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An empirical analysis of the KMV-Merton model

A case of Swedish real estate companies

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Master thesis in Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

1. Abstract

This thesis examines the contribution of applying the KMV-Merton model on Swedish real estate companies listed at the NASDAQ OMX Nordic Real Estate Index. Comparing the KMV-Merton model credit rating to frequently applied credit metrics, we find that the model adequately captures relevant information contained in these metrics. Additionally, the model proves robust when using long time series. Applying data from the time interval 2007-2014, we estimate econometric models to decompose significant predictor variables for credit spread variation at issuance. We obtain data directly from financial statements to assure statistically useful estimates. A univariate econometric model including the KMV-Merton default probability explains pooled cross-sectional regularities in credit spreads rather well. Combining firm financials, macroeconomic predictors and bond characteristics with the pure structural model, we conclude that a comprehensive hybrid model has improved fit. This result suggests that the KMV-Merton model is unable to capture all information contained in financial- and macroeconomic data. In particular, a model including the default probability, loan-to-value, the 3-month annualized interbank rate, coupon structure and credit rating is able to explain 80.19% of credit spread variation. Including a time variable enables us to exclude the existence of spurious time correlations and construct a model that is unconstrained in the parameters. Overall, the explanatory power achieved aligns with empirical research. In summary, we conclude that the KMV-Merton model yields significant statistics for credit risk assessment of Swedish real estate bonds at issuance. However, the statistic does not prove sufficient, as the comprehensive hybrid outperforms the univariate model.

2. Preface

This thesis concludes five years of studies at the Norwegian School of Economics (NHH). We have by this, completed our Master of Science in Financial Economics. The writing process has been interesting and contributed to increased insight in a rapidly growing financial market.

The thesis is a result of time-consuming data gathering, challenging model construction and extensive research. Several persons have contributed during the writing process. First, we would sincerely thank our supervisor, Aksel Mjøs, for professional and prolific discussions. We believe that the academic guidance and input have significantly increased the quality of this paper. We also like to thank Jarle Møen for valuable contributions to our econometric analysis.

Further, we thank Anders Buvik and Lene Christin Våge from DNB Asset Management for showing interest in our work. They introduced us for the KMV-Merton model and the emerging fixed income market in the Swedish real estate sector. We also like to thank Nordic Trustee for granting us access to Stamdata and Mads Solberg for clarifying data details.

Lastly, we would like to direct our gratitude to NHH for high quality courses and a stimulating learning environment. Especially, we acknowledge the inspiring and enriching content in our Master of Science program provided by the Finance Department. This has motivated our carrier path and we believe it has made us well equipped for the future.

Norwegian School of Economics

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3. Introduction

3.1 Background

In general, the fixed income market has experienced significant growth since the turn of the century. The increase is especially evident in Europe, where banks historically have acted as the main provider of debt financing for corporations. A substantial increase in traded volumes of credit derivatives, e.g. credit default swaps (CDS) underpin the recent interest in the fixed income market. Consequently, academicians and practitioners such as credit rating agencies, corporate bond fund managers and speculators on credit quality have increased their interest in models that assess creditworthiness of corporations and specific assets. Amongst others, these methods include structural models, pure accounting models and hybrid models.

The Swedish real estate sector has experienced a significant recapitalization after the financial crisis in 2008, increasing the relative proportion of bond financing. From 2010 to 2015, the accumulated outstanding volume is up from SEK 22.702 billion to SEK 94.349 billion for real estate companies, which also has been the most frequent issuer of corporate bonds in recent years. In our opinion the combination of e.g. more stringent banking requirements through Basel III and eagerness amongst companies to ease exposure towards shocks in the banking sector are important for the development. Clearly, the Swedish corporate bond market for real estate companies is a new and unexplored market. Though many researchers have applied credit models on large samples, few studies are small and sector specific, opening for a thorough analysis of input parameters. More importantly, to our knowledge, there is no empirical research on credit risk through structural models in the Swedish real estate sector, which has been the motivation behind our thesis.

3.2 Research Questions

The thesis provides a comprehensive assessment of companies listed on the Real Estate Index (REI) at NASDAQ OMX Nordic from 2007 to 2015. Our empirical objective is to examine the contribution of the KMV-Merton model and further apply the results in econometric models, ultimately allowing us to examine the relationship between a set of predictor variables and observed credit spread variation at bond issuance.

Essentially, we separate the thesis into two parts. The first part focuses on extracting probabilities of default (PD)[1] applying the KMV-Merton model[2], frequently used by both academicians and practitioners. The model employs derivatives theory based on Merton (1974) and solely exploits publicly available information. We replicate a simpler version of the KMV-Merton model than used by the credit rating agency Moody's. Applying the model on our sample allows us to investigate if the relative ranking of PD, in light of less extensive data, i.e. frequently used credit metrics, proves meaningful. Furthermore, the small sample size allows us to review the input metrics thoroughly for each observation and control for model robustness. We emphasize that this part does not put weight on statistical inference.

In the second part, we evaluate the KMV-Merton model's fit to credit spreads using econometric models. Constructing a univariate econometric model enables us to assess to what extent the structural default probability is significant in explaining corporate bond spread variation at issue date for Swedish real estate companies. In theory, higher PD will imply higher credit spreads, as investors will require compensation for the additional risk associated with the investment. We expand the econometric model by including other potential determinants of credit spreads, decomposing potential predictors into firm-specific factors, macroeconomic factors and bond characteristics. Thus, we can examine if the KMV-Merton model in fact is sufficient in explaining variation in credit spreads at issuance. If the structural model proves exhaustive, all other factors added to the model will be redundant, and the model fully explains investor's risk pricing at issuance date.

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[1] PD and default probability are used interchangeably throughout the thesis.

[2] Developed by the KMV Corporation.

Combining the parts, we open for a comprehensive credit risk analysis of the Swedish real estate sector and an empirical assessment of the KMV-Merton model. In light of the discussion above, we derive the following hypotheses:

(1) The PDs from the KMV-Merton model provide a rational credit risk ranking and robust estimates.
(2) The KMV-Merton model is significant in explaining credit spread variation in corporate bonds issued by Swedish real estate companies.
(3) The KMV-Merton model is sufficient in explaining credit spread variation in corporate bonds issued by Swedish real estate companies.

3.3 Mapping the Swedish Corporate Bond Market

This section provides an overview of the Swedish corporate bond market with emphasis on the real estate sector, as this is the market of interest.

Historically, the primary financing source for Swedish corporations has been banks. An obvious implication of the strong bank presence is an underdeveloped corporate bond market. However, since Riksbanken (2014) findings in 2011, indicating reluctant investors due to low transparency and absent statistics[3], the market has gradually evolved. An important contribution to a more transparent market is Nordic Trustee's database, Stamdata. The database describes reference data for Nordic debt securities, including detailed information on bonds, structured debt securities and certificates. Nordic Trustee established Swedish Trustee AB in January 2012 and integrated all Nordic corporate bond markets into one database, www.stamdata.com, March 2014 (Stamdata, 2015).

We define the Swedish corporate bond market as all bonds issued by Swedish real estate companies[4], in both SEK and other currencies. Note that we do not consider foreign issuers. However, Bonthron (2014) finds that foreign companies in 2014 account for 25% of outstanding bond volume in Sweden. Further, foreign investors represent 61% of investments in corporate bonds issued by Swedish companies (Bonthron, 2014).

Table 3.1 shows that Industrials and Real Estate represents the vast majority of outstanding bond volume, constituting almost 50% as of May 2015. The total outstanding bond volume aggregates to SEK 490 billion. Further, the average size of an outstanding bond is approximately SEK 900 million. Real estate companies display the second lowest average bond size, however representing the most frequent issuer with 285 issuances currently outstanding. For issuances in the primary market, Swedbank and SEB Merchant Banking represents the top corporate bond managers ranked by currently outstanding volume arranged (Appendix 10.1).

[3] Bonds are traded over-the-counter (OTC) or by phone.

[4] Swedish real estate companies are companies traded at NASDAQ OMX Nordic REI as of 05.02.2015.

Table 3.1: *Overview of Swedish corporate bonds outstanding per 21st of May 2015*

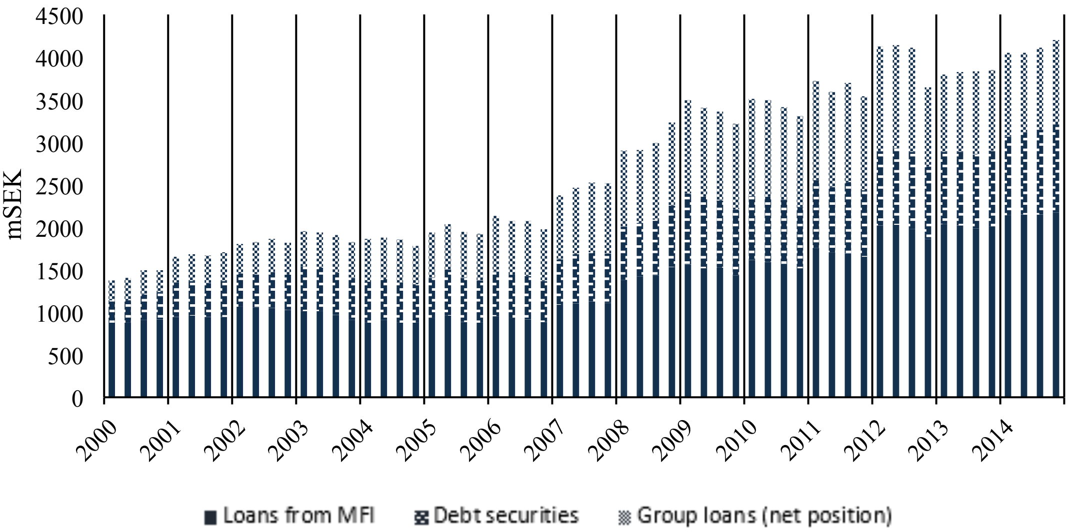
Sector	**Volume (mSEK)**	**Share (%)**	**Avg. bond (mSEK)**	**# of issues**
Industrials	119 201	24.3	1 046	114
Real Estate	115 826	23.6	406	285
Auto	75 291	15.4	1 421	53
Utilities	40 291	8.2	1 389	29
Telecom/IT	35 471	7.2	1 478	24
Consumer	31 278	6.4	1 251	25
Pulp, paper and forestry	21 996	4.5	687	32
Transportation	19 084	3.9	596	32
Health Care	10 862	2.2	987	11
Convenience	9 736	2	695	14
Pharmaceuticals	3 550	0.7	592	6
Insurance	3 422	0.7	856	4
Media	2 402	0.5	801	3
Oil and Gas	1 503	0.3	376	4
Total	489 913	100	899	636

Datasource: Stamdata

Statistics for the secondary market are significantly more challenging to obtain. There is no daily trading information of corporate bonds, neither their market prices nor volumes. Hence, it is difficult to observe the changes perceived by the market in credit risk for a specific bond over time. However, the Swedish Central Bank and Finansinspektionen, a government authority supervising the Swedish financial market, have collected some statistics regarding the turnover and prices. The increased monthly turnover from 4% in 2011 to 6% in 2014 supports the growing interest in the corporate bond market; however, liquidity is still low compared to other fixed income classes, as large investors tend to hold assets until maturity (Bonthron, 2014). Further, the statistics indicate that the yield on corporate bonds in the secondary market has decreased since 2011. However, these statistics are based on indicative prices, i.e. the price banks are willing to buy and sell bonds for, and are only available for part of the outstanding volume in Sweden. We were unable to collect information on the indicative prices in the secondary market.

In general, more stringent capital requirements for banks have driven the corporate bond market after the financial crisis in 2008. Effectively, banks have become reluctant to issue loans and thus created room for alternative sources of financing, such as preferred stock and corporate bonds. The total outstanding bond volume has evolved significantly in recent years, displaying an increase of almost 26% in the period 2011 to Q2 2014 (Bonthron, 2014). Figure 3.1 shows the development of outstanding debt mix for Swedish non-financial companies. Including the last two quarters of 2014, the growth has been 35% since 2011. As loans from monetary financial institutions (MFI), debt securities and group loans[5] have increased, the share of bond financing seems to remain somewhat constant over the most recent period. However, according to Rubin, Giczewski & Olson (2013), the implications of Basel III are especially critical for commercial real estate companies as the general risk-based capital requirement apply standard weights of 100% to commercial real estate loans[6]. Catella, an asset management firm with expertise within the real estate sector, shows that sector returns were at a historical high in 2012. However, simultaneously the average interest rates for listed Swedish real estate companies were high due to substantial credit premiums on bank loans (Tollesson, 2012). More stringent capital requirements may explain that the share of outstanding bond volume relative to the total outstanding debt for real estate companies has increased from 4% in 2012 to 15% in 2014 (Catella Corporate Finance, 2014).

Figure 3.1: *Outstanding debt mix for Swedish non-financial companies, 2000-2014*



Datasource: Statistics Sweden

Further, EU regulations have forced several international banks to retire their business in Sweden, as their operations were outside their "main market". Prior to the crisis, these banks

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[5] Group loans are net positions. Primarily, it represent inter-company loans.

[6] Risk-weighted capital = $\sum_{\forall_i} W_i * A_i$ where W = weight and A = asset.

offered real estate companies up to 80-85% debt financing for real estate investments, thus constituting a significant financing source. As less capital has become available, remaining banks have been forced to prioritize their capital allocation. Real estate companies have been categorized as a less attractive segment based on historical returns, and thus available bank financing has decreased (Hartomaa, 2013). According to Corem Property Group, one of the assessed real estate companies, a consequence of less available capital is that 10-20% of the financing previously obtained through banks has to be covered by issuing bonds (Ekot, 2012).

According to Catella, management of Swedish real estate companies has pursued corporate bonds as this bodes for diversification of the capital structure. Consequently, companies have less exposure towards shocks in the banking sector, and capital structures align more with Swedish industrials (Tollesson, 2012). This has contributed to the rapid growth in issuances by Swedish real estate companies. The increased competition between bank financing and alternative financing sources has resulted in a declining trend in average interest rates for the listed real estate companies. However, lower policy interest rate induced by the Swedish central bank has also contributed to the declining trend (Catella, 2014). In response to lower policy interest rates, global fixed income investors have tilted their portfolios towards more risky asset classes, especially corporate bonds (Joyce et al., 2014). Thus, debt investors searching for yield have established high demand pressure, making the corporate bond market a more affordable financing source for Swedish real estate companies.

Furthermore, findings by Landeman & Bergin (2014) imply that the Swedish government's indirect or direct ownership in various real estate companies has affected average credit spreads. The non-listed real estate company Vasakronan AB, where the Swedish government holds 85%[7], was the largest issuer with close to 30% of the outstanding bond volume issued by Swedish real estate companies in 2014. For real estate companies with government ownership interests, it has become cheaper to obtain financing in the bond market than it is for several Swedish banks. From an investor perspective, these bonds are attractive due to the safety of government ownership (Landeman & Bergin, 2014). Further, in 2012 the demand side constituted primarily of small institutional investors and private placements,

[7] Owned by the sixth AP Fund (Swedish Pension Fund).

which constrained the issued volume. Many large Swedish and international institutional investors were restricted to invest due to mandates requiring assets to have a high official rating (Tollesson, 2012). Obtaining official ratings by credit rating agencies (CRAs) on bond issuances is expensive, and there has been a strong trend towards issuing unrated bonds in Sweden. In 2014, approximately 53% of all new issues were unrated. However, large fractions of these bonds are subject to shadow rating[8]. In recent years newly established funds, such as the government sixth AP Fund, have removed official rating requirements of BBB[9] or better from their credit risk management mandates, and hence increased the inflow of capital in Swedish bonds. The increase has especially been strong in the high-yield[10] segment; in 2011, the segment constituted 9% of total bond issues, while high yield bonds in Q1 2015 represent 25% of the outstanding bonds. According to Bonthron (2014), the largest investors in 2014 were government institutions and mortgage institutions, representing a market share of 27% and 47%, respectively. The large institutions represents three quarters of the transactions (frequency), while 75% of the transactions are in volumes less than SEK 5 million, i.e. primarily small investors trade and liquidity is still lower than other markets.

The increased competition from Swedish banks does not seem to put a strain on the bond market going forward, as the investment activity in the real estate sector is expected to remain at high levels (Catella, 2015). Investments in Swedish real estate led to the second strongest quarter ever recorded, ending at SEK 148 billion in Q4 2014, which is equal to 60% of the total invested capital in 2013 (Newsec, 2015). Further, five large listed real estate companies (Wihlborgs Fastigheter AB, Catena AB, Diös Fastigheter AB, Fabege AB and Platzer Fastigheter Holding AB) jointly established a financial company with the sole purpose of obtaining a secured medium-term-note (MTN) of SEK 8 billion in 2015 (Wihlborgs, 2015). A MTN-Program enables companies to issue several bonds applying the same base prospectus, and hence allow the issuer to have constant cash flows available

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[8] Shadow ratings are unofficial and typically performed by the investment bank issuing the bond. These ratings are common in both Sweden and Norway. Stamdata does not separate between shadow ratings and official ratings directly. However, the prevailing ratings are available in each bond prospectus. We do not separate between shadow ratings and official ratings, as this is not important for our analysis.

[9] An obligation rated BBB exhibits adequate protection parameters. However, the obligation is exposed to adverse economic conditions or other changing circumstances, which are likely to weaken the capacity of the obligor to service its financial commitments (Standard & Poors, 2012).

[10] See Appendix 10.2 for Moody's credit rating definitions.

(Fabozzi & Polack, 2000). In essence, this puts pressure on banks, as the MTN provides support to their current lending structure. According to Catella (2015), the strong balance sheets of listed real estate companies, represented by declining leverage ratios and interest rates, bodes for debt expansion going forward. Thus, one should expect bond issuance frequency and volume in the real estate sector to accelerate and reinforce the strong trend observed the recent years.

In light of the discussion in this section, analyzing the contribution of applying a structural model to estimate default probabilities should be interesting for debt investors. The fact that Anders Buvik, responsible for high-yield bonds in DnB Asset Management, introduced us for the idea of applying the KMV-Merton model on Swedish real estate companies supports this.

4. Theory

According to Altman & Saunders (1999), models assessing credit risk have changed significantly, as investment banks, investors and credit rating agencies apply models that are increasingly more sophisticated. Typically, literature separates between three main branches of credit risk models: structural models, accounting models and hybrid models. Structural models are employed extensively to assess credit risk by utilizing an explicit relationship between the capital structure and default risk (Wang, 2009). Further, accounting models assess credit risk exploiting historical data from financial statements. Lastly, hybrid models are comprehensive models comprising information from structural models, accounting data, macroeconomic variables and rating data (Chan-Lau, 2006). As mentioned, the focus in this thesis is structural and hybrid models.

4.1 Credit Spreads

We briefly introduce the theoretical composition of credit spreads in the following section, as this is the unit of interest in our empirical model.

Credit spreads theoretically reflect the additional compensation over the risk-free interest rate debt investors require for taking on default risk, and comes to play when corporations issue bonds. A theoretical simplification of credit spreads employs two variables, the loss-given-default rate (LGD) and PD (Hull, 2012):

$$Credit\ spread = LGD * PD \tag{4.1.1}$$

The LGD is the percentage exposure for the investor based on the expected loss rate, i.e. one minus the recovery rate. In other words, LGD depicts the extent of the loss incurred if the obligor defaults. Schuermann (2004) emphasizes that the most important determinant of LGD is the bond's place in the firm's capital structure (e.g. subordinated), and whether it is secured or not. Additionally, LGDs are contingent on type of industry; these are empirically lower for asset-intensive industries than service industries.

The other component of theoretical spreads in Equation 4.1.1, PD, constitutes the probability for the borrowing entity failing to service its obligations, e.g. interest payments. In practice, PDs are non-observable, and often approximated through models including different relevant firm metrics such as debt levels, coverage ratios and returns.

Under the assumption that the only reason for yield differences between corporate bonds and government risk-free bonds is due to PD and LGD, extracting default probabilities should according to Hull (2008) be a trivial exercise. For a given LGD and observed credit spread the PD is found by rearranging Equation 4.1.1:

$$PD = \frac{Credit\ Spread}{LGD} \tag{4.1.2}$$

However, empirical research on corporate bond spreads suggest otherwise. Elton et al. (2001) find that for 10yr A-rated industrials the LGD only explains 17.8% of the spread, with both tax implications and systematic risk premiums having higher explanatory power. Additionally, it might be hard to find measures for LGD for specific bonds, as they will vary with firm composition of assets, industry and capital structure amongst others. Further, Anneart, De Ceuster and De Jonghe (1999) stress the important impact of credit migration risk. This term comprises changes in credit quality, effectively changing the portfolio value. Fansworth & Li (2003) support this, finding that highly rated bonds typically have upward sloping credit spread curves, while companies with low ratings have downward sloping credit spread curves. For example, when investing in an Aaa rated company, this implies that debt investors require additional compensation for the risk of the company being downgraded to Aa or lower. Lastly, empirical research suggest that more illiquid bonds have higher credit spreads (Chen, Lesmond & Wei, 2007). Hence, debt investors are compensated for the risk of not being able to sell the bond. Nevertheless, for bonds with low credit ratings, Mjøs, Myklebust & Persson (2011) confirms Huang & Huang (2003) findings that credit risk accounts for a much higher fraction of yield spreads in high yield bonds than for investment grade bonds.

In summary, given the existence of several influential components in credit spreads, extracting PDs from traded bonds is a challenging task. Hence, utilizing advanced credit risk models may be beneficial for debt investors to obtain adequate PD estimates.

4.2 Credit Risk Modeling in Practice

As our thesis applies the KMV-Merton model to assess credit risk, we include a description of credit risk modeling in practice.

CRAs such as Moody's, Fitch and S&P represent the major players in credit risk modeling, and apply several methods to assess firm and asset creditworthiness. They base their business model on information asymmetries influencing the market dynamics between creditors and debtors. In debt-capital-markets, bond issuers have more information on the inherent risk of the company compared to the pool of debt investors. Since corporate disclosure is a key component for efficient capital markets, conflicting incentives between different market players can create dysfunctional capital markets, i.e. a market for "lemons" (Akerlof, 1970). In the fixed income market, this theory refers to the risk of investing into a bond that is more likely to default than other bonds due to existence of private information. Ceteris paribus, bond issuers possess the opportunity to shift risk to debt holders by affecting the flow of information to the public. These information disturbances may have different origins. For example, Nissim (2014) argues that flexibility in financial reporting bodes for earnings management to induce an intentional bias in financial reports, resulting in a strong presence of earnings overstatement when firms engage in capital-raising activities, as they are able to borrow at lower interest rates.

To overcome this, CRAs assess a combination of market position, financial position, debt levels, governance and covenants (Moody's Investor Service, 2009). Implicitly, this means that CRAs compute the PD for assets traded in the open market based on public information. As mentioned, the informational gap drives the existence of such intermediates, and enables investors to have increased confidence in capital seeking corporations (Healy & Palepu, 2001). When corporations issue bonds, CRAs typically compute the issuer's PD, and rarely assess the bond PD itself. Thus, when CRAs rate specific issues/maturities they apply the PDs of the company. From a financial perspective, this is reasonable, as research suggest that due to cross-default clauses a firm that defaults on one bond typically defaults on all outstanding bonds (Crosbie & Bohn, 2003). Additionally, this line of reasoning is consistent with the application of structural models, such as the Merton (1974) model, where firm characteristics, e.g. asset value and asset volatility are key determinants in PD computations.

A significant difference between CRA methodologies and ours is the application of different approaches. CRAs traditionally use a through-the-cycle approach, implying that they disregard the implications of temporary effects on PDs. Effectively, this results in default probabilities being limited to long-term structural factors, including one or more business cycles (Altman & Rijken, 2006). On the other hand, models such as the KMV-Merton model have a point-in-time perspective, i.e. include temporary factors affecting the PDs. In the event of an economic downturn leading to depressed equity values, PDs from our model will increase immediately. The benefit of point-in-time models is the ability to react rapidly to market changes. Altman & Rijken (2006) conclude that a through-the-cycle approach delays rating migrations by 0.56 years on the downgrade side and 0.79 years on the upside relative to point-in-time models. An obvious implication is that we expect PDs that are more volatile from our KMV-Merton model.

4.3 The KMV-Merton Model

In this section, we describe the theoretical framework and the assumptions behind the KMV-Merton model. Further, we include important theoretical extensions of the Merton (1974) model, as well as empirical research.

The KMV-Merton model builds on the application of financial derivatives theory and assumes that equity is a call option on a firm's assets with strike equal to the face value of outstanding debt FV. The model requires strict assumptions regarding the asset, i.e. that the market value of assets follow a geometric Brownian motion and that asset returns are log-normally distributed.

The core of the model is that both the underlying market value of assets A and the related asset volatility σ_A are unobservable, and thus need to be inferred from a system of two non-linear equations. To solve the equations, the KMV-Merton model makes use of an iterative procedure. Subsequently, the KMV-Merton model applies the inferred variables as input in the abovementioned Merton (1974) framework.

4.3.1 Stochastic Processes

The following section introduces the formal asset process applied in the KMV-Merton model[11].

A stochastic process defines variables where the value over time changes in an unpredictable manner. One specific stochastic process is the Markov process, which assumes that only the current value of the variable is relevant for future values. In stock markets, this implies that the price of a stock today reflects all relevant historical information. Empirical studies of developed financial markets provide evidence of weak market efficiency, e.g. Fama (1970). As market values of assets tend to move randomly in the short-term, describing the process mathematically by a stochastic process is convenient. Applying the Merton (1974) framework assumes that the market value of assets follow a Markov process. In particular, the model assumes that assets follow a Wiener process, defined as a Markov process with the following properties:

1. The change in a variable Δx during a small time interval Δt is:

$$\Delta x = \varepsilon\sqrt{\Delta t} \tag{4.3.1}$$

Where ε is a random number from the normal distribution $N\ (0,1)$. From property (1) it directly follows that Δx is normally distributed with a mean of zero and a variance of Δt.

2. Values of Δx at different points in time are independent of one another.

Property (2) implies that the variable follows a Markov process. Since the variables at time $t = i$ and $t = i + 1$ where $i = 1, 2,3 \dots n$ are independent, the mean and variance of the two separate normal distributions is additive. Hence, the standard deviation over time will be proportional to the square root of time $\sigma\sqrt{T}$. When $\Delta t \to 0$ the stochastic variable will follow a more irregular process, as $\sqrt{\Delta t} > \Delta t$. Applying a standard Wiener process for financial assets has clear limitations given that the drift rate μ is zero. In a stochastic process, μ denotes the mean change per time interval. For μ equal to zero, the variable will follow a

[11] The section is largely based on Merton (1974), Hull (2012) and Tung, Lai & Wong (2010).

stochastic process where the outcome at any time t solely depends on the variance rate. Thus, if one simulates $n \rightarrow \infty$ processes, the value will be close to the initial value of the asset. The financial implication will be that investors have limited rationale to hold financial assets, as the expected return over a long time horizon would be zero. The solution is therefore to define a general Wiener process.

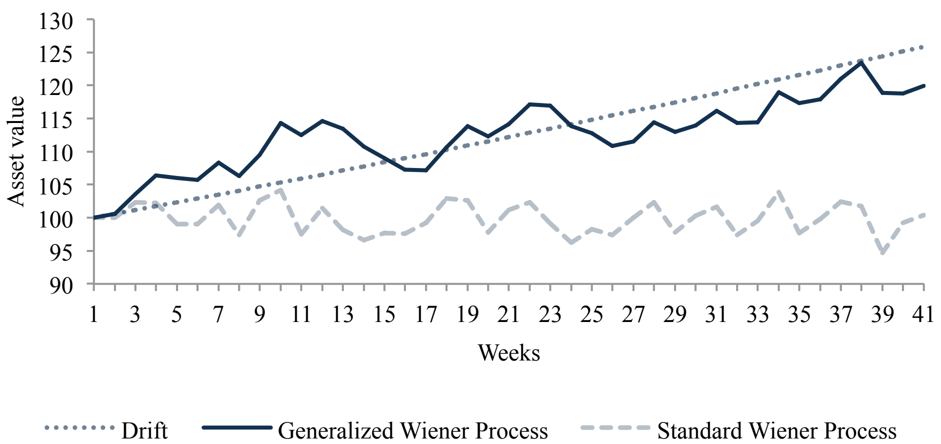
As opposed to a standard Wiener process, a generalized process allows for the incorporation of a drift rate aligning the process with how we observe actual financial asset behavior. Equation 4.3.2 depicts the mathematical expression for the generalized Wiener process:

$$dx = \mu dt + \sigma dz \tag{4.3.2}$$

Where $dz = \varepsilon\sqrt{\Delta t}$ since $\Delta t \rightarrow 0$

The first logic on the right-hand side defines the drift rate, and indicates the expected change in the variable for any given time interval, while the second logic is the volatility of the asset σ_A multiplied with a standard Wiener process (Equation 4.3.1). For assets with higher values of σ_A, one will observe larger deviations between time intervals. Modeling this under the assumption of $\mu_A = 30\%$ and $\sigma_A = 15\%$ with weekly time intervals gives a process as depicted in Figure 4.1.

Figure 4.1: *Simulated Wiener process with* $\mu_A = 30\%$ *and* $\sigma_A = 15\%$



Datasource: Own contribution

While the generalized Wiener process moves around the drift line, the standard Wiener process moves around the starting point, i.e. $\mu_A = 0\%$. However, the weakness of a generalized process is that the market value of assets can become negative. One solves this by implementing a process defined as a geometric Brownian motion, where both the asset drift and volatility is proportional with the market value of assets A over short time intervals. Formulated differently, investors are equally uncertain of the asset return independent of the initial value and require the same percentage return, ceteris paribus. The geometric Brownian motion is defined as:

$$dA = \mu A dt + \sigma A dz \tag{4.3.3}$$

Dividing the expression by A one obtains the percentage asset return for a time interval dt (Equation 4.3.4):

$$\frac{dA}{A} = N\ (\mu_A dt, \sigma_A dz) \tag{4.3.4}$$

As the Merton (1974) is a derivatives model, the derivative value will depend on both market asset value and time. Assuming that the market value of assets follow an Ito's process, $\mu_A$and σ_A will be a function of A and t (Equation 4.3.5):

$$da = \mu(A, t)dt + \sigma(A, t)dz \tag{4.3.5}$$

Again, dz defines the standardized Wiener process depicted in Equation 4.3.1. Ito's lemma shows that a function G of A and t follows the process in Equation 4.3.6:

$$dG = \left(\frac{dG}{dA}\mu + \frac{dG}{dt} + \frac{1}{2}\frac{d^2G}{dA^2}\sigma^2\right)dt + \frac{dG}{dA}\sigma dz \tag{4.3.6}$$

Defining $G = ln(A)$, i.e. the function is the logarithmic return on assets one can apply Ito's lemma and derive Equation 4.3.7:

$$d(lnA) = \left(\mu_A - \frac{\sigma_A^2}{2}\right)dt + \sigma_A dz \tag{4.3.7}$$

Solving the equation for A, one obtains that the market value of assets follow a Brownian motion (Equation 4.3.8):

$$A_T = A_0 e^{\left(\mu_A - \frac{\sigma_A^2}{2}\right)t + \sigma_A dz} \tag{4.3.8}$$

As we apply the model to the real estate sector, we interpret whether a Brownian motion could describe the market value of assets. Real estate values are marked based, and the upside is not limited. In comparison to companies with assets that have limited market values, such as banks with loans denominating their balance sheet, we find it reasonable to assume a geometric Brownian motion for market values of assets (Mjøs, 2015)[12].

4.3.2 Structural Framework

The KMV-Merton model builds on the Merton (1974) framework, and estimates default probabilities for firms at any given point in time based on inferred asset value and volatility combined with observable variables. Based on Section 4.3.1, the KMV-Merton model assumes that the market value of assets follow a geometric Brownian motion with drift μ_A and a diffusion parameter σ_A. Further, the model incorporates a strict assumption that the company's outstanding debt is accumulated into one zero-coupon bond maturing at time T. Under the strict assumptions equity value E is defined as a call option with strike equal to FV, which is described using the Black-Scholes-Merton formula:

$$E = AN(d_1) - FVe^{-rT}N(d_2) \tag{4.3.9}$$

While the left-hand side is equal to E, the right-hand side includes the total market value of assets A and face value of outstanding debt FV. The cumulative normal distribution is denoted $N(\cdot)$, with the respective parameters d_i, $i = 1{,}2$ equal to:

$$d_1 = \frac{ln\left(\frac{A}{FV}\right)+(r+0{,}5\sigma_A^2)T}{\sigma_A\sqrt{T}}, \quad d_2 = d_1 - \sigma_A\sqrt{T} \tag{4.3.10}$$

Where r = continuously compounded risk-free interest rate.

Equity volatility σ_E is obtained from observable market prices. Exploiting the properties of the Black-Scholes-Merton formula using Ito's lemma, equity volatility is defined as a proportion of asset volatility:

$$\sigma_E = \left(\frac{A}{E}\right)N(d_1)\sigma_A \tag{4.3.11}$$

The two non-linear Equations 4.3.9 and 4.3.11 are key components in the KMV-Merton model. As the model infers the market value of assets and asset volatility, it requires that companies are publicly listed. However, a clear limitation is that Equation 4.3.11, describing the relationship between asset and equity volatility, only holds instantaneously as market

[12] Personal communication with Aksel Mjøs, February 11 2015.

leverage fluctuates too much for the equation to give reasonable estimates. Additionally, the model at this form will bias the PDs in the opposite direction of what one would expect from a financial perspective. If leverage decreases quickly the model tends to overstate asset volatility, thus increasing the PD and vice versa. To cope with these problems, the model implements an iterative process to solve the non-linear equation system (Crosbie & Bohn, 2003). The KMV-Merton model calculates market asset values for all of the observations, and extracts the daily asset log return r_A. From the inferred market asset values, the model estimates the implied σ_A, subsequently used as input in the iterative process to produce a new series of asset values and returns. The procedure is repeated until σ_A converges (see e.g. Bharath & Shumway (2004) or Tung, Lai & Wong (2010)).

The intuition of the model is that equity investors will hold a residual claim, and if $A < FV$ the firm will default on its obligations and debt investors will take over the assets. In the KMV-Merton model, default will only occur at the time of maturity, usually defined as one year. Thus, debt investors position can be expressed as a portfolio of a risk-free bond and a short put on the firm's assets with strike equal to the FV. Applying the put-call parity[13], one can derive the expression in Equation 4.3.12:

$$\begin{aligned} Risky\ debt\ &= FVe^{-rT}(1 - N(-d_2)) + AN(-d_1) \\ &= FVe^{-rT}N(d_2) + AN(-d_1) \end{aligned} \tag{4.3.12}$$

Intuitively, the short put position entirely reflects the difference between risk-free debt and credit-sensitive debt. It directly follows that the credit spread effect on the bond valuation is equal to the value of the put, as investors require a lower price, and thus a higher yield. Merton (1974) characterizes credit spreads by assuming constant leverage denoted as $d = \frac{FVe^{-rT}}{A}$, and defines the yield-to-maturity of a risky bond as R in $RD = FVe^{-RT}$. Replacing the left-hand expression in Equation 4.3.12 with RD, gives an expression for credit spreads in the Merton (1974) model:

$$R_T - r = -\frac{1}{T} ln[AN(-d_1) + (FV)N(d_2)] \tag{4.3.13}$$

[13] The put-call parity is based on the no-arbitrage argument, and expresses that a portfolio of a call with strike = K and a risk-free bond with face value K will have the same value as a put option with strike K and the underlying asset ($Coupon + PV(FV) = Put + Stock$). The argument holds if both options are on the same asset, time to maturity is equal, option strikes are equal and there is no differentiation between borrowing and lending interest rates. Thus, one can easily manipulate the expression to derive the debt portfolio (Hull, 2012).

Effectively, the credit spreads in the model depend on the same variables as depicted in Equation 4.3.9. The Merton (1974) framework allows one to derive the PDs based on risk-neutral probabilities. However, Crouhy, Galai & Mark (2000) and Correia, Richardson & Tuna (2011) provide alternative methods to convert risk-neutral probabilities into objective probabilities. As this thesis focuses on the credit ranking from the KMV-Merton model based on PDs, we do not estimate credit spreads, nor convert into objective probabilities. Aligned with Bharath & Shumway (2004), the relative rankings should be unaffected by the risk-neutral probability measure.

The Merton (1974) risk-neutral probability of an asset value being below FV at the time of maturity is:

$$PD = P(A \leq FV \, \mathrm{I} \, A_0 = A) \tag{4.3.14}$$

Using Equation 4.3.9 one can replace and rearrange Equation 4.3.14 to obtain the following expression:

$$PD = N\left[\frac{ln\left(\frac{A}{FV}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right] = N(-DTD) \tag{4.3.15}$$

From a financial perspective, the DTD makes sense. When the asset value decreases the relative difference between A and FV decreases, resulting in a higher PD. Additionally, the default probability will increase with the diffusion parameter σ_A. If the market value of an asset tends to move more during small time intervals, debt investors will assess higher risk when investing in the company's debt. Consequently, the distance to default is interpreted as how many standard deviations the asset, in our case the respective company, is clear of default.

4.3.3 Theoretical Extensions of the Merton (1974) Model

In this section, we provide a brief theoretical review of important theoretical extensions to highlight the shortcomings of the Merton (1974) framework.

The introduction of the Black & Scholes model (1973) and Merton model (1974) has laid a foundation for several theoretical frameworks within credit risk analysis. As mentioned, the Merton (1974) model requires certain, arguably stylistic, assumptions. An often advocated shortcoming is the assumption of all debt reflected by one zero-coupon bond, oversimplifying the capital structure of companies. In general, the existing theoretical literature on structural models divides credit risk models into two branches. One branch is exogenous models, i.e. frameworks where the default boundary that determines when a company defaults is specified outside the model. Since the Merton (1974) model defines the default boundary outside the model through FV, the model is exogenous. The other branch represents endogenous models, where default boundaries represent an optimal decision problem for management determined within the model (Imerman, 2013). Nevertheless, the most important theoretical expansions follow the analytical tools provided by Merton (1974).

Longstaff & Schwartz (1995) expand the Merton (1974) introducing a first time passage framework with an exogenous and constant default boundary k, and constant recovery rates w. The first time passage feature implies that the company defaults the first time the stochastic asset process enters the time dependent k, i.e. the firm can default at any given point in time. In the standardized Merton (1974) framework, default only occurs at the specified time horizon T. The exogenous recovery rates in Longstaff & Schwartz (1995) imply that debt write-offs are dependent on the pecking order of the liability, accounting for the capital structure. Furthermore, Longstaff & Schwartz (1995) develop a two-factor framework, which is an exception from other comparable models (Dufresne & Goldstein, 2001). The two-factor framework implies that the default boundary depends on both the geometric Brownian asset motion, as well as stochastic interest rates. Interest rates follow a Markov process where they mean-revert towards a long-term level, as opposed to the standardized Merton (1974) model assuming constant short-term interest rates, implying a flat interest rate term structure. Note that both the Merton (1974) and Longstaff & Schwartz (1995) models assume that the market value of assets follow the same process, implying an increasing market value for assets over time. The default boundary is assumed to be a monotonic function of the current outstanding debt, i.e. debt remains constant over time. Thus, the leverage ratios of firms will decrease over time. This is an unrealistic assumption as empirical evidence suggests target leverage ratios amongst firms (Dufresne & Goldstein, 2001).

Black & Cox (1976) represent another important contribution to structural credit models. They construct a first time passage model allowing debt investors to take over assets when the stochastic process enters an endogenous default boundary. Equal to Longstaff &

Schwartz (1995), this creates ex ante uncertainty about the default time. Additionally, Black & Cox (1976) investigate important features often found in bond indentures. They assess safety covenants, senior/subordinated debt and restrictions concerning coupon and interest payments. All these aspects seem to affect the value of debt, thus having significant impact on overall valuations. By combining the endogenous default boundary and the role of different indentures, Black & Cox (1976) find the effects on credit spreads. While Merton (1974) determines the default boundary outside the model, Black & Cox (1976) find the optimal default boundary by maximizing the equity value (Sundersan, 2013).

The next major contribution to endogenous models is Leland (1994). His framework includes both the effect of taxes and bankruptcy costs. Thus, Leland (1994) is able to construct a trade-off model assessing optimal capital structure, debt capacity and credit spreads (Sundersan, 2013). While the possibility of bankruptcy decreases the firm value through e.g. liquidation costs, the tax deductibility of interest rates creates a tax shield increasing the total asset value. Leland (1994) views bankruptcy costs as a strictly convex function of market asset value, i.e. moving towards zero for increasing market values of assets, while the tax shield value is strictly concave. Hence, the model draws upon familiar corporate finance concepts being the trade-off between bankruptcy costs and tax shields, both affecting the default boundary. Using the framework, Leland (1994) is able to (i) derive the optimal default boundary by maximizing the value of the equity and (ii) determine the optimal leverage by maximizing the firm value. Thus, he is able to derive the optimal capital structure for the company (Sundersan, 2013). Hence, Leland (1994) suggest that defaulting will depend on multiple variables e.g. tax shields and bankruptcy costs.

In general, the reviewed models are more comprehensive than the Merton (1974) model, and pinpoint some of the weaknesses of our KMV-Merton model. Nevertheless, the Merton (1974) framework is widely acknowledged by both academicians and practitioners.

4.3.4 Empirical Research on Credit Risk Models

In the following section, we delve into empirical research on credit risk models. According to Das, Hanouna & Sarin (2006), related research consists of two areas: PD analysis and credit spread analysis. Essentially, the difference is that the former focuses on extracting and analyzing the PD, while the latter indirectly assesses PD through a decomposition of credit spreads.

Sobehart et al. (2000) construct a model including the KMV-Merton PD, but extends the regression model implementing additional factors such as Moody's credit rating, financial statement information and macroeconomic variables. By including information on credit ratings, which is a proven indicator of long-term solvency, defined as the capability of a company to encounter its long-term financial obligations, the hybrid model makes use of key credit metrics applied by CRAs. The rationale behind the regression is that the form of the KMV-Merton model is not exhaustive enough to capture all relevant information (Sobehart et al., 2000). They support this by arguing that there are empirical discrepancies between implied estimated spreads using the KMV-Merton model and observed spreads. By applying power curves[14], which essentially evaluate the models ability to rank defaulters based on their estimated default probability, Sobehart et al. (2000) conclude that the hybrid model outperforms the standardized KMV-Merton model. They further support their results by arguing that structural models such as the Merton (1974) model do not account for decreases in stock prices driven by non-fundamental factors, and that historical performance of these models often assign low credit scores to investment grade instruments. Hence, they claim that focusing on equity alone does not distinguish between changes due to fundamental factors related to the company e.g. future earnings power or capital structure, and non-fundamental factors related to investor allocation preferences or temporary periods of increased market volatility.

Kealhofer & Kurbat (2001) try to verify these findings by comparing the KMV-Merton model to Moody's rankings and key financial metrics applied by Sobehart et al. (2000). Their results indicate the opposite, namely that the KMV-Merton model stands out superior, and thus seems to capture information in ratings and accounting metrics. They claim that revisions on credit ratings (credit migrations) are quickly reflected in equity prices, i.e. other variables are redundant. Though Kealhofer & Kurbat (2001) find support for a stand-alone KMV-Merton model, it is noticeable that they do not compare their model explicitly to a hybrid, as they construct two separate univariate models when assessing the benefit of including financial metrics.

[14] Power curves, or Cumulative Accuracy Profiles, test the models accuracy to predict defaults. A perfect model would be able to place all defaults in the sample within the percentile equal to the share of defaulted firms. With the percentiles of risky firms on the horizontal axis, and the proportion of defaulted firms on the vertical axis, a more accurate model will be closer to the north-west corner of the graph (Tudela & Young, 2005)

However, both Sobehart et al. (2000) and Kealhofer & Kurbat (2001) conclude that applying financial ratios on a stand-alone basis in empirical models yield the least accurate results. Vassalou & Xing (2004) provide two possible explanations for the superiority relative to pure accounting models. First, the KMV-Merton model applies market values of equity as input and calculates the market value of debt, instead of using (i) time series of historical data not necessarily representative for future performance and (ii) book value of debt. If investors are assumed to be forward looking, and markets somewhat efficient, stock prices would reflect both expectations regarding future performance and historical data. Secondly, pure accounting models ignore asset volatility, which effectively ignores the uncertainty related to the underlying business.

Bharath & Shumway (2004) conduct extensive test to evaluate the KMV-Merton model's contribution in default predictions. Applying a Cox proportional hazard model[15], they test if other variables than the estimated PD are significant in explaining an event of default using data 12 months prior to a default. Amongst others, they add the individual observation's net income to total asset ratio, and find that the ratio is a significant predictor variable. This result implies that the KMV-Merton model is not sufficient in predicting defaults, and is in line with earlier results that support hybrid models. When including a handful of other factors, the influential power of PD diminishes, but stays significant. In addition, Das, Hanouna & Sarin (2006) examine cross-sectional regularities in CDS pricing using econometric hybrid models. They suggest that there is information contained in the financial statements not captured by the KMV-Merton model. Hence, their comprehensive hybrid model is superior to the models solely based on market variables or firm financials[16].

Further, Bharath & Shumway (2004) perform tests on the contribution of the iterative process by constructing a naïve model, where asset volatility is determined as a weighted function of equity volatility and debt volatility, the latter being somewhat arbitrary estimated[17]. Their findings suggest that the structural form, describing equity as a call

[15] Other variants of this might be simpler versions such as a probit model where the dependent variable is either one or zero, see e.g. Tudela & Young (2005).

[16] Results of Collin-Dufresne, Goldstein, & Martin, (2001), Blanco, Brennan, & Marsh, (2005) and Wu, & Zhang, (2008) also support this.

[17] Debt volatility is not estimated using the return on bonds for firms, but as a proportion of equity volatility. The debt volatility measure is given by $\sigma_D = 0.10 + 0.25\sigma_E$. Asset volatility is estimated as a weighted average of the two components.

option, is more important than the iterative process solving the two equations simultaneously. While Vassalou & Xing (2004) may be right that asset volatility is a key component in hybrid models performing better, these findings suggest that the iterative process behind the estimation is not necessarily as important. Further, the KMV-Merton model reflects increased PD faster than other models, but critically depends on markets being efficient (Bharath & Shumway, 2004). For example, companies experiencing stock appreciation during bubbles will have low PD estimates, ex ante. Hence, adjusting for factors other than the input in PD makes sense, as abnormally high stock prices amongst companies will bias PDs downwards.

Structural models largely tend to exclude macroeconomic variation in default predictions, which is a potential pitfall. Longstaff & Rajan (2006) decompose credit spread variation of the Dow Jones CDX Index into tranches: economy-wide factors, industry-specific factors and firm-level factors. Their results indicate that the majority of credit spread variation can be explained by firm-level factors, while one-third of the variation is attributable to factors significant for multiple firms defaulting together. Examining the role of macroeconomic factors, Wu & Zhan (2004) suggest that bond spreads are a function of inflation, financial market volatility and real output growth. In addition, Huang & Kong (2005) proves a relationship between the spreads of high yield bonds and the release of macroeconomic news (i.e. surprises in leading economic indicators and employments reports). Moreover, evidence indicates that both PD and LGD are increasing with economic downturns. Chen (2010) constructs a model that includes macroeconomic conditions. First, he argues that recessions are times of "high marginal utilities", implying that any LGD will affect investors more in an economic downturn. Additionally, he claims that cash flows will grow at a more conservative rate during recessions, and become more correlated with the market in general. Combined with higher risk premiums and lower terminal values, this increases PD. Lastly, there is a strong tendency that companies perform poorly during recessions, and due to limited liquidity need to sell assets at a discounted price relative to the fair value. Shleifer & Vishny (2010) use the term "fire sale", and argue that during economic downturns firms within one sector may experience the same distress, causing non-specialized firms to purchase their assets at a heavily discounted value. Hence, LGD rates during recessions are likely to increase significantly. Chen (2010) proves that defaults are more frequent during downturns, i.e. that the default probability will increase by taking into account macroeconomic factors.

4.3.5 Comparing Our Model to Moody's

Since we apply a model based on Bharath & Shumway (2004) and Vassalou & Xing (2004), we acknowledge the differences relative to the model applied by Moody's in their credit research.

The origin of the differences is that several of the features employed by Moody's are proprietary. While all employ the same procedures to derive the asset value and volatility, Moody's divides the firm's debt into different tranches. The Moody's model takes into account five tranches of liabilities e.g. senior debt and subordinated debt, in addition to convertibility and dividends paid to investors (Crosbie & Bohn, 2003). Furthermore, the Moody's model is able to implement the fact that equity is a perpetual call option, while we apply $T = 1$. More importantly, our model is based on the assumption that default probabilities follow a normal cumulative distribution function, as depicted in Equation 4.3.15. However, empirical evidence does not support the notion that the DTD in large samples is normally distributed. According to Vassalou & Xing (2004), the probability output from our model does not align with actual firm default probabilities. Research suggests that a more realistic distribution would be leptokurtic, implying a more clustered formation around the mean, and thus a large positive kurtosis. This implies that the distribution has fat-tails, which essentially means that extreme events are far more likely relative to the normal distribution (Acharya & Schaefer, 2009). Hence, the implication of applying the normal distribution is that our model will underestimate default probabilities. Moody's model solves this problem by using a database of 250,000 company-years, including 4,000 defaults to approximate a probability of default based on different frequencies of distance to default (Crosbie & Bohn, 2003). They define defaults as events where companies are delisted from stock exchanges due to bankruptcy. For a distance to default of 3.2 the Moody's model will estimate an annual default rate of 0.25%, while the normal distribution will yield 0.069%. Assuming normality for defaults will imply that over 50% of all US companies would be Aaa rated, which obviously is not the case (Acharya & Schaefer, 2009). Evidentially, this will yield errors to our PD results; however, since the DTD is independent of the choice of distribution, the ranking should be unaffected. Bharath & Shumway (2004) are able to apply their model on the same dataset as the Moody's model. The results did not suggest to large a bias per se; comparing results from the two models on the same data yielded a 79% rank correlation.

We temporarily conclude that extracting PDs from assets may be challenging due other components affecting credit spreads. Related literature suggests that structural models can be applied to compute default probabilities for companies. However, structural models require certain stylistic assumptions affecting the accuracy of PD estimates. As we choose to employ the KMV-Merton model, we acknowledge the limitations related to the theoretical framework. Longstaff & Schwartz (1994), Black & Cox (1976) and Leland (1995) all provide extensions accounting for different shortcomings of the Merton (1974) framework. Nevertheless, empirical research by e.g. Bharath & Shumway (2004) implies that the KMV-Merton model provides valid credit rankings. In addition, there seems to be a strong precedence amongst researchers that hybrid models, including output from structural models combined with financial-, and macroeconomic variables, provide more accurate assessments of credit risk. Thus, the KMV-Merton model and empirical findings constitute the basis for our further analysis.

4.4 Empirical Strategy

In this section, we motivate our choice of econometric model and give a brief review of relevant theory.

To assess statistical inference about a dependent variable Y_i and a selection of m factors, defined as independent or predictor variables $X_{1i} + X_{2i} + \cdots + X_{mi}$, one can choose between several regression methods. For example, Tudela & Young (2005) and Bharath & Shumway (2004) apply a probit/hazard model to assess the explanatory power of predictor variables, i.e. if the predictor variables explain actual defaults. However, no Swedish real estate company at the NASDAQ OMX Nordic has been delisted due to bankruptcy since 1997[18]. Hence, we do not have sufficient information to construct a survival model. Further, related empirical research frequently exploits time series dynamics using panel data. Panel data includes both multiple units and time periods, displaying both time series variation and cross-sectional variation (Wittink, 1988). As mentioned in the introduction, we extract bond data from Stamdata, Nordic Trustee's database. The database only provides reference date information, i.e. the information on each bond is updated to the date of extraction. Hence, all

[18] Information prior to this is not available.

historical monthly information on bond coupons display the same value. This clearly prevents us from conducting regressions on panel data or preform standard time series regressions. Lastly, Das, Hanouna & Sarin (2006)[19], apply Ordinary Least Square (OLS) regressions to check for significant predictors. As Stamdata provides reference date information on all bonds issued in different points in time, we have a modified version of cross-sectional data, termed pooled cross-sectional data (Wittink, 1988). OLS regression models are a commonly applied method used to assess cross-sectional variation, and thus we consider this an adequate model for our empirical analysis.

Utilizing the observations of the dependent and independent variables, the OLS regression model computes the unknown parameters $\alpha, \beta_1, \ldots, \beta_m$ and assumes linear effects for each predictor variable X_i. Mathematically, the regression equation is:

$$Y_i = \alpha + \beta_1 X_{1i} + \cdots + \beta_m X_{mi} + u_i \tag{4.4.1}$$

The last argument u_i describes the error term[20] in the model. By applying the OLS method, one can find parameters that yield a regression line minimizing the sum of squared deviation, expressed as:

$$\min_{\beta_i} \sum \hat{u}_i^2 \tag{4.4.2}$$

The squared deviation specifies the squared value of the difference between the observed and estimated value of the dependent variable, $\hat{u}_i^2 = (Y_i - \hat{Y}_i)^2$. For the OLS regression model to be valid (lack of bias) and reliable (small standard error) four assumptions need to be satisfied. When all the assumptions concerning the error term hold simultaneously, the OLS regression model provides the best linear unbiased estimators (BLUE) of the population parameters Wittink, 1988).

Appendix 10.5 shows the methodology of initial feasibility assessment for OLS regression analysis, as well as the four error term assumptions. Further, it includes the methodology used to examine existence of unusual and influential observations in our dataset.

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[19] Bharath & Shumway (2004) conduct OLS regressions on spreads in later sections of their paper.

[20] Error term and residuals are used interchangeably.

5. Methodology and Data

5.1 KMV-Merton Methodology and Input

This section describes how we implement the KMV-Merton model using Visual Basic for Applications (VBA). Further, we elaborate on the data collection and important assumptions for our KMV-Merton model. The last part of the section provides an overview of the financial metrics used when assessing our first hypothesis, that the PDs from the KMV-Merton model provide a rational risk ranking and robust estimates.

We implement the KMV-Merton model using VBA in Excel[21]. The routine CalDefProb performs the iteration and estimates the relevant parameters to infer the theoretical PD (Equation 4.3.15). Our initial guess for asset volatility is the product of equity volatility and equity ratio. We use the initial guess as input in the Newton-Raphson sequence, which successively estimates inferred asset values A_T, returns $r_{A,T}$ and volatility $\sigma_{A,T}$. The model stores the results from period $T-1$ $(A_{T-1}, r_{A,T-1}\ \sigma_{A,T-1})$ and controls the convergence term by evaluating the difference between asset volatility estimates $(\sigma_{A,T} - \sigma_{A,T-1})$. We define our convergence limit as 10^{-8}. The VBA code in Appendix 10.3 depicts the entire process.

Our structural estimation of PD focuses on companies currently trading at the NASDAQ OMX Nordic REI[22]. As of 05.02.2015, the index included 22 companies and 26 tradable instruments. A handful of the companies, amongst others AB Sagax and Victoria Park, have both A and B class instruments trading on the exchange. Thus, when calculating necessary inputs for the KMV-Merton model we choose to include all traded instruments, as they will affect the default boundary through the equity value as well as the volatility measures. We apply rolling series including observations from 2007 to 2014 for all companies in our sample, as averaging yearly PDs masks the changes in credit quality perceived by the equity market (Crosbie & Bohn, 2003). The primary reason for a long period is to assure that we

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[21] The VBA routine is based on "Professional Financial Computing Using Excel and VBA" by Tung, Lai & Wong (2010). The most important chapters for the code implementation are Chapter 3 ("Finitie Difference Methods"), Chapter 5 ("Newton-Raphson Method") and Chapter 13 ("KMV-Merton Model").

[22] Appendix 10.9 shows the companies traded at the NASDAQ OMX Nordic REI

have sufficient data points to estimate asset drift rate and asset volatility. Additionally, this is consistent with Bharath & Shumway (2004) applying long time series up to 20 years.

We obtain daily market capitalization for the total traded equity for each company using both Factset and Bloomberg's databases. To assure that the information is consistent we perform cross-examinations of the data, and make necessary adjustments if we observe deviations. For example, for some companies daily equity values are missing in the Bloomberg database, and thus we use values from Factset. The equity value is calculated as the product of shares outstanding and price per share at any given time. For companies with more than one stock class trading at the REI we simply aggregate the products. Equity volatility σ_E is estimated as the annualized standard deviation of returns assuming 260 trading days. Initially we obtain book debt values using Factset and Bloomberg's database and their respective functions for short-term (ST) borrowings and long-term (LT) borrowings. When performing cross-examinations of reported figures in quarterly reports for each company, Bloomberg and Factset proved erroneous for many of the observations.

