Do credit spreads predict corporate default events?

Analysis on the distressed bond market

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1. Motivation and research question

The motivation of my thesis is to measure the credit risk information accuracy in credit spreads on the distressed corporate bond market. There are many economic agents who worry about the credit risk of a company. Corporate bondholders, investment banks ready to sell CDS contracts to cover a counterparty’s risk, and shareholders who worry about the potential loss of stock value and control given their company fails to serve its obligations. Information available about this risk eventually shows in the prices of different securities issued by the company. (Forte and Peña, 2009). My goal in the following will be to determine the content of this kind of information in corporate bond prices.

Blanco, Brennan and Marsh (2003) point out the importance of the credit spread as an individual risk factor by stating, hedge funds usually have exposure only to credit spreads, not yields, due to hedging strategies. Since its complete separation from the risk-free rate, credit spread has become the main instrument for price discovery. Several former research papers elaborated on the versatile risk sources that are incorporated in the credit spread, commonly calling this phenomenon the credit spread puzzle. As an unusual approach, I will not try to break down the credit spread into constituents, but use it as a market variable in statistical tests to explain credit events. Investors in distressed debt markets care about whether and when their investment defaults. This will be the main focus of my research: I try to use the credit spread to analyze and predict the probability and timing of a default event. For such analysis, I apply empirical default and liquidation data, derived from the distressed bond market.

Distressed debt, which is the field of my interest, represents a special investment asset class. It is a common name for bank loans, bonds and other tradable debt assets that are the obligations of financially distressed companies. The distressed bond market shares characteristics of fixed-income and equity markets, with a rather malformed market structure. As it is an exotic region for investors, it lures professional investors primarily. Altman (2014) states these investors usually have a large impact on the wealth of other stakeholders in the issuer company as well as on bankruptcy procedures. In the analysis of results, I will refer to both the equity-like behavior and to the market structure.
The analysis of credit spreads on this market is favorable for two reasons. Once, Hull, Predescu and White (2004) note that due to the discrepancy between real-word and risk-neutral default probabilities, bond traders tend to earn more than risk-free rate on average from holding corporate bonds. As the credit rating deteriorates, the extent of the higher return increases. My research focuses on the lowest credit rating of all: it would be valuable to know, how much more risk is priced into these bonds. Second, an objective comparison of market-implied and real-world default processes is finally possible on this market, as there are numerous empirical credit events. An even competition depends on the efficiency of the market where no investor has an advantage in predicting the return on the investment because no one has access to information not already available to everyone else. If this is so, we can strongly believe that the market predicts the default events well, and if it is not so, my test results will provide some measure of market efficiency.

As distressed debt incorporates a subtle and inextricable network of credit risks, it is wise to use statistics on larger samples than analytics on individual assets to evaluate the prediction accuracy of credit spreads. I apply three different statistical analyses. First, I separate my daily data into defaulted / liquidated and survived subsets and see whether their average credit spreads are statistically different. Then, I run fixed effect panel data regressions explaining the bonds’ real-world time to default with market-implied estimates. Third, I use logistic regression to predict default events on quarterly data. The first two methods only provide insights ex-post, while the third one also shows the ex-ante application of statistical tools.

The remainder of the thesis is organized as follows: Section 2 explains the takeaway of former research on credit spreads and distressed debt analysis, Section 3 establishes the methodology for assessing market efficiency and describes the dataset I analyzed. Section 4 presents the empirical results and the robustness checks of the tests and draws a connection between expected and experienced statistical values. Section 5 concludes the research and shows potential ways of enhancement.
2. Literature review

The relevant academic literature covers the topics of (1) credit spread attribution, (2) the ability of the bond market to adapt to new information, (3) the economics of financial distress and (4) the market patterns of the distressed bond market. I consider all four topics necessary to understand the processes behind credit spread evolution on distressed bond markets, which is a real puzzle at first sight.

2.1 Credit spread attribution

Concerning credit spread attribution, the main question of researchers has been how well do credit spreads represent credit risk on the market. An equivalent research question is about the risk type breakdown of the credit spread.

The credit spread stands for a quantified measure of the credit risk primarily, as Forte and Peña (2009) describe it. Credit risk is ‘risk due to losses associated with the event of failure to pay by the borrower, or the event of deterioration of its credit rating. Given that loss due to credit rating deterioration (downgrading) is a loss that stems from an increase in risk due to losses associated with the failure to pay, the key element is the possibility of failure (default).’ (Forte and Peña, 2009, p. 2015) And they define the measure of credit risk as: ‘the credit spread, or excess return that agents of a certain market would claim for the debt with a possibility of default by a certain company, in relation to a debt of the same nature, but with no possibility of default.’ (Forte and Peña, 2009, p. 2015) In this interpretation, the credit spread is a compensation for credit risk, a credit risk premium. One must note that credit risk itself consists of two factors: the probability of default (PD) and the loss given default (LGD), the latter factor identical to 1 minus the recovery rate (RR) on defaulted debt.

It is a stylized fact that the amount of the credit spread does not only represent the risk associated with the probability of default and the loss given default computed from historical data. In a mathematical language, the risk-neutral credit risk and the real-world (historical) credit risk are not equal. In academic papers, this is referred to as the ‘credit spread puzzle’.

Amato and Remonola (2003) list a bunch of other factors that inflate the credit spread. (1) The difficulty of diversifying away unexpected losses linked to default risk. This is
mainly due to the negatively skewed distribution of returns on corporate bonds and the strong cross-correlation of defaults across entities (contagion risk). (2) The discrepancy in after-tax return between corporate bonds and Treasury securities. This inflator emerges when one uses Treasury securities as risk-free benchmark bonds. (3) The volatility of the unexplained spread (a market risk premium), (4) liquidity premia due to thin bond markets. Hull, Predescu and White (2004) add a couple more factors, such as (5) the exposure to the state of the economy, (6) present value interest rate risk premium, (7) the credit spread’s sensitivity to the interest rate and (8) supply / demand effects.

Amato and Remonola (2003) point out that while ‘spreads clearly magnify expected losses; this relationship is not one of simple proportions.’ (Amato and Remonola, 2003, p.53.) As the credit rating of an issuer deteriorates, the relative difference between its credit risk premium and its credit spread closes. Elton et al (2001) suggested that expected losses accounted for 3.5%-34.7% of the credit spreads (from AA to BBB rated bonds) while the risk premium, that is the compensation for bearing undiversifiable risk of future losses and taxes range from 19.4% to 30%, again influenced by the credit rating of the issue. Driessen (2005) computes that risk premium explained 17.9%-52.1% share of the credit spread in his sample, dependent of credit rating. Driessen (2005) also names liquidity premium as a significant factor, accounting for 25%-13.8% of the risk incorporated in credit spread.

The credit spread puzzle has since been opposed by Feldhütter and Schaefer (2014). They provided evidence that the calibrations in previous research papers were biased and had low statistical power for model testing. They argued that using average model-implied spread for comparison between model and historical spreads is inconsistent with the distribution properties of firm credit spreads. Besