of k for highest explanatory power. Results of analysis using distance to default from the standard Merton model and market CDS spreads.

Period	Optimal k	β_0	β_1	R^2	N
Full	0.3	67.1458*** (2.6882)	-0.8712*** (0.0777)	0.0674	1742
2015	0.2	96.2837*** (17.0793)	-1.5243*** (0.4479)	0.0631	174
2016	0.3	68.0003*** (6.0875)	-0.8966*** (0.1688)	0.1409	174
2017	0.2	43.6392*** (3.6526)	-0.3501*** (0.0755)	0.1111	174
2018	0.3	43.7605*** (4.0247)	-0.4088*** (0.1144)	0.0691	174
2019	0.4	42.9877*** (3.5048)	-0.4232*** (0.0955)	0.1025	174
2020	0.1	108.5876*** (14.7196)	-2.6068*** (0.6279)	0.0911	174
2021	0.4	67.7592*** (6.4625)	-0.9993*** (0.1901)	0.1384	174
2022	0.4	86.3073*** (9.3086)	-1.5937*** (0.3734)	0.0958	174
2023	0.1	74.6232*** (7.9413)	-0.7917*** (0.2194)	0.0704	174
2024	0.3	73.8194*** (8.3256)	-0.9903*** (0.2443)	0.0872	174

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Note: Distance to default estimates are computed using half of the long term debt (i.e. $k = 0.5$). Outliers in the 99th percentile of distance to default estimates are dropped.

Table B.4: Results of analysis using implied CDS spreads from the VIX volatility adjusted Merton model and market CDS spreads.

Period	β_0	β_1	R^2	MAE	MAPE	N
Full	64.6823*** (3.8243)	-0.0073 (0.0048)	0.0002	76.5758	133.65%	482
2015	78.6259*** (13.0606)	24.4137*** (1.4657)	0.3350	88.3660	99.82%	29
2016	70.6966*** (11.1418)	9.7604*** (0.7345)	0.1391	74.8361	99.72%	37
2017	38.4823*** (4.7686)	-56.4625 (34.4585)	0.0210	36.8200	99.82%	45
2018	41.7621*** (5.0064)	-21.2412* (11.2632)	0.0142	39.9898	99.65%	57
2019	40.7798*** (4.9387)	-13.4334 (13.9140)	0.0053	39.6587	99.73%	53
2020	85.6478*** (16.4361)	-0.0196** (0.0091)	0.0027	154.4225	297.49%	83
2021	81.1903*** (11.9764)	-5.6319*** (1.0132)	0.0423	78.3617	97.08%	28
2022	64.1926*** (10.9106)	166.1711 (114.1240)	0.0864	72.7323	99.86%	51
2023	60.4739*** (9.9869)	74.2538*** (15.1761)	0.1221	67.7515	99.86%	47
2024	68.6880*** (12.3821)	13.0181 (40.9851)	0.0020	69.9017	99.66%	52

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Note: Implied CDS spreads are computed using half of the long term debt (i.e. $k = 0.5$). Solely positive estimates of implied CDS spreads and distance to default are included in the analysis.

Table B.5: Results of analysis using distance to default from the VIX volatility adjusted Merton model and market CDS spreads.

Period	β_0	β_1	R^2	N
Full	64.2163*** (3.5381)	-1.5658*** (0.1635)	0.0549	1742
2015	94.8267*** (22.7841)	-3.6443*** (1.1500)	0.0558	175
2016	69.2250*** (9.7339)	-1.7206*** (0.4358)	0.1378	174
2017	44.0549*** (3.9830)	-0.7806*** (0.1477)	0.1117	172
2018	42.6578*** (4.1027)	-0.8226*** (0.1815)	0.0630	174
2019	40.5703*** (3.8624)	-0.6894*** (0.1559)	0.0722	173
2020	93.8786*** (17.5263)	-3.9094*** (1.0853)	0.0672	175
2021	71.9037*** (8.3862)	-2.1580*** (0.3981)	0.1624	175
2022	69.0776*** (11.3652)	-1.5220** (0.7501)	0.0330	175
2023	62.8745*** (9.0808)	-0.9261* (0.4841)	0.0260	173
2024	68.0207*** (10.0133)	-1.5577*** (0.4864)	0.0582	176

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Note: Distance to default estimates are computed using half of the long term debt (i.e. $k = 0.5$). Outliers in the 99th percentile of distance to default estimates are dropped (18 observations in total).

C Figures

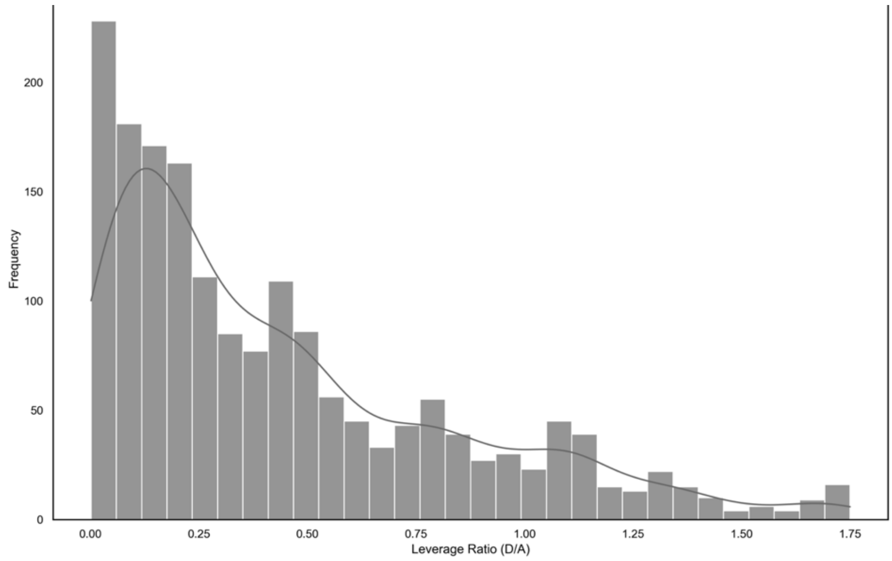

Figure C.1 : Distribution of Leverage Ratio for the 44 firms quarterly 2015-2024. (Source: Capital IQ (2025) & authors calculations). Higher leverage ratio is approaching 1 or higher.

Accounting for generative AI use

Generative AI tools were employed in this thesis to resolve programming errors in Python (which was used for the empirical analysis) and to perform grammatical checks. The tools used include ChatGPT, Claude, and Grammarly. These tools were not used in the development of the research idea, the execution of the analysis, or the formulation of the thesis objectives. All substantive academic work was conducted independently by the authors.