There are typically two repeating reasons for the reporting errors. First, the algorithm gathering data occasionally includes all liabilities, i.e. not only the interest bearing debt. Non-interest bearing liabilities are not relevant when calculating default boundaries in the KMV-Merton model, as failure to service such obligations will not force the company into bankruptcy. Second, for most companies Bloomberg/Factset unsuccessfully disaggregate the total debt into a ST component and LT component. In our PD estimation, it is critical to distinguish the two components, as the ST debt is fully included into the default boundary and volatility, whilst LT debt is included at a 50% proportion:

$$FV_T = ST\ debt + 0.5 * LT\ debt \tag{5.1.1}$$

Our default boundary suggests that failure to service ST debt will automatically cause the firm to default on all its obligations. We further include 50% of LT debt in our boundary. The weighting implies that LT debt is less important when assessing default boundaries, as re-financing risk is substantially lower and liquidation opportunities larger. However, the LT debt component may induce a barrier for refinancing ST debt if companies are heavily indebted. This will reduce the ability to roll over short-term debt (Vassalou & Xing, 2004). Our suggested debt weight follows standard KMV procedure and is arbitrarily set (Bharath & Shumway, 2004). One might argue that relevant determinants for the percentage of LT debt should be properties such as debt maturity concentration and asset liquidity, as both will imply higher refinancing risk and limited liquidation opportunities. For example, Patel & Vlamis (2006) estimate PDs for listed real estate companies in the UK and fully include LT debt. They argue that real estate companies are more levered than other sectors and that most financing is floating interest, making the sector vulnerable for increases in the reference interest rate. Additionally, real estate is a relatively illiquid asset. On the other hand, real estate is a tangible asset investors easily accept as collateral, and thus have lower LGD than for example intellectual property, which can explain the high leverage. We apply the standard practice of 50% LT debt weighting, which in our opinion also will reduce discretionary biases, since the proportion effectively can be “any proportion that is of interest” (Saunders, 1999).

To solve the reporting quality issue detected in the cross-examination, we consulted each quarterly report for the entire time span, and disaggregated the reported debt into ST and LT. However, for several of our companies quarterly reports were less detailed than annual reports, and the balance sheet itself was not comprehensive in separating the debt component appropriately. In some reports, we were able to track the ST debt in notes, while we for a significant fraction had to apply the information given in the overview of the debt structure. Most of the quarterly reports included an updated overview of the debt maturity structure, including both used and unused credit. The structure depicts the proportion of debt outstanding maturing in different points in time. This allows us to report complete figures for both ST and LT debt.

For one of the companies in our sample, Balder AB, significant data was missing. The annual and quarterly reports post 2009 did not disaggregate the total interest bearing debt, nor did they have information in notes or regarding their maturity structure. As the company constitutes four of the 48 issued bonds in our empirical sample, we argue that including the company has statistical benefits. Hence, we calculate the ST debt proportion relative to the total debt for 2007-2010. In line with our expectations, the proportion was rather stable over the period. We average the proportion of ST debt, and assume a constant proportion for the period 2010-2014. In essence, this approach is a trade-off between volatility and debt information. Since the proportion is constant, one might expect reduced volatility. In our case, this seems to be less of a problem as the proportion was stable at approximately 30%. Since we weight ST debt 100%, all else being equal, this will affect the results for Balder AB by increasing the PD.

For the risk free interest rate, we apply the 10yr yield on Swedish Treasuries reported on a quarterly basis. One might argue that 10yr US Treasuries are a better approximation for risk-free interest rates. However, since our sample contains solely Swedish real estate companies traded on the REI, it is reasonable to assume that Swedish Treasury yields are more relevant. To reduce volatility with respect to interest rates we average the quarterly reported yields for each year. The interest rates are collected from the Swedish Central Bank.

Since the market value of equity and book debt levels have different frequencies[23], we need to make certain assumptions about debt levels between quarter $q-1$ and q. For debt investors investing in bonds at time q, publicly available information is limited to the end of period in the previous quarter[24], i.e. $q-1$. Hence, our calculation of default probabilities implies that debt levels at time q are equal to the debt balance at the end of $q-1$. Under this assumption, we imply that companies either leverage or deleverage at the end of each quarter. This might seem stylistic, as companies typically tend to issue debt in a more continuous manner. More importantly, it will bias our results since asset volatility implied by the iterative procedure in the KMV-Merton model will be underestimated. Ceteris paribus, this will reduce our calculated default probability. However, debt levels are not available on daily basis. A possible solution for the frequency discrepancy is to use cubic spline interpolation to calculate debt levels for each day (see for example Tudela & Young, 2003). Cubic spline interpolation is a statistical method to estimate unknown data points based on two or more observable values (see Chapter 6 in Tung, Lai & Wong, 2010 for a detailed description). However, we argue that this may induce a systematical source of error to our results, as the interpolated data points will be systematically related to one another by a cubic polynomial, thus violating the assumptions of independent error terms in our OLS regression model (Columbia Economics, 2010).

To assess if the PDs from the KMV-Merton model provide a rational risk ranking (Hypothesis 1), we include the following four metrics. Our selection of credit metrics is based on Moody's (2007) and Standard & Poor's Investor Services (2009):

[23] Market value of equity is updated on a daily basis, while book debt levels are reported quarterly.

[24] Financial reports are issued with a time lag. However, when companies issue bonds, it is likely that investors will gain access to more recent data. Hence, if a bond is issued 01.04.20xx, we assume that the investor will gain access to the debt figures for Q1 20xx.

1. Leverage ratio:

$$\frac{Interest\ Bearing\ Debt(IBD)}{Total\ Assets}$$

2. Debt payback time (assuming constant IBD and EBITDA):

$$\frac{Interest\ Bearing\ Debt}{EBITDA}$$

3. Interest coverage ratio:

$$\frac{EBITDA}{Net\ Interest}$$

4. Operating margin:

$$\frac{EBITDA}{Rent\ Income}$$

We gather the metrics using Factset and cross-examine the figures relative to financial reports. As an endnote, we assess the hypothesis by calculating metrics for two companies with PDs lower than the median and two companies with PDs above the median.

To assess if the KMV-Merton model produces robust PDs, we compute estimates based on short time series, defined as one year. We compute the aggregated average default probability (ADP) for the sample following Tudela & Young (2005). The computation represents the simple average PD of all firms within one year, and should yield a valid metric for the overall sector default rate. The results from this basic sensitivity analysis will provide information on how to best utilize the firm information when computing structural default probabilities, used in our empirical model.

5.2 Market and Data Description

This section describes how we collect our initial dataset of bonds issued by Swedish real estate companies using Stamdata. Further, we discuss our methodology for credit spread calculations and give a descriptive overview of the sample.

5.2.1 Data Collection

Tables and statistics depicted in this section describe all corporate bonds issued by Swedish real estate companies, both issued in SEK and other currencies. The data for corporate bonds issued in Sweden is available through Nordic Trustee's Stamdata (Function: Statistics, Time Series). This database includes complete detailed information regarding e.g. issuance dates, reference spreads, coupon structure, ratings and security for the Swedish corporate bond market. In our analysis, we define reference spreads as "credit spreads". Stamdata provides information for debt securities held by both listed and non-listed companies. We filter the series for bonds issued by Swedish real estate companies, which in total yields 9,000 bond observations in the period 2003-2014. The initial data series obtained from Stamdata includes monthly observations on 323 issued bonds. Note that the dataset does not contain information on daily market prices for listed bonds, which prevents us from exploiting time series dynamics in our empirical model. As mentioned, we focus our empirical methodology on assessing cross-sectional variation in credit spreads at issuance date. In order to obtain the unit of interest, we manually enter each unique ISIN-number[25] and isolate the first observation of each bond. In grand total, this results in 323 observations.

Bonds issued by Swedish real estate companies have either had a fixed or floating coupon structure[26]. The distribution concerning coupon structure for both matured and active bonds is even, with floating representing 57% of the issued bonds. For floating bonds, we obtain the credit spreads directly from Stamdata, since it typically is a margin over the 3-month annualized interbank rate (STIBOR3M). However, for fixed bonds, spreads are unavailable in Stamdata. We therefore estimate a proxy for all bonds with fixed coupon structures (FC_{Issue}). Given that most of the issued fixed bonds are bullet loans, i.e. the principal is equal to the issue price of the bond (issued at par), we employ a simplistic but yet reasonable assumption regarding yields on issuance date. All else being equal as of issuance date, the coupon obtained from Stamdata coincide with the bond yield ($YTM_{Issue} = FC_{Issue}$). In order to calculate the credit spread proxy for fixed bonds, we follow Fredriksen & Minehuber (2012) estimating spreads as the bond yield markup relative to a benchmark

[25] International Security Identification Number.

[26] No zero coupon bonds have been issued.

for the risk-free interest rate being government bond yields $(YTM_{Corporate\ bond,Issue} - YTM_{Government\ bond,Issue})$. We apply yields from Swedish Treasuries to be consistent with the risk-free interest rates in our PD estimations. Collecting data from Macrobond, we obtain Treasury yields from bonds with maturities of 2, 5 and 10 years. We apply Treasury yields from the same date as the issuance date of the respective bond. To remove liquidity effects in credit spreads, we estimate spreads using Treasuries with identical maturity as the respective bond. In addition, this does not affect the duration risk, which is related to the interest rate risk of fixed bonds. For bonds with maturities deviating from 2yr, 5yr and 10yr, we estimate benchmark yields using linear interpolation:

$$YTM = YTM_0 + (YTM_1 - YTM_0)\left[\frac{Maturity - Maturity_0}{Maturity_1 - Maturity_0}\right] \tag{5.1.2}$$

However, we are fully aware of the fundamental differences in Treasuries versus corporate bonds. According to Feldhütter & Lando (2008), Treasuries include a convenience yield. This arises due to several factors, e.g. (i) it is the main instrument in hedging interest rate risk and (ii) financial institutions invest in Treasuries to fulfill regulatory requirements as government bonds have low capital risk weights. Effectively, this biases the proxy for risk-free interest rate downwards, which might exaggerate our credit spreads. We argue that applying Swedish instead of US Treasuries leads to less a bias; investors often categorize the latter as a "safe haven", i.e. the convenience yield will be higher than for Swedish Treasuries. Thus, we consider our choice of benchmark yield to generate a sufficient proxy aligned with previous research. Nevertheless, we note that floating bond spreads are relative to STIBOR3M, which has significantly higher inherent credit risk compared to government yields. Hence, the estimated fixed bond spread versus the risk-free interest rate will be somewhat higher than the floating spread.

Note that one bond in our sample is denominated in NOK[27] with the Norwegian 3-month annualized interbank interest rate as reference rate. This may bias the credit spread if dependence between default events and the exchange rate persists, i.e. the credit spread and a currency are systematically related compared to a benchmark currency (Rathgeber, Stöckl & Rudolf, 2011). However, we include the NOK bond under the assumption of zero correlation

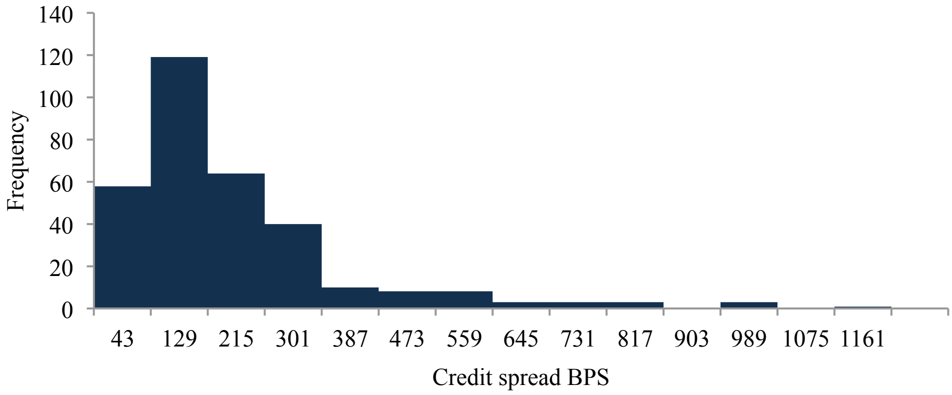
[27] ISIN number NO0010572357 issued by Kungsleden AB 30.04.2010. The floating coupon, ceteris paribus at issuance date, is 535 BPS – with a spread over the 3-month annualized Norwegian interbank rate (NIBOR) of 300 BPS.

between the reference rate and default risk for bonds denominated in different currencies, making the credit spreads directly comparable[28].

5.2.2 Overview and Descriptive Statistics

The following descriptive statistics include both currently outstanding and matured bonds in the period 2003-2014. Figure 5.1 shows the distribution for the entire sample of estimated credit spreads. We define the entire sample as listed and non-listed Swedish real estate companies. The discrepancy between the median and average in Table 5.1 indicates a positive skew of 2.53, i.e. the distribution has a right tail. The fact that the distribution has a kurtosis of 8.01 implies that credit spreads are highly clustered around the mean of 164 basis points (BPS) [29]. The positive skew and kurtosis aligns with our expectation for a credit spread sample. Few observations yield negative spreads or spreads close to zero, while bonds issued by risky companies deviate significantly from the mean.

Figure 5.1: *Histogram of observed credit spreads at issuance for the entire sample*



Datasource: Stamdata and the Swedish Central Bank

The differences between the respective percentiles indicate significant variance in our sample. We estimate an average maturity of five years for the entire sample and observe a declining trend for the real estate sector aligned with the findings for the Swedish market in general (Bronthron, 2014). Overall, we observe that 88% of the bond issuances have maturities of 5 years or less, with only a handful of bonds surpassing maturity of 10 years.

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[28] For an empirical discussion whether correlations between currencies and default probabilities exist, see e.g. Rathgeber, Stöckl & Rudolf (2011).

[29] 100 BPS = 1%

Table 5.1: *Descriptive statistics of credit spreads for Swedish real estate bonds, entire sample*

Statistic	**BPS**
Mean	164.17
25^{th}	55.00
50^{th}	112.00
75^{th}	214.00
Skewness	2.53
Kurtosis	8.01

Datasource: Stamdata and the Swedish Central Bank

As our empirical analysis relies upon publicly available information, i.e. market values of equity and financial reports, we separate between issuances by listed companies and non-listed companies. We find that listed companies constitute 15% of the overall issued volume, while the private sector represents the dominant mass at 85%. This clearly indicates that most borrowers using the bond market are private companies. Table 5.2 shows that the average spread for listed companies is 240 BPS at issuance, while non-listed companies on average issue bonds at a spread of 148 BPS.

Table 5.2*: Credit spread distribution, segmented*

Sample	**25^{th} percentile (BPS)**	**50^{th} percentile (BPS)**	**75^{th} percentile (BPS)**	**Mean (BPS)**
Non-listed sample	49	100	178	148
Listed sample	143	228	330	240
Entire sample	55	112	214	164

Datasource: Stamdata and the Swedish Central Bank

Table 5.3 depicts the relative proportion of floating/fixed, unsecured/secured[30] and high-yield/investment-grade bonds issued by Swedish real estate companies in the period 2003-2014.

Table 5.3: *Bond properties, segmented*

Sample	**Floating**	**Fixed**	**Unsecured**	**Secured**	**HY**	**IG**
Non-listed sample	53 %	47 %	56 %	44 %	10 %	90 %
Listed sample	76 %	24 %	82 %	18 %	60 %	40 %
Entire sample	57 %	43 %	60 %	40 %	18 %	82 %

Datasource: Stamdata

[30] Secured bonds in our sample are guaranteed bonds, priority/-subordinated bonds and bonds with pledge/ negative pledge.

We find that 60% of listed Swedish real estate companies are classified as high-yield in Stamdata, compared to only 10% in the non-listed sample. This aspect may explain the higher credit spreads observed for listed companies relative to non-listed. Further, we find that 44% of all issued bonds by non-listed companies are secured, while listed companies prefer to issue unsecured bonds (18% secured). Due to guarantees/collateral, all else being equal, an investor will require lower compensation for the risk when investing in secured bonds. Further, our observation is consistent with findings in e.g. Kovner & Wei (2014) that US non-listed companies more often issue secured bonds relative to listed companies. In our sample, debt investors allocating funds into bonds issued by non-listed companies tend to receive collateral, which further supports the lower spreads for non-listed companies. We observe that a larger proportion of bonds in the non-listed segment are fixed. Since fixed bonds are exposed to interest rate fluctuations, estimated credit spreads should be higher. Our calculations depicted in Table 5.4 supports this notion, as the fixed (floating) bonds for the listed companies yield 306 BPS (219 BPS), while for non-listed fixed (floating) bonds yield 208 BPS (100 BPS).

Table 5.4*: Bond spreads for different properties, segmented*

Sample	Fixed coupon (BPS)	Floating coupon (BPS)	Unsecured (BPS)	Secured (BPS)
Non-listed companies	208	100	74	174
Listed companies	306	219	240	236

Datasource: Stamdata and the Swedish Central Bank

For listed companies a difference of 4 BPS appears between secured and unsecured issuances. We note that the marginal difference in credit spread between the two bond classes offers a possible explanation for the reluctance of listed companies to increase their issuance of secured bonds. The additional spread on unsecured bonds is negligible relative to secured bonds, and hence the benefit of more flexibility concerning the external capital seems to be “worth paying for”, supported by the argumentation of Landeman & Bergin (2014). Surprisingly, unsecured bonds issued by non-listed companies have an average credit spread of 74 BPS, while secured bonds are issued at 174 BPS. However, we note that Vasakronan AB accounts for 72% of the issued unsecured bonds. Recall that the Swedish government holds an 85% ownership stake in the company. Thus, this may serve as an explanation for the lower spreads on unsecured bonds issued by non-listed companies. As an endnote, we observe a highly positive trend in issuance, with approximately 84% of issuances stemming from 2010 or later.

5.2.3 Sample Construction and Presentation

As mentioned before, we utilize Stamdata to collect information on 323 bond issuances from the period 2003-2014. We restrain our analysis to listed companies, as this is a prerequisite for the KMV-Merton model. The restriction secures access to relevant market and company specific information available through Factset/Bloomberg and financial reports, which are key components for our empirical model. Accounting for the restriction reduces the number of bond issuances to 50 bonds. Consequently, the sample is confined to bonds with issuance dates in the time interval 01.01.2010-31.12.2014. As previously stated, we choose to include bonds issued at different points in time by different companies, which implies that our estimations apply pooled cross-sectional data. We further restrict our sample to companies that have a minimum of one year of listing history, as shorter series produce less accurate parameter estimations, i.e. asset drift and volatility[31]. The restriction aligns with Bharath & Shumway (2004) and Tudela & Young (2005). Our last restriction implies that we exclude two issued bonds, resulting in 48 observations in our empirical sample. Appendix 10.4 shows information on all bonds. Thus, we argue that our sample bodes for a precise assessment of credit spreads at bond issuance. As our sample solely consists of bonds with maturities of more than one year, we fulfill the restriction employed by Bharath & Shumway (2004) requiring minimum one year maturity. Lastly, as we aim to explain credit spreads for real estate companies on a general basis, not for specific subgroups or structures of bonds, we utilize both floating and fixed bond observations.

Table 5.5*: Summary statistics of listed companies, empirical sample*

Statistic	**BPS**
Mean	235.7
Median	225
St.dev	129.2
99^{th} percentile	493
1^{st} percentile	38
# Observations	48

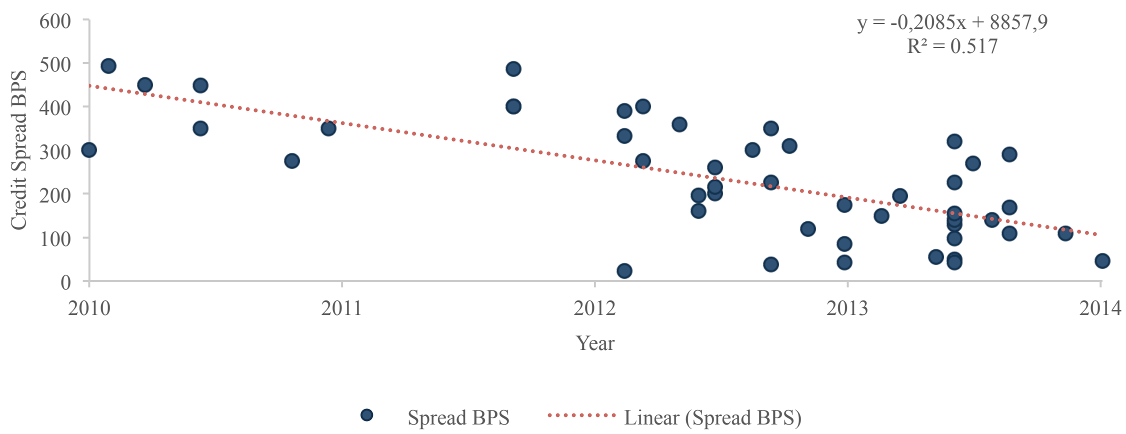
Datasource: Stamdata and the Swedish Central Bank

Recall that credit spreads (BPS) at issuance date is the dependent variable in our empirical model. According to Equation 4.1.1, we define credit spreads as an indicator for investor's

[31] Implications of using short time series is discussed in Section 6.1.2.

required compensation for default risk. Table 5.5 indicates an average of 235.7 BPS and median of 225 BPS, i.e. the discrepancy between the two measures indicate negligible skew for the distribution. We note that the increase between percentiles seems convenient and that observations are evenly distributed around the mean, with a sample standard deviation of 129.2 BPS. Compared to the entire sample depicted in Section 5.2.2 the average is significantly higher (235.7 BPS versus 164 BPS), which we expect in light of characteristics for listed and non-listed segment. We further find that the difference between minimum and maximum credit spread indicates significant variation in our sample. On aggregate, characteristics concerning the unit of interest constitutes a solid base for our empirical model. When analyzing the trend in credit spreads, we detect a negative relationship between credit spreads, with a corresponding residual-squared of 51.7% (Figure 5.2). The trend is especially evident for bonds issued after 2012.

Figure 5.2: *Credit spread development 2010-2014*



Datasource: Stamdata and the Swedish Central Bank

The trend observation results in a common statistical trade-off. When including all observations, we have a larger dataset to rely on, which provides better statistical calculations. However, including all historical observations without controlling for time effects may suppress the observed trends in most recent years. In addition, the empirical model might compute results driven by spurious correlations between predictors, i.e. results seem statistically significant even though relationships actually do not exist (Wittink, 1988). To solve the problems, we include a time dummy for the period 2010-2012. Table 5.6 displays descriptive statistics for the periods, and supports our choice of time variable due to large differences in average credit spreads and number of bond observations. Note that we have considered the possibility of including calendar year dummies. However, as our dataset consists of 48 observations including four more variables will seize limited freedom degrees. Furthermore, the main proportion of issued bonds stems from the two most recent years, and when running regressions including all calendar year dummies the OLS regression assumptions were not satisfied.

Table 5.6: *Descriptive statistics, Credit spreads BPS listed real estate companies*

Periods	Average (BPS)	Standard deviation	Observations (#)
2010-2012	372.2	79.89	15
2013-2014	173.7	95.08	33

Datasource: Stamdata and the Swedish Central Bank

Further, Table 5.7 displays relevant summary statistics for our assessed predictor variables, disaggregating into issuer, macroeconomic and bond characteristics. For all relevant statistics, we solely base our estimates on a priori information available for the investor at time of issuance. We obtain all financial metrics from each company's financial reports to ensure statistical precision.

We analyze the issuer's size measured in (i) company rental income (annual) and (ii) market value of properties for the trailing 12-months prior to issuance. Based on both metrics no trend in issuer size is detected, i.e. both small and large companies issue bonds. The average annual rental income is SEK 1,757 million, approximately four times the average bond size, while annual operating profitability ranges between 62% and 86%. To account for the different capital structures amongst our sample companies, we use loan-to-value. Real estate companies have high asset concentration within properties, which in turn are the most relevant assets when investors assess collateral. The measure explains how much property is debt financed and is a frequently used credit metric for real estate companies.

We define LTV as depicted in Equation 5.1.3:

$$LTV = \frac{Total\ Interest\ bearing\ debt}{Market\ value\ of\ property} \tag{5.1.3}$$

The LTV varies from 20% to 79%, with a corresponding standard deviation of 0.16, implying that capital structures amongst the issuing companies differ significantly. The average and median asset volatility estimated using the KMV-Merton model coincides at 23%. However, the related minimum value and maximum value is ranging from 14% to

37%. We observe similar trends in the statistics for equity volatility derived from daily stock observations. The average profitability, defined as annual return on invested capital (ROIC), is 8.3% with corresponding median of 3.7%. Using the structural model, we find that the average PD[32] is 0.9%. In our estimates, we utilize rolling series from 01.01.2007 to issuance date, as these prove more robust to temporary fluctuations than short time series (see Section 6.1.2). We observe significant variance for the sample PDs, fluctuating between 0% and 7.42%.

To account for the economic climate we include statistics for a subset of macroeconomic variables. When analyzing the Economic Tendency Indicator and SEB Boprisindikator the indicators yield a mean of 100 and 39, respectively. Both indicators assess the prevailing sentiment in the economy from both industry and households at time of issuance, and the indicator ranges support a positive sentiment as the maximum levels of 118 and 64 were reached in 2014. The average NASDAQ OMX Nordic REI level is 1152 with a corresponding standard deviation of 206. Further, to account for expectations from financial institutions, we include the prevailing 3-month annualized interbank rate, consistent with Das, Hanouna & Sarin (2006). We obtain the daily STIBOR3M from the Swedish Central Bank's database and pair the interest rate with the respective issuance dates of sample bonds. We observe that the interbank interest rate ranges from 0.27% to 2.45% in the relevant period.

Further, assessing the bond characteristics, we find an average maturity of 3.69 years, and only one bond that has maturity above five years. The issue sizes range from SEK 125 million to SEK 1,100 million, whilst the average bond issuance is SEK 452 million. In addition, as we expect, a coherence between rating and default probabilities within our sample persists, as high yield rated companies on average have a greater PD than investment grade companies. Lastly, we include categorical characteristics for each bond concerning rating (high yield/investment grade), coupon structure (floating/fixed) and security (secured/unsecured). A discussion of these bond characteristics are provided in Section 5.2.2.

[32] We choose to include PDs in the empirical model aligned with Bharath & Shumway (2003) and Tudela & Young (2005). However, other empirical estimations apply DTD, e.g. Mjøs, Myklebust & Persson (2011) and Das, Hanouna & Sarin (2006).

***Table 5.7**: Summary statistics of predictor variables*

Issuer Characteristics	**Mean**	**Median**	**St.dev**	**Max**	**Min**	**Observations**
Company Rental Income (mSEK)	1 757	1 745	824	3 314	413	48
Market Value of Property	22 609	24 452	10 221	39 733	4 733	48
Loan-to-value	57 %	61 %	0.16	79 %	20 %	48
Equity Volatility	36 %	35 %	0.06	49 %	28 %	48
Asset volatility	23 %	23 %	0.05	37 %	14 %	48
Operating profitability	70 %	68 %	0.07	88 %	62 %	48
ROIC	8.3%	3.7%	0.15	64.4%	0.3%	48
PDs	0.9 %	0.003 %	1.72 %	7.42 %	0.0 %	48
Macroeconomic Characteristics	**Mean**	**Median**	**St.dev**	**Max**	**Min**	**Observations**
Economic Tendency Indicator	100	101	7	118	86	48
NASDAQ OMX Nordic REI	1 152	1 124	206	1 454	696	48
SEB Boprisindikator	39	44	18	64	1	48
STIBOR3M	1.23 %	1.20 %	0.49 %	2.45 %	0.27 %	48
Bond Characteristics	**Mean**	**Median**	**St.dev**	**Max**	**Min**	**Observations**
Bond size	452	475	215	1100	125	48
Maturity	3.69	4	1,31	6	1	48
Credit spread BPS	235.7	225	129.2	493	38	48

Datasource: Stamdata, financial reports, FactSet, Bloomberg, the Swedish Central Bank, Swedish Statistics, Konjunkturinstitutet and NASDAQ OMX Nordic

The inclusion of the structural PD combined with relevant company financials, macroeconomic factors and bond characteristics enables us to test our hypotheses if the KMV-Merton model is (2) significant in explaining credit spreads and (3) sufficient in explaining credit spreads. If hypothesis (3) proves invalid, this opens for the construction of a hybrid model that is able to explain a higher fraction of cross-sectional credit spread variance at time of issuance.

6. Empirical Results

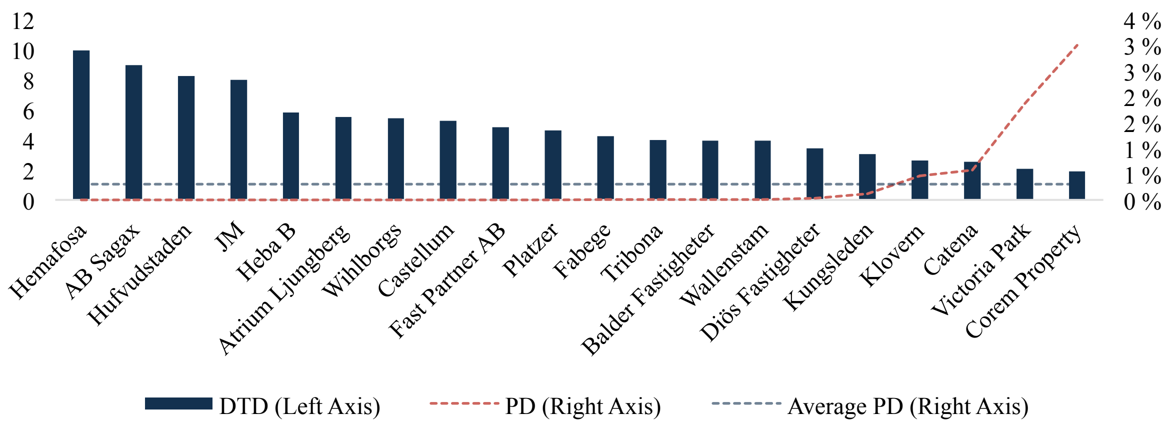
6.1 KMV-Merton Model Results

In this section, we discuss our results using the KMV-Merton model on bonds issued by listed Swedish real estate companies. Additionally, we assess the results from the robustness tests, which indicate how we should calculate PDs used in our empirical model.

6.1.1 Implied Default Probabilities

The results from our KMV-Merton model imply that the average default probability for Swedish real estate companies is 0.304%. Recall, this is the probability of defaulting one year from 31.12.2014. According to Moody's the expected default rate among the largest Swedish bond issuers in Q2 2014 was 0.06%. However, these estimates solely consist of companies with high credit ratings (Bonthron, 2014). Thus, we argue that our results are meaningful, as several of our sample companies are high yield rated. We find that Klovern, Catena, Victoria Park and Corem Property have default probabilities above average. Again, to secure meaningful results, we remove companies at the NASDAQ Nordic OMX REI with less than one year of data. The restriction requires us to remove NP3 Fastigheter and Besqab AB. Figure 6.1 displays our estimates as of 31.12.2014. The estimations are based on rolling series, i.e. time series from 2007-2014.

Figure 6.1: *KMV-Merton DTD and PD per 31.12.2014, rolling series 2007-2014*



Datasource: Own contribution

With lower DTD and higher PD than the average real estate company Klovern, Catena, Victoria Park and Corem Property should have the highest credit risk. All else being equal, if the KMV-Merton model is significant in explaining credit spreads, a bond issued 31.12.2014 will yield higher credit spread for Corem Property Group than for Wihlborgs Fastigheter.

Table 6.1: *Estimated PDs and DTD, rolling series 2007-2014*

Company	**PD**	**DTD**
Corem Property Group	2.9935 %	1.88
Victoria Park	1.8655 %	2.08
Catena	0.5802 %	2.52
Klovern	0.4661 %	2.60
Kungsleden	0.1236 %	3.03
Diös Fastigheter	0.0288 %	3.44
Wallenstam	0.0045 %	3.92
Balder Fastigheter	0.0040 %	3.95
Tribona	0.0033 %	3.99
Fabege	0.0011 %	4.24
Platzer	0.0002 %	4.63
Fast Partner AB	0.0001 %	4.84
Castellum	0 %	5.26
Wihlborgs Fastigheter	0 %	5.42
Atrium Ljungberg	0 %	5.51
Heba B	0 %	5.79
JM	0 %	7.96
Hufvudstaden	0 %	8.21
AB Sagax	0 %	8.94
Hemafosa	0 %	9.95

Datasource: Own contribution

** $PDs < 10E^{-0.8}$ is rounded to 0%

Further, we assess whether this credit risk ranking is rational and if the estimates are robust (Hypothesis 1). We compare the ranking to financial credit metrics and then perform a basic sensitivity analysis using short time series. To analyze the ranking, we compare two companies on each side of the median PD (0.0007%). Thus, we focus our analysis on Corem Property Group, Kungsleden, Hufvudstaden and Wihlborgs Fastigheter.

Table 6.2 exhibits the credit metrics assessed when evaluating the PDs credit ranking. Corem Property Group has the lowest coverage ratios of 1.7x and 1.8x in 2013 and 2014, respectively. Additionally, the company sticks out with the highest IBD/EBITDA, and a corresponding leverage of 71% in 2014. Hence, the credit metrics align with the PD estimates of 2.99%, ranking the company as the most risky of the four. Further, we observe that the metrics are ambiguous in ranking Wihlborgs Fastigheter and Kungsleden. While the coverage ratio ranks Wihlborgs above Kungsleden concerning creditworthiness, the IBD/EBITDA supported the by leverage ratio implies the opposite. According to Standard & Poor Rating Services (2015), an IBD/EBITDA above five and coverage ratio below two characterize highly levered companies. Thus, ranking Kungsleden and Corem Property Group as the most risky supports our KMV-Merton estimates. Analyzing Hufvudstaden, we observe overall strong credit metrics compared to the peer group, and consequently ranking the company top tier concerning creditworthiness aligns with the PD.

Table 6.2: *Key credit metrics for selected companies*

Key Credit Metrics	Hufvudstaden		Wihlborgs		Kungsleden		Corem Property	
	2013	2014	2013	2014	2013	2014	2013	2014
Leverage	25%	22%	61%	56%	55%	54%	75%	71%
IBD/ EBITDA	5.2x	5.1x	11.2x	10.2x	11.3x	8.4x	12.4x	11.3x
EBITDA/ Interest cost	8.8x	8.8x	2.6x	2.8x	1.9x	2.2x	1.7x	1.8x
EBITDA margin	68%	68%	70%	55 %	51%	59%	70%	73%

Datasource: FactSet and financial reports

Our initial analysis indicates that the KMV-Merton model seems to provide a rationale credit risk ranking, as the PDs and financial metrics largely overlap. In summary, we cannot reject our first hypothesis. Before drawing a conclusion, we address the robustness of the KMV-Merton model to determine how to best utilize input information in the estimation of structural default probabilities.

6.1.2 Model Robustness

Table 6.3 shows the average default probability for our sample within each year. We observe that the ADP is highly sensitive to specific conditions in any given year. The volatile estimates are in line with our expectations as the KMV-Merton model has a point-in-time perspective. Analyzing the estimates, this becomes evident when assessing the APD in 2008. The estimate indicates a movement from 0.58% to 13.54% from the prior year. The corresponding standard deviation for 2008 is 0.163. Applying the figures directly will imply that credit ratings migrate significantly over short periods. As mentioned, Altman & Rijken (2006) find that severe credit rating migrations rare as CRAs apply through-the-cycle models.

***Table 6.3**: KMV-Merton model ADP*

Year	ADP	St.dev	Firms (#)
2007	0.58%	0.014	15
2008	13.54%	0.163	16
2009	1.83%	0.051	16
2010	0.33%	0.013	16
2011	0.99%	0.014	15
2012	0.25%	0.009	15*
2013	0.20%	0.007	18
2014	0.09%	0.004	21

Datasource: Own contribution

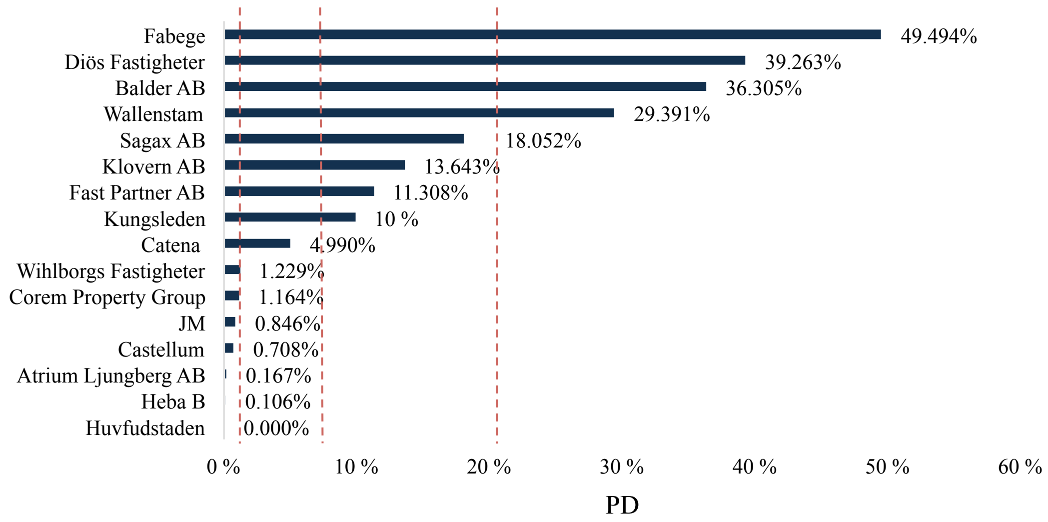
(*) Implies that observations have been removed due to anomalies.

Since our 2008 estimates classify as an outlier, we investigate the results to control for model error or erroneous data entry. First, according to the Investment Property Databank (2014) the real estate sector reached a peak in 2007, with values deteriorating through 2008. The REI went from trading at a premium to discount relative to OMXN40[33] between 2007 and 2008, implying a larger relative change (NASDAQ OMX Nordic, 2015). Hence, there is sufficient reason to believe severe credit implications for real estate companies during the economic downturn. Figure 6.2 disaggregates the ADP into the estimated PD for each company within the sample. The stipulated lines indicate the 25th, 50th and 75th percentiles (0.777%, 7.449% and 23.721%, respectively). We find that the companies in the upper quartile have PD values ranging from 29% to 49%. Vassalou & Xing (2004) find that companies in their sample with credit rating C have an average DLI[34] of 46.5602%, while A and B rated companies have DLI's of 0.0892% and 4.8130%, respectively. Hence, we argue that the PD estimates align with prior research. On aggregate, we have no reason to question the results from 2008, as these are explained by fundamental changes.

[33] OMX Nordic 40 Index is a market-value-weighted index consisting of the 40 most traded stock classes in the Nordics (NASDAQ OMX Nordic, 2015).

[34] Vassalou & Xing (2004) define DLI as "Default Likelihood" since the application of the cumulative normal distribution gives an imprecise measure of default probability. Thus, there is no difference between our defined PD and DLI.

***Figure 6.2:** KMV-Merton PDs per 31.12.2008, 12-month series*



Datasource: Own contribution

Further, we analyze the estimates for each year and observe an anomaly in the 2012 PD for Kungsleden. We find that Kungsleden has a PD of 56% with a corresponding asset volatility and asset drift of 42% and -60%, respectively. Consulting our spreadsheet, we observe a reduction in debt from SEK 1.7 billion to SEK 1.0 billion. The 2012 annual report provides an explanation for the reduction; Kungsleden was subject to changes in accounting policy due to the implementation of IFRS 11 Joint Arrangements, changing their joint venture reporting from proportional reporting to equity-method[35]. We remove the PD from the sector average. We observe that the effect of changed accounting policy is negligible when applying longer time series. Estimates based on short time series may be affected by non-fundamental factors, which constitute a potential error source. As our results indicate that longer time series are less exposed to non-fundamental factors, we apply rolling time series from 2007 to issuance date in our empirical model.

In summary, the credit risk ranking implied by the KMV-Merton model seems rational and the PDs robust. We find that the implied ranking aligns with financial metrics. Further, we note that the estimates are sensitive to time series characteristics when applying short series.

[35] Proportional reporting implies full consolidation of the percentage share in the joint venture in the same lines in the income statement, balance sheet and cash flow statement. On the other hand, the equity method only requires the company to report their fraction of the ownership in reports, i.e. separated from the others. Net income from the joint venture only accounts for the fraction of net income in the JV, while the balance sheet only includes the percentage claim on the JV´s equity. The effects of the accounting change for Kungsleden are available at http://www.kungsleden.se/konsolidering-av-hemso, while IFRS accounting rules give a more detailed overview.

Hence, we stress the importance of controlling for transitory effects and interpret the results with caution. In our opinion, it is surprising that former research seems to ignore this issue. For example, Tudela & Young (2005) estimate default probabilities based on the latest 12 months of observations, and do not report any data correction or potential pitfalls. We acknowledge that prior papers have larger samples; still, we expect researchers to address such potential sources of error in short time series. Using longer time series, the sensitivity seems to elude, and thus bodes for a more robust estimation. Hence, we apply longer time series in our PD estimates included in the OLS regression. On aggregate, we conclude that Hypothesis 1 holds, i.e. that the KMV-Merton model provides a rational credit risk ranking and robust estimates.

6.2 OLS Regression Model Results

In this section, we present our OLS regression models and interpret the empirical output. We also discuss the validity of the error term assumptions and check for the existence of outliers and influential observations.

6.2.1 Presentation of the Regression Variables

The motivation behind our empirical model is to assess the prevailing risks associated with investing in Swedish real estate bonds at issuance. Our model should optimally consist of as few predictor variables as possible (simplicity) and as many predictor variables as needed (fit). We run numerous regression analyses utilizing different subsets of independent predictor variables to reach our empirical base model. The issuer's financials, macroeconomic factors and bond characteristics analyzed in Section 5.2.2 and 5.2.3 provide the basis for the subsets. On aggregate, our dataset consist of 18 potential predictor variables. However, the sample of 48 bonds is in the lower end for statistical inference. Consequently, we stress that including many predictor variables seizes degrees of freedom, and select our base OLS regression model on the criterions of simplicity and fit. Amongst the different subsets, Table 6.4 depicts the subset that proved best relative to the model criterions[36]. Appendix 10.5 exhibits the excluded independent variables. As we discuss in detail in

[36] The subset in Table 6.4 provided the highest explanatory power amongst the different combinations, also when including the time dummy discussed in Section 5.2.2.

Section 5.2.3, the statistics display significant variance in the continuous variables. In addition, the categorical variable means indicate that our sample consists of an equal proportion of high yield/investment grade and fixed/floating bond (1 if present, 0 if else).

Table 6.4: *Summary Statistics, OLS Regression variables*

Variable	Mean	St. Deviation	Max	Min	Observations
PD	0.009	0.0172	0.0742	8.20E-19	48
STIBOR3M	1.2253	0.4973	2.45	0.273	48
LTV	0.5745	0.1559	0.7872	0.2038	48
dummy_fixed	0.2083	0.4104	1	0	48
dummy_HY	0.5625	0.5013	1	0	48
dummy_time	0.3125	0.4684	1	0	48

Datasource: Swedish Central Bank, financial reports, FactSet, Bloomberg, Stamdata

Table 6.5 shows the correlation between credit spreads at issuance and the predictor variables included in our empirical model. We compute the correlations to give the reader an indication of how the variables are related to credit spreads at issuance, and thus the outcome of our hypotheses. In particular, we note that the correlation between our estimated PDs and credit spreads at issuance depicts a correlation of 47.63%.

Table 6.5*: Correlation matrix, OLS regression variables*

Variable	Credit Spread	PD	STIBOR3M	LTV	dummy_fixed	dummy_HY	dummy_time
Credit Spread	1						
PD	0.4763	1					
STIBOR3M	0.4599	0.0302	1				
LTV	0.6767	0.4263	0.1885	1			
dummy_fixed	0.2970	-0.0426	0.0135	-0.1067	1		
dummy_HY	0.7064	0.4615	0.2767	0.7282	-0.0646	1	
dummy_time	0.7194	0.3244	0.5938	0.4098	0.2075	0.4134	1

6.2.2 The Regression Model

The F-test performed, addressing the regression relationship between the response variable Y and the predictor variables X_i, implies that there is sufficient statistical evidence to reject the null hypothesis at 5% significance level for all three models. Thus, the coefficients β_i cannot all be zero at the same time. Table 6.6 suggests that all the models are feasible, as the residual-squared proves high. Further, the results advocate Model 3 as the superior model. Note that we remove one highly influential observation, which reduces the number observations in the regression to 47 (see Section 6.2.4).

***Table 6.6**: Bond Spread Regression Models, BPS*

Variable	Model 1	Model 2	Model 3
Const.	195.83***	-100.15**	-51.59
	(17.78)	(44.04)	(46.95)
PD	3761.73***	1787.34***	1309.66**
	(913.14)	(586.67)	(595.85)
STIBOR3M		91.42***	55.08**
		(18.83)	(23.91)
LTV		253.33***	223.99***
		(83.54)	(23.91)
dummy_fixed		93.37***	82.79***
		(22.36)	(21.78)
dummy_HY		69.65**	71.02***
		(27.57)	(25.30)
dummy_time			63.14***
			(27.51)
Obs.	47	47	47
R^2	0.2738	0.8019	0.8249
R^2_{adj}	0.2577	0.7777	0.7987

Standard errors in parentheses
***p<0.01 **p<0.05 *p<0.10

Model 1: $CreditSpreadBPS = \alpha + \beta_1 * PD + u$

We construct a univariate OLS regression model to check if the KMV-Merton model is significant in explaining credit risk variation at issuance (Hypothesis 2). Model 1 in Table 6.6 depicts the statistical output. As expected, the model displays that spreads at issuance increase with the company's estimated PD. We observe high explanatory power, yielding an adjusted residual-squared of 25.77%. Our findings support previous empirical research. Recall from Section 4.3.4 that Bharath & Shumway (2004) apply a regression model on implied default probabilities from credit default swaps. They obtain an explanatory power of 10% including PD as the only independent variable. Though their choice of independent variable differs from ours, the intuition aligns, as the model successfully explains risk pricing at issuance. A higher explanatory power in our model is not surprising as they find a correlation coefficient of 0.3150, while the corresponding correlation in our sample is 0.4763. This confirms a relatively strong relationship between the credit spread at issuance and PD.

Interpreting the PD coefficient suggests that the credit spread on average increases by 37.62 BPS following a 1% change in PD, ceteris paribus. From the descriptive statistics in Table 5.6, we observe that the 99% percentile and 1% percentile is 493 BPS and 38 BPS, respectively. Thus, an increase of 37.62 BPS is economically reasonable. Furthermore, the regression output illustrates a highly significant relationship at a 1% level. Hence, companies with higher structural PDs tend to issue loans that are more expensive. The results from Model 1 imply that 80% of the variation in credit spreads at issuance is associated with the error term. Hence, we should expect other factors to explain cross-sectional variation as well.

In summary, we conclude that default probabilities significantly explain investors risk pricing at issuance. Accounting for the results when evaluating the KMV-Merton model credit ranking against financial metrics in Section 6.1.1, the result is expected. On aggregate, we do not have statistical evidence to reject Hypothesis 2.

Model 2: $CreditSpreadBPS = \alpha + \beta_1 * PD + \beta_2 * LTV + \beta_3 * STIBOR3M +$

$\beta_4 * dummy_{fixed} + \beta_5 * dummy_{HY} + u$

To assess if predictors other than the structural PD computed from our KMV-Merton model affect credit risk pricing at issuance, we expand the model including loan-to-value, 3-month annualized interbank rates, coupon structure and credit rating. The regression output under Model 2 in Table 6.6 depicts our comprehensive hybrid model. The model displays high explanatory power with a corresponding adjusted residual-squared of 77.77%. Following the discussion in Section 4.3.4, higher explanatory power than Model 1 is consistent with prior research. Still, we are somewhat surprised that the inclusion of accounting, macro and categorical variables increase the adjusted residual-squared with as much as 52%. Furthermore, we argue that our model has good fit (fewer independent variables) compared to other studies. Bharath & Shumway (2004) find similar relationships when performing regressions on credit spreads from bonds using different subset of variables. Their model is marginally subordinated to ours concerning explanatory power, however we interpret comparisons across models with caution.

The independent variables prove different in magnitude and significance, the latter at least at 5% level. We observe the same relationship as indicated by Model 1, i.e. that credit spreads at issuance highly relate to the issuer's PD. The variable is still significant at 1% level. We note that the magnitude of the coefficient is lower in the hybrid model, 1787.34 BPS, compared to the univariate model. Hence, on average, a 1% increase in PD implies a 17.87 BPS increase in credit spreads. Comparing our results with Bharath & Shumway (2004), the coefficient magnitude is larger, as their results depict a 0.5 BPS increase in credit spreads for 1% increase in PD, ceteris paribus. As they point out themselves, this relates to the inclusion of categorical variables, as "…bond ratings capture a large fraction of the variation in spreads" (Bharath & Shumway, 2004, p. 22). Hence, the coefficient is conditional on coupon structure and rating information. Further, we argue that many of the accounting variables included in their model reflect information already priced in the PD, aligned with the analysis in Section 6.1.1. Lastly, Das, Hanouna & Sarin (2006) conduct regressions using DTD instead of PD as the independent variable and find a negative relationship between DTD and credit spreads. Recall, higher DTD implies lower PD.

From Model 2 we observe that STIBOR3M is significant at a 1% level, aligned with Das, Hanouna & Sarin (2006) suggesting a positive relationship between spreads on US corporate bonds and the 3-Month T-bill Rate. STIBOR3M reflects the cost for a bank to obtain financing in the interbank market, and thus in times of weak economic outlook typically increases. We note that increases in interbank rates can occur due to both liquidity and credit premiums. However, according to von Thadden (1999) it is difficult to distinguish between the two for financial institutions, as the liquidity premium becomes elusive. Nevertheless, the variable is not economically significant as the coefficient depicts a value of 91.42, i.e. a 1% change in inter-bank rate implies a 0.91 BPS increase in credit spreads.

We observe, as we would expect, a significant positive relationship between the observed credit spread at issuance and the LTV for the quarter prior to issuance. The coefficient is 253.33, implying that higher LTV ceteris paribus will yield higher credit spread on the issued bond. The coefficient aligns with the less sector specific long-term debt to assets ratio applied by Bharath & Shumway (2004). The economic impact of the coefficient seems rather reasonable in light of the LTV variation within our sample, spanning from approximately 0.2 to 0.8. Investing in a bond with 30% higher LTV elevates bond credit spreads by 75.99 BPS at issuance, which is a considerable premium for the issuer. High correlation between LTV and rating underlines that the coefficient has to be interpreted conditional on the rating, as results indicate that the magnitude will be significantly higher when we exclude ratings.

Further, the results show that fixed bonds have significantly higher spreads equal to 93.37 BPS, ceteris paribus. As we expect, this likely reflects the investor's exposure to interest rate risk, implying that the bond in case of an interest rate appreciation will become less valuable, effectively deteriorating returns. Hence, compared to floating bonds, the relationship makes economic sense.

We control for bond ratings as high yield bonds account for 56% of our sample. The results show that high yield rating is significant at a 5% level. The coefficient implies that high yield rated companies issue bonds with an average spread of 69.65 BPS higher than companies rated as investment grade. Further, the magnitude and t-statistic is lower than for dummy_fixed even though the correlation with credit spread is significantly higher. However, this relates to the mentioned correlation between dummy_HY and LTV, implying that LTV is a considerable determinant of rating. De facto, one might argue that inclusion of both variables makes one of them redundant. However, as several other factors determine the rating of issuers (Section 4.2), we argue that the rating dummy contains information not reflected in LTV. Further, we do not observe collinearity between the variables, and accordingly keep both variables in our model.

Model 3: $CreditSpradBPS = \alpha + \beta_1 * PD + \beta_2 * LTV + \beta_3 * STIBOR3M +$

$\beta_4 * dummy_{fixed} + \beta_5 * dummy_{HY} + \beta_6 * dummy_{time} + u$

To control for the observed time effects in Section 5.2.2 we include a time dummy allowing the model to be unconstrained in the parameters. Including the time predictor, results in the adjusted explanatory power increasing to 79.87% (Model 3). Aligned with our expectations, we find statistical evidence of a positive relationship between credit spreads at issuance and the period 2010-2012, implying 63.14 BPS higher credit spreads. We conclude that the same model does not apply for both periods, i.e. the model significantly differs between the periods 2010-2012 and 2013-2014. In general, the economic interpretations remain intact relative to Model 2, though PD and STIBOR3M become less significant, both at a 5% level. As our results are largely status quo, we can exclude spurious time series correlations in our model.

The increase in explanatory power in Model 2 and Model 3 concludes that a model merging data from structural models with variables containing financial and macroeconomic information, as well as bond characteristics, proves better. Hence, we reject our third hypothesis that the PD from the KMV-Merton model is exhaustive concerning credit risk pricing at issuance for Swedish real estate companies. However, PDs provide influential information and stays significant in explaining credit risk in all three models. We find it interesting that excluded accounting and macroeconomic predictors such as market value of property, bond principal and economic indices have little or no significance in credit pricing at issuance. However, for a different sample, these factors might have an effect.

On aggregate, based on the analysis in Section 6.1.1 the KMV-Merton model seems to capture information contained in frequently used credit metrics, i.e. leverage, IBD/EBITDA, coverage ratio and EBITDA margin. Further, the empirical results in this section confirm that the PD itself is useful when assessing the credit risk of companies.

6.2.3 Controlling the Assumptions about the Error Terms

We present the results concerning error terms for our baseline model, but stress that the results are consistent for Model 1 and 3 as well. Appendix 10.6 reviews the four assumptions, while Appendix 10.7 depicts the formal STATA tests.

As described in Appendix 10.6, it is trivial to assume that the error term has an expected value of zero for each observation as long as we have a constant term in the model. Hence, the first condition $E(Y_i|X_i) = \alpha + \beta_i X_i$, for all i is satisfied.

The second assumption, $Cov(u_i, u_j) = 0 \; for \; i \neq j$ is satisfied as we have cross-sectional data and no obvious relationship between the observations, resulting in independent error terms. We do not test for autocorrelation, as this is redundant (Møen, 2015)[37].

For the third assumption, $Var(Y_i|X_i) = Var(u_i) = \sigma^2$ the pattern in the residuals plotted against the fitted (predicted) values seem to have minor indications of heteroskedasticity since variation increases for higher fitted values. Hence, we conduct a White test and Breusch-Pagan test. For both tests, we do not have sufficient evidence to reject the null

[37] Personal communication with Jarle Møen, March 24 2015.

hypothesis that residuals are homogenous at a 5% level. Consequently, the third assumption is satisfied.

The assumption regarding error terms u_i being normally distributed seems satisfied as the Kernel density estimate indicates that residuals largely overlap with the Gauss-curve. Besides, the inter-quartile range test does not indicate any presence of severe outliers, supported by the Shapiro-Wilk test yielding a P-value of 0.2629. Thus, we cannot reject the null hypothesis of normally distributed residuals at a 5% level.

Finally, we ensure that the results from the regression analysis are valid by conducting an assessment on the existence of multicollinearity in the model. The variance inflation factor (VIF) finds the degree of collinearity (1/VIF), which for our sample is above the tolerance level of 0.1. Hence, there is no indication of multicollinearity.

6.2.4 Unusual observations

We argue that in a small dataset, every observation contains important information, and thus we initially are reluctant to remove observations. However, a thorough analysis of the observations might justify removal. Appendix 10.6 describes the method behind the assessment of the observations, and in Appendix 10.7 we exhibit the formal tests conducted in STATA.

The stem-and-leaf plot, a graphical method of displaying the studentized residuals, indicates existence of four outliers in our sample. The observations have quite large residuals of absolute values higher than two. However, by carefully assessing each of the four bonds, we cannot find any data entry error or any other reason to remove the observations. We find that there is one observation with higher leverage than the cut-off point $\frac{2k+2}{n}$, yielding leverage of 0.4479. When we remove the bond from our dataset using the if-function in STATA, we do not observe severe changes in our model. Hence, we chose not to exclude it from our sample. Since some data points have both large residuals and leverage, we investigate the influence on the regression line. The plot of leverage versus residual-square implies that some observations can induce a bias to the line. When we run regressions excluding the observations with Cook's distance higher than the cut-off point, especially one has higher effect on the regression line than the others do[38]. Thus, we remove the observation from our dataset, as it will affect the regression line.

[38] Observation denoted SE0003331552 has a Cook's distance 0.3193, while the cut-off point is 0.0833. See Appendix 10.7 Figure 10.1 and 10.9 for a STATA output.

7. Limitations and Further Research

In this section, we discuss the limitations of our analysis and highlight some potential weaknesses, which constitute a basis for further research. In an empirical thesis of this kind, certain assumptions are a necessity, and the validity of these will always be a subject for discussion.

Our final dataset consists of 48 observations for the dependent variable, which is in the lower end for conducting econometric analysis. In addition, we remove one observation due to anomalies. Since our bond sample is restricted to a limited number of listed issuers, it might be problematic to generalize the results even though the models have proven feasible. We propose that a possible solution for a larger sample could be to include non-listed real estate companies, currently excluded due to lack of market information. To estimate theoretical PDs for non-listed companies, we suggest constructing a regression model where possible determinants of asset volatility are regressed against the estimated asset volatility of listed companies. However, we observe poor reporting from several non-listed companies. Hence, we stress that the calculated PDs for non-listed companies can be an error source. In addition, non-listed real estate companies constitute the majority of the corporate bond market, which amplifies the potential error source. Further, the limited sample size restricts the number of predictor variables in our empirical model, as inclusion of variables seize degrees of freedom. Thus, we have excluded variables that could have explanatory power. Additionally, an effect may well be real and important though it does not appear statistically significant. The problem may be related to high variance and too few observations (Keller, 2012).

Further, our calculation of spreads for fixed bonds is a potential error source. We have applied yields from Swedish Treasuries with equal maturity as the respective bonds, using linear interpolation, to determine spreads. However, a better proxy is to calculate the floating rate a fixed bond would yield using an interest rate swap (IRS) at the time of issuance. An IRS gives a precise estimate of what spread over STIBOR3M the market would be willing to accept in exchange for the fixed coupon. Another solution is to apply credit default swaps, as taxes and liquidity affect these to a lesser extent than bond spreads (Das, Hanouna & Sarin, 2006). However, due to limited data regarding IRS and CDS, we were not able to apply these in our OLS regression model.

As a supplement to the discussion of the KMV-Merton model's applicability to the Swedish real estate sector, it would be interesting to investigate if the model aligns with other applied credit models. Since several of these models are survival models (logit/probit), the dataset needs to include defaulted companies to assess default probabilities. As no listed Swedish real estate company has defaulted, one could expand the sample either by including other sectors in Sweden or real estate companies in other countries.

Further, our estimates of PDs are derived assuming normal distribution of DTD, which is empirically inconsistent with observed defaults. A possible solution would be to obtain data on Swedish companies, both non-defaulted and defaulted, and construct a frequency table for different DTDs. From a frequency table, one could establish the correct distribution and apply it in the PD calculations.

Evidentially, there is room for improvement in our analysis. We acknowledge the limitations, but stress that overcoming these would require significant effort and resources. Mainly, limitations related to time and scope of this thesis and availability of data has created a barrier in providing a more extensive analysis.

8. Conclusion

In this thesis, we have examined the contribution of the KMV-Merton model in explaining credit risk for Swedish real estate companies. We utilize rolling times series in our estimation of default probabilities as these prove to be adequately robust to non-fundamental anomalies. Our credit ranking based on default probabilities relative to frequently applied credit metrics, confirms that the model provides a rational credit ranking. While previous research has focused on time series dynamics, our model employs pooled cross-sectional data. By applying a univariate econometric model, it appears that the KMV-Merton model significantly explains credit spread variation at issuance. The adjusted explanatory power of 25.77% achieved in the univariate model is high. However, a hybrid model that includes the default probability and other covariates seems to preform significantly better, increasing the adjusted explanatory power to 77.77%. The variables we incorporate are the KMV-Merton default probabilities, loan-to-value, 3-month annualized interbank rate, coupon structure and credit rating. All variables are significantly correlated with changes in credit spreads at issuance. Thus, we are able to address regularities in credit spreads, which is defined as an indicator for investor's required compensation for default risk. Even though the default probability becomes less significant, its contribution in explaining cross-sectional spread variation is more than satisfactory. Further, we note that the economic influence, i.e. the magnitude of the default probability coefficient is remarkably higher than in previous research. In contrary to most empirical research, our model includes a smaller subset of predictor variables, and thus we propose a good fit for our sample. When controlling for time effects we can exclude the existence of spurious time correlations. Looking at the model, we detect a positive relationship between the credit spread variation at issuance and the period 2010-2012. Lastly, our models rely on 48 cross-sectional data points with a time interval of five years. Our dataset differs from prior research due to the small sample size; however, it enables us to conduct a thorough analysis of the input and results. Thus, applying correct data from financial reports is statistically useful.

By adding financial, macroeconomic and categorical variables to a model based purely on the KMV-Merton default probability, we are able to explain the credit spread variation accurately. The findings from our empirical model indicate the usefulness of employing structural models in credit risk pricing at issuance. In addition, the analysis gives an insight to the credit risk dynamics for Swedish real estate companies.

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10. Appendix

10.1 Top Managers in the Swedish Corporate Bond Market

Table 10.1: *Top Managers ranked by currently outstanding volume arranged*

Managers	**Volume (mSEK)**	**Share (%)**	**# of issues**
Swedbank	16 797	24.53	44
SEB Merchant Banking	16 700	24.39	29
Nordea	12 615	18.42	38
Danske Bank Markets	10 875	15.88	30
Handelsbanken	7 930	11.58	28
ABG Sundal Collier	1 350	1.97	4
DNB	1 250	1.83	1
Nordic Fixed Income	475	0.69	2
Pareto	419	0.61	2
Other	46	0.07	3
Aqurat Fondkommission	10	0.01	1
Total	68 467	100	182

Datasource: Stamdata

10.2 Moody's Credit Rating

Table 10.2: *The assigned creditworthiness implied by Moody's credit ratings*

Moody's rating	**Creditworthiness**
Aaa	Strongest
Aa	Very strong
A	Above average
Baa	Average
Ba	Below average
B	Weak
Caa	Very weak
Ca	Extremely weak
C	Weakest

Source: Moody's Investor Services (2009)

10.3 VBA Code

Appendix 10.3 displays the VBA code applied to calculate the KMV-Merton model PDs.

** code commands in black
** all comments in red

```
'KMV Merton Visual Basic (VBA) code
'Defining variables and maximum number of iterations
Option Explicit
Private Const mMax = 2600
Private maturity As Double
Private equity(1 To mMax) As Double
Private debt(1 To mMax) As Double
Private riskFree(1 To mMax) As Double
Private iptr As Integer
Private sigmaAssetLast As Double

'Calling KMV (DefProb) sub. Defining ranges and iteration procedure. Determine initial guess on asset volatility and size
Sub CalDefProb()
maturity = Worksheets("Output").Range("C2").Value
Dim m As Integer: m = WorksheetFunction.CountA(Worksheets("Data").Range("A:A")) - 1
Dim i As Integer
For i = 1 To m
    equity(i) = Worksheets("Data").Range("Equity").Offset(i - 1, 0)
    debt(i) = Worksheets("Data").Range("Debt").Offset(i - 1, 0)
    riskFree(i) = Worksheets("Data").Range("Maturity").Offset(i - 1, 0)
Next i
Dim equityReturn As Variant: ReDim equityReturn(2 To m)
Dim sigmaEquity As Double
Dim asset() As Double: ReDim asset(1 To m)
Dim assetReturn As Variant: ReDim assetReturn(2 To m)
Dim sigmaAsset As Double
Dim meanAsset As Double
Dim x(1 To 1) As Double, n As Integer, prec As Double, precFlag As Boolean, maxDev As Double
For i = 2 To m: equityReturn(i) = Log(equity(i) / equity(i - 1)): Next i
sigmaEquity = WorksheetFunction.StDev(equityReturn) * Sqr(260)
sigmaAsset = sigmaEquity * equity(m) / (equity(m) + debt(m))

'Call NewtonRaphson to perform iterative procedure
nextItr: sigmaAssetLast = sigmaAsset
For iptr = 1 To m
x(1) = equity(iptr) + debt(iptr)
n = 1
prec = 0.00000001
Call NewtonRaphson(n, prec, x, precFlag, maxDev)
asset(iptr) = x(1)
Next iptr
For i = 2 To m: assetReturn(i) = Log(asset(i) / asset(i - 1)): Next i
sigmaAsset = WorksheetFunction.StDev(assetReturn) * Sqr(260)
meanAsset = WorksheetFunction.Average(assetReturn) * 260
If (Abs(sigmaAssetLast - sigmaAsset) > prec) Then GoTo nextItr
Dim disToDef As Double: disToDef = (Log(asset(m) / debt(m)) + (meanAsset - sigmaAsset ^ 2 / 2) * maturity) /
(sigmaAsset * Sqr(maturity))
Dim defProb As Double: defProb = WorksheetFunction.NormSDist(-disToDef)
Worksheets("Output").Range("riskFree").Value = riskFree(m)
Worksheets("Output").Range("Debt").Value = debt(m)
Worksheets("Output").Range("Equity").Value = equity(m)
Worksheets("Output").Range("sigmaEquity").Value = sigmaEquity
Worksheets("Output").Range("Asset").Value = asset(m)
Worksheets("Output").Range("sigmaAsset").Value = sigmaAsset
Worksheets("Output").Range("meanAsset").Value = meanAsset
Worksheets("Output").Range("disToDef").Value = disToDef
Worksheets("Output").Range("defProb").Value = defProb
```

```
End Sub

'Construct Sub NewtonRaphson for iterative procedure.
Sub NewtonRaphson(n As Integer, prec As Double, ByRef x() As Double, ByRef precFlag As Boolean, ByRef maxDev As
Double)
Const nItrMax As Integer = 1000
Dim xOld() As Double: ReDim xOld(1 To n)
Dim xShift() As Double: ReDim xShift(1 To n)
Dim gShift() As Double: ReDim gShift(1 To n)
Dim g() As Double: ReDim g(1 To n)
Dim omega() As Double: ReDim omega(1 To n, 1 To n)
Dim Dx() As Double: ReDim Dx(1 To n)
Dim i As Integer, j As Integer, k As Integer, nItr As Integer
For nItr = 1 To nItrMax

'Initiate the array of variables and set the function values. Call Function Array to perform DefProb calculation
For i = 1 To n: xOld(i) = x(i): Next i
Call FunctionArray(n, xOld, g)

'Determine the matrix omega for iterative procedure
For j = 1 To n
For k = 1 To n: xShift(k) = xOld(k) + prec * IIf(j = k, 1, 0): Next k
Call FunctionArray(n, xShift, gShift)
For i = 1 To n: omega(i, j) = (gShift(i) - g(i)) / prec: Next i
Next j

'Iterate and update the area of variables - iterative procedure repeated until precision is granted OK
Call SolveAxb(omega, g, Dx, n, 1, 1, 1)
For i = 1 To n: x(i) = xOld(i) - Dx(i): Next i

'Controlling if iterative precision is achieved and updating the precision "flag" in Excel
For i = 1 To n
If Abs(x(i) - xOld(i)) <= prec Then
precFlag = True
Else
precFlag = False
Exit For
End If
Next i
If precFlag Then Exit For
Next nItr

'Calculating the maximum standard deviation in the iterative process yielded through the process
Call FunctionArray(n, x, g)
maxDev = 0
For i = 1 To n
If Abs(g(i)) > maxDev Then maxDev = Abs(g(i))
Next i
End Sub

'Matrix used for iterative procedure
Sub SolveAxb(Amatrix() As Double, bvec() As Double, ByRef xvec() As Double, _
n As Integer, iptr As Integer, jptr As Integer, kptr As Integer)
Dim wsAmatrix As Variant: ReDim wsAmatrix(1 To n, 1 To n)
Dim row As Integer, column As Integer
For row = 1 To n
For column = 1 To n: wsAmatrix(row, column) = Amatrix(iptr + row - 1, jptr + column - 1):
Next column
Next row
Dim wsbvec As Variant: ReDim wsbvec(1 To n, 1 To 1)
For row = 1 To n: wsbvec(row, 1) = bvec(kptr + row - 1): Next row
Dim wsxvec As Variant:
   With Application.WorksheetFunction
   wsxvec = .MMult(.MInverse(wsAmatrix), wsbvec)
   End With
   Dim i As Integer
   If n = 1 Then
```

```
    For i = kptr To kptr + n - 1: xvec(i) = wsxvec(i - kptr + 1): Next i
    Else
    For i = kptr To kptr + n - 1: xvec(i) = wsxvec(i - kptr + 1, 1): Next i
    End If
End Sub

'Defined function array used to calculate default probabilities using normal distribution. Specifying the two non-linear equations that are solved
Sub FunctionArray(n As Integer, x() As Double, ByRef g() As Double)
    Dim maturityUse As Double: maturityUse = maturity
    Dim equityUse As Double: equityUse = equity(iptr)
    Dim debtUse As Double: debtUse = debt(iptr)
    Dim riskFreeUse As Double: riskFreeUse = riskFree(iptr)
    Dim sigmaAssetUse As Double: sigmaAssetUse = sigmaAssetLast
    Dim d1 As Double, d2 As Double
        d1 = (Log(x(1) / debtUse) + (riskFreeUse + sigmaAssetUse ^ 2 / 2) * maturityUse) / (sigmaAssetUse * Sqr(maturityUse))
        d2 = d1 - sigmaAssetUse * Sqr(maturityUse)
    With Application.WorksheetFunction
    g(1) = equityUse - x(1) * .NormSDist(d1) + debtUse * Exp(-riskFreeUse * maturityUse) * .NormSDist(d2)
    End With
End Sub
```

10.4 Bond Sample

Table 10.3: *Issued bonds 2010-2014, with their respective issue date, DTD and PD*

Company bond issue	Issuance date	DTD	PD
Kungsleden AB 10/15 FRN	30.04.2010	1.58	5.707 %
AB Sagax 10/15 7,00% C	20.05.2010	4.98	0.000 %
Corem Property Group AB 10/15 6,75%	08.07.2010	1.44	7.423 %
Fast Partner AB 10/15 6,75% C	06.10.2010	3.80	0.007 %
Kungsleden AB 10/15 FRN	18.10.2010	2.36	0.915 %
Kungsleden AB (publ.) 11/14 FRN	09.03.2011	2.50	0.616 %
Corem Property Group AB 11/16 FRN C	30.05.2011	2.06	1.985 %
Klövern AB 12/15 FRN C	02.03.2012	2.06	1.982 %
Klövern AB 12/15 FRN C	02.03.2012	2.06	1.982 %
AB Sagax 12/17 6,50% C	22.03.2012	7.47	0.000 %
Castellum AB 12/15 FRN	03.09.2012	4.15	0.002 %
Castellum AB 12/15 4,00%	03.09.2012	4.15	0.002 %
FastPartner AB 12/16 FRN	28.09.2012	3.93	0.004 %
Fastighets AB Balder 12/15 FRN	10.10.2012	2.31	1.051 %
Klövern AB 12/17 FRN C	19.10.2012	1.74	4.083 %

Klövern AB 12/15 FRN C	21.12.2012	1.72	4.309 %
Hufvudstaden AB 13/19 3,35%	21.01.2013	7.10	0.000 %
Hufvudstaden AB 13/18 3,00%	22.01.2013	7.09	0.000 %
Fabege AB 13/16 FRN C	15.02.2013	3.12	0.089 %
Fabege AB 13/16 3,70% C	15.02.2013	3.12	0.089 %
Castellum AB 13/17 FRN	01.03.2013	4.48	0.000 %
Klövern AB 13/18 FRN FLOOR C	04.04.2013	1.90	2.857 %
Corem Property Group AB 13/15 FRN C	06.05.2013	1.70	4.501 %
Fastighets AB Balder 13/17 FRN C	16.05.2013	3.66	0.013 %
Hufvudstaden AB 13/14 FRN	30.05.2013	6.80	0.000 %
AB Sagax 13/18 FRN C	25.06.2013	7.48	0.000 %
Wihlborgs Fastigheter AB 13/15 FRN C	12.07.2013	4.45	0.000 %
Hufvudstaden AB 13/15 FRN	24.09.2013	6.80	0.000 %
Castellum AB 13/15 FRN	26.09.2013	4.28	0.001 %
Castellum AB 13/18 FRN	26.09.2013	4.28	0.001 %
Atrium Ljungberg AB 13/17 FRN	15.11.2013	4.25	0.001 %
Kungsleden AB 13/16 FRN C	20.12.2013	2.84	0.222 %
Wihlborgs Fastigheter AB 14/19 FRN FLOOR	18.02.2014	4.87	0.000 %
Klövern AB 14/18 FRN	04.03.2014	2.11	1.750 %
Castellum AB 14/19 FRN	07.03.2014	5.07	0.000 %
AB Sagax 14/19 FRN EUR C	11.03.2014	8.56	0.000 %
Hufvudstaden AB 14/16 FRN	12.03.2014	7.64	0.000 %
Fastighets AB Balder 14/19 FRN	12.03.2014	2.76	0.285 %
Hufvudstaden AB 14/15 FRN	14.03.2014	7.61	0.000 %
Atrium Ljungberg AB 14/19 FRN	19.03.2014	4.68	0.000 %
Atrium Ljungberg AB 14/16 1,764%	21.03.2014	4.58	0.000 %
Corem Property Group AB 14/17 FRN FLOOR	11.04.2014	1.87	3.093 %
Hemfosa Fastigheter AB 14/17 FRN FLOOR	08.05.2014	12.60	0.000 %
Hemfosa Fastigheter AB 14/17 3,375%	08.05.2014	12.60	0.000 %
Fastighets AB Balder 14/18 FRN	21.05.2014	3.70	0.011 %

Wallenstam AB 14/17 FRN	05.06.2014	3.46	0.027 %
Wallenstam AB 14/17 2,125%	05.06.2014	3.46	0.027 %
AB Sagax 14/19 FRN C	18.06.2014	8.78	0.000 %
Castellum AB 14/18 FRN	26.09.2014	4.98	0.000 %
Castellum AB 14/16 FRN	07.11.2014	4.89	0.000 %

Datasource: Stamdata and own contributions
*** Bonds marked in grey removed due to insufficient data*

10.5 Regression Analyses

Table 10.4: *Description of predictors excluded from the regression model.*

Variable name	Description
ECT_IND	Economic Tendency Indicator. In essence, the indicator is a combination of the leading PMI (purchasing manager's index) and key private consumption indicators (equivalent to Conference Board's Consumer Confidence). Included to measure macro factors and expectations. Obtained from Konjunkturinstitutet.
NASDAQOMX	NASDAQ OMX Nordic historical index price. Pro-cyclical indicator that accounts for current and forward economic climate. Included to measure macro-economic risk, and should lead on GDP. Obtained from NASDAQ OMX Nordic.
PortfolioValue	Market value of total property. Obtained from the quarterly report prior to issuance date. Applied as a key component in several models, amongst them Norges Bank's SEBRA model (default model). Included to assess firm specific risk.
SEB_IND	Independent variable regarding SEB Housing Price Index. Based on a survey including 600 households conducted by the Nordic Investment Bank SEB Enskilda. Included to assess macro factors and expectations. Obtained from Swedish Statistics.
Maturity	Bond maturity. Obtained from Stamdata and included to account for duration risk.
Income	Gross rental income ("Hyresintäkter"). Calculated as the accumulated 12- month income from the quarter prior to issuance date. A measure for size, and included to assess firm specific risk.
SigmaEquity	Standard deviation of equity. Obtained from the estimated KMV-Merton model. Included to assess firm specific risk.
ROIC	Net income minus dividends divided by the total invested capital. Calculated as the 12-month net income prior to issuance over the beginning of the year capital. Included to account for firm specific risk.
OperatingProfitability	Operating results over gross rental income. Obtained from the quarterly reports prior to issuance date, and included to assess firm specific risk.
SigmaAsset	KMV-Merton model asset volatility. Included to accounts for firm-specific risk

BondSize	Size of the bond, measured in principal. Obtained from Stamdata and included to account for bond specific risk.
Security	Bond security such as pledge, negative pledge, guarantee etc. Included in the original dataset downloaded from Stamdata. Categorical variable assessing the features of the bond.

10.6 OLS Regression Properties

In this section, we provide the theory behind an OLS regression assessment. We elaborate on central measures for the applicability of an OLS regression, as well as the error term assumptions. Lastly, we briefly describe vital properties of data points necessary for an adequate OLS regression analysis[39].

10.6.1 The Feasibility of the OLS Regression Model

To examine whether an OLS regression model is an adequate statistical model to apply, one should interpret the goodness of fit of the model. Goodness of fit is denoted as R^2 (coefficient of determination) and measures the ratio of explained variation in Y to the total variation in Y. If the value is high, the predictor variables explain a large proportion of the variation in credit spread.

The pure coefficient of determination is, however, not a compatible measure when comparing OLS regression models with different number of predictor variables. Adding more predictor variables will by definition result in higher explained variation. To overcome this, the R^2 is adjusted for the degrees of freedom, providing an estimate of explanatory power that can be compared between models.

To assess the statistical significance of the OLS regression model one should examine the regression equation as a whole, before considering the individual variables. By conducting an F-test and examining the corresponding P-value, one can interpret the following hypotheses:

$$H_0: \beta_0 = \beta_1 =, \dots, = \beta_K = 0$$
$$H_1: \beta_0 \neq 0 \vee \beta_1 \neq 0 \vee \dots \vee \beta_K \neq 0$$

[39] This section is based on Wittin, D. R. (1988). *The Application of Regression Analysis.* Massachusetts: Allan and Bacon, Inc.

Failing to reject the null hypothesis indicates that none of the independent variables have any relation to the dependent variables, and thus the model is unfeasible.

The F-statistic determines the ratio of explained variation over unexplained variation, adjusted for degrees of freedom. In summary, interpretation of the F-statistic and the R^2 give indications about feasibility and performance of the regression line.

10.6.2 Controlling the Error Term Assumptions

An OLS regression model relies on several assumptions regarding the process of the movement in the estimated variables. First, the model assumes that the response in Y_i to changes in X_i follows linearity in the regression parameters. Thus, Y_i is a linear function of the parameters, $\alpha, \beta_{1,} \beta_2, \dots, \beta_m$, however not necessarily of the predictor variables, $X_{1i}, X_{2i}, \dots, X_{mi}$ (Williams, Grajales & Kurkiewics, 2013). Further, there are four vital assumptions about the error terms in the OLS regression model that has to be satisfied in order to make statistical inference about the parameters in the equation.

1. Zero conditional mean of errors. The expected values of the error term of all the observations need to be zero (Equation 10.5.1). This is necessary for the estimate to be unbiased.

$$E(Y_i|X_i) = \alpha + \beta X_i, \qquad for\ all\ i \tag{10.6.1}$$

When the regression equation contains a constant term, the assumption is satisfied. Hence, this assumption is considered trivial.

2. Independence of errors. The errors are assumed to be uncorrelated over time. In other words, the error term has a covariance of zero between any two arbitrary observations:

$$Cov(\ u_i u_j) = \ 0, i \neq j, given\ any\ two\ values\ for\ X \tag{10.6.2}$$

If this assumption does not hold, there is negative or positive autocorrelation in the model. Consequently, the OLS regression model will not give the best estimates and inference is invalid. However, the coefficients remain unbiased.

In time series, dependence between error terms is often present, violating the independence assumption. However, since we apply pooled cross-sectional data, there is no obvious relationship between error terms.

3. *Homoskedasticity of errors*. The unobservable variance of the errors is assumed constant and finite for each observation. If this is not true, i.e. heteroskedasticity is present, the OLS regression model estimates are unbiased, but will not be efficient and thus inference becomes unreliable (Williams, Grajales & Kurkiewicz, 2013). Additionally, F- and t-tests for the OLS estimators are not valid when heteroskedasticity is present. The mathematical description of the assumption is:

$$Var(Y_i|X_i) = Var(u_i) = \sigma_i^2 = constant, \quad for\ all\ i \tag{10.6.3}$$

To test for homoskedasticity of errors, one can consult graphical plots of residuals against fitted values. If the plot depicts a trend there is indications of a non-constant variance in errors, which can be statistically tested using a Cameron & Trividi's test or/and a Breusch-Pagan test. Both statistics test the null hypothesis of homoskedasticity at a 5% significance level.

4. *Normal distribution of errors*. This is a critical assumption that has to hold in order to draw reliable conclusions from the confidence interval and significance tests. However, the coefficients are both consistent, efficient and unbiased even though the errors are not normally distributed (Williams, Grajales & Kurkiewicz, 2013). If a Gauss-curve is present, one can argue that error terms are normally distributed. However, to ensure normality one can conduct a Shapiro-Wilk test and an inter-quartile range (iqr) test. In the Shapiro-Wilk test the null hypothesis is that the errors are normally distributed, while the iqr test assumes a symmetric distribution and controls for severe outliers. Severe outliers are points over or below the third inter-quartile range. Presence of a severe outlier provides sufficient statistical evidence to reject the null hypothesis of normality at 5% significance level.

Multicollinearity

In an OLS regression model, it is important to consider correlation between predictors, as this can reveal either collinearity (between two predictors) or multicollinearity (between more than two predictor variables). This is especially important when the aim is inference about parameters, rather than predictions (Williams, Grajales & Kurkiewicz, 2013). In case of (multi)collinearity, the causal importance of each variable can be difficult to distinguish. Consequently, the results will be problematic to interpret, as it will be difficult to determine the effect each predictor X_i has on the dependent variable Y_i. If correlation is high, confidence intervals and standard errors are exaggerated. Contrary, low correlation will provide more confidence in the coefficient estimates. A popular test for collinearity is the Variance Inflation Factor test.

10.6.3 Unusual Observations

In order to assure that a regression model provides valid results, it is important to examine whether the dataset contains any unusual observations, implying that the data point either is an outlier, has leverage and/or influence. An observation is termed as an outlier if the residual is large, while observations with extreme values in one of the predictor variables, i.e. value far from the mean, have leverage. If observations with leverage are present, these may potentially bias the estimates of the coefficient β_i. The product of outlierness and leverage indicates the influential power of an observation, and removal of such observations may change estimates of β_i substantially.

To control the dataset for outliers one can examine the studentized residuals r applying a stem-and-leaf plot. Observations with $-2 < r < 2$ bode for further analysis. More specifically, one should control these for any data entry error or sample peculiarity. Similarly, a stem-and-leaf plot can be used to identify observations with significant leverage, which should be less than:

$$lev = \frac{(2k + 2)}{n} \tag{10.6.4}$$

Where k = number of predictor variables and n = number of observations

To investigate whether an observation has influence, one can plot leverage against normalized residual squared[40]. As the plot can be subjectively interpreted, one should apply Cook's distance to reach statistical evidence of influential points. Higher Cook's distance implies more influential observations, and a $d > 4/n$ implies significant effect. If estimates affect the regression significantly, this can justify removal.

[40] Residual square preserves the relative position of the data.

10.7 Stata Output

In this section we display the statistical tests performed to check for outliers, observations with leverage or/and influential power, and to test the error term assumptions.

Outliers

Table 10.5: *Stem-leaf-plot of studentized residuals.*

```
Stem-and-leaf plot for r (Studentized residuals)

r rounded to nearest multiple of .01
plot in units of .01

 -3** | 02
 -2** |
 -2** | 38,03
 -1** | 62
 -1** | 43,43,25
 -0** | 92,76,67,57,52
 -0** | 43,35,33,29,24,19,17,10,08
  0** | 04,09,15,18,21,30,32,32,36,37,37,46,47,48
  0** | 57,61,65,74,78,86,93,94
  1** | 27,39,40
  1** | 61
  2** |
  2** | 61
```

Observations with r higher than the absolute value of two are categorized as outliers. According to the stem-and-leaf plot, four observations exceed the limit: 02, 38, 03 and 61.

Table 10.6*: List of the 10 largest and smallest studentized residuals with the respective ISIN number*

```
. list r stamdata r in 1/10
```

	r	stamdata	r
1.	-3.019902	SE0005731403	-3.019902
2.	-2.381497	SE0005222924	-2.381497
3.	-2.028676	SE0005798881	-2.028676
4.	-1.624739	SE0003845296	-1.624739
5.	-1.431634	SE0005036084	-1.431634
6.	-1.428442	SE0005994266	-1.428442
7.	-1.246958	SE0003963586	-1.246958
8.	-.9229814	SE0005424306	-.9229814
9.	-.7637982	SE0005757358	-.7637982
10.	-.6737737	SE0005878352	-.6737737

```
. list r stamdata r in -10/l
```

	r	stamdata	r
39.	.7370017	SE0004951648	.7370017
40.	.7825238	SE0006027041	.7825238
41.	.8615602	SE0005249760	.8615602
42.	.9302353	SE0004868453	.9302353
43.	.9446251	SE0005095635	.9446251
44.	1.27106	SE0003559772	1.27106
45.	1.391243	SE0003552819	1.391243
46.	1.395601	SE0005796398	1.395601
47.	1.610605	SE0004810158	1.610605
48.	2.606926	SE0003331552	2.606926

By rearranging the residuals and employ each r with the related ISIN number, we obtain a list of the 10 largest and smallest residuals. The outliers indicated above are thus SE0005731403, SE0005222924, SE0005798881 and SE000331552 with studentized residuals -3.02, -2.38, -2.03 and 2.61, respectively.

Table 10.7: *Stem-leaf-plot of leverage*

```
Stem-and-leaf plot for lev (Leverage)

lev rounded to nearest multiple of .001
plot in units of .001

  0** | 48,51,57,57,59
  0** | 61,65,67,67,67,68,69,69,70
  0** | 81,82,85,85,89,94,95,98
  1** | 05,06,07
  1** | 20,23,26,26,32
  1** | 41,44,44,45,46,48,49,49,55
  1** | 75
  1** | 84,99
  2** | 19
  2** | 20,22
  2** | 40,43
  2** |
  2** |
  3** |
  3** |
  3** |
  3** |
  3** |
  4** |
  4** |
  4** | 48
```

The stem-leaf-plot of the leverage gives an initial indication of possible observation with high leverage. The plot specifies one observation (number 48) that potentially has high leverage.

Table 10.8: *List of observations with leverage higher than cut-off point*

```
. display (2*5+2)/48
.25

. list lev stamdata if lev>.25
```

	lev	stamdata
12.	.4479329	SE0003395656

The cut-off point for observations that are of concern, is $\frac{(2k+2)}{n} = 0.25$. Each calculated leverage point is assigned the associated ISIN number and then compared to the cut-off point.

Influence

Figure 10.1: *Leverage vs. Residual-squared plot*

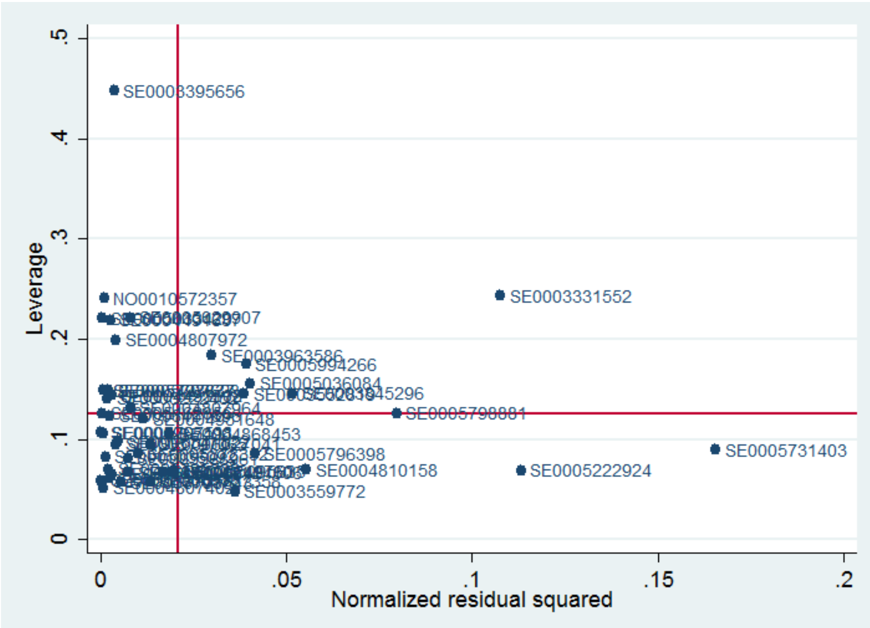


Figure 9.1 depicts the leverage versus residual squared plot. Each point is labeled with ISIN numbers. The reference line indicates the cut-off point for influential observations. Particularly, SE0003331552 reveal itself as a point with potentially high influence.

Table 10.9: *List of influential observations with Cook`s D higher than the cut-off point*

```
. list d stamdata if d>4/48
```

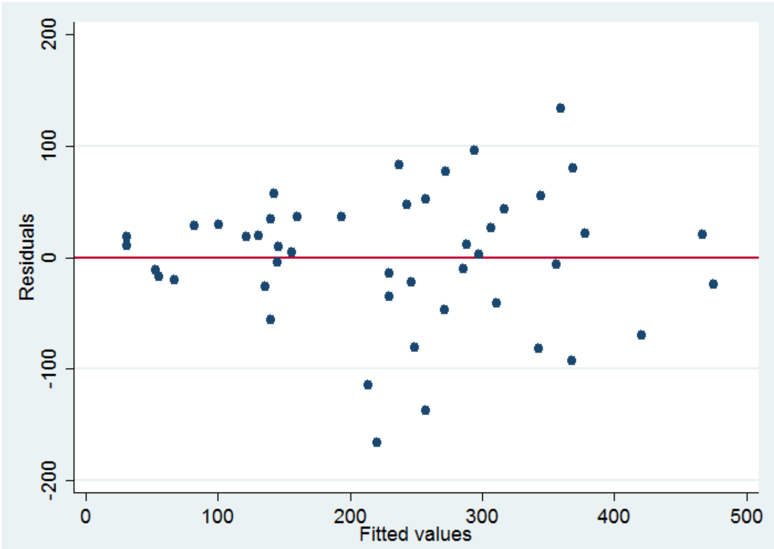
	d	stamdata
1.	.1249695	SE0005731403
3.	.0921277	SE0005798881
48.	.3192557	SE0003331552

Observations with Cook´s D higher than the cut-off point $\frac{4}{n} = 0.08333$.

Assumptions about the error term

Assumption 3: Homoskedasticity of errors

Figure 10.2: *Residuals vs. Fitted values plot*



We observe indications of an increasing variance in the residuals. This justifies further statistic tests.

Table 10.10: *Cameron-Trividi information matrix*

```
. estat imtest

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	23.93	18	0.1573
Skewness	5.55	5	0.3522
Kurtosis	1.12	1	0.2909
Total	30.60	24	0.1657

The Cameron & Trividi´s decomposition of information matrix test at 5% significance level exhibits an information matrix with a chi-square result and an accompanying p-value of 0.1573 for heteroskedasticity. Hence, one cannot reject the null hypothesis of homoskedasticity at 5% significance level.

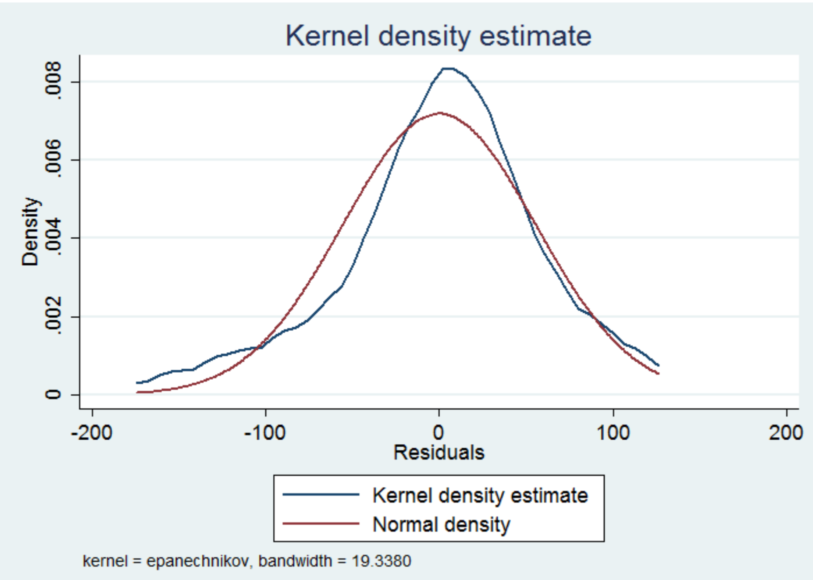
Table 10.11: *Breusch-Pagan / Cook-Weisberg test for heteroscedaticity*

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of spreadbsp

         chi2(1)      =     2.47
         Prob > chi2  =   0.1160
```

Breusch-Pagan tests for any linear form of heteroskedasticity at 5% significance level. The chi-square result is 2.47 with a p-value of 0.1160. Thus, the Breusch-Pagan test does not provide statistical evidence for a rejection of the null hypothesis of homoskedasticity at 5% significance level.

Assumption 4: Normality of the errors

Figure 10.3: *Kernel density estimate of residuals vs. normal density*



The nonparametric Kernel density estimate visualizes the underlying distribution plotted against a normal density function. The estimate deviates somewhat from the normal density function, which justifies further investigation.

Table 10.12: *Shapiro-Wilk test for normality in the residuals*

```
. swilk r

                   Shapiro-Wilk W test for normal data
```

Variable	Obs	W	V	z	Prob>z
r	47	0.96991	1.348	0.634	0.26292

The W statistic tests if the sample has a normal distribution. The calculated W and the accompanying p test do not provide sufficient statistical evidence to reject the null hypothesis of normality in the residuals at 5% significance level.

Table 10.13: *Inter-quartile range test for normality in the residuals*

```
. iqr r

   mean= -2.6e-07         std.dev.=   55.58          (n= 47)
 median=   5.919   pseudo std.dev.=   46.41        (IQR=    62.6)
10 trim=   2.899
                                                low         high
                                                -------------------
                              inner fences    -121.4         129
                         # mild outliers      2           0
                         % mild outliers      4.26%       0.00%

                              outer fences    -215.3       222.9
                         # severe outliers    0           0
                         % severe outliers    0.00%       0.00%
```

To support the Shapiro-Wilk test the inter-quartile range shows evidence of three mild outliers, but none severe outliers. Consequently, we cannot reject the null hypothesis that the residuals are normally distributed at 5% significance level.

10.8 Regression Analysis Removing Leverage Point SE0033956565

Table 10.14: *Estimation results from an OLS regression excluding bond ISIN SE0033956565*

Bond Spread Regression, BPS (if stamdata!="SE003395656")

Variable	**Model 1**	**Model 2**	**Model 3**
Const.	203.18***	-111.38**	-45.01
	(19.16)	(47.21)	(48.05)
PD	3694.32***	1669.35**	1317.23*
	(1183.89)	(756.76)	(696.27)
STIBOR3M		76.50***	33.94
		(19.66)	(22.46)
LTV		303.43***	246.65***
		(87.95)	(81.90)
dummy_fixed		117.79***	98.27***
		(24.49)	(23.10)
dummy_HY		73.72**	71.81***
		(28.75)	(86.11)
dummy_time			82.63***
			(26.48)
Obs.	47	47	47
R^2	0.1779	0.7768	0.8205
R^2_{adj}	0.1596	0.7496	0.7936

Standard errors in parentheses

***p<0.01 **p<0.05 *p<0.10

10.9 Securities Trading at the NASDAQ OMX Nordic Real Estate Index (SX8600) as of 05.02.2014

Full name (Securities)	Full name (Companies)
Fastigheter Balder AB	Fastigheter Balder AB
Besqab	Besqab
Castellum	Castellum
Catena	Catena
Corem Property Group	Corem Property Group
Diös Fastigheter	Diös Fastigheter
Fabege	Fabege
Fast Partner	Fast Partner
Heba B	Heba B
Hemfosa Fastigheter	Hemfosa Fastigheter
Hufvudstaden A	Hufvudstaden
Hufvudstaden C	JM
JM	Kungsleden
Kungsleden	Klövern
Klövern A	Atrium Ljungberg
Klövern B	NP3 Fastigheter
Atrium Ljungberg	Platzer Holding AB
NP3 Fastigheter	Sagax
Platzer Holding AB	Tribona
Sagax A	Victoria Park
Sagax B	Wallenstam
Tribona	Wihlborgs Fastigheter
Victoria Park A	
Victoria Park B	
Wallenstam	
Wihlborgs Fastigheter	
26 securities	**22 companies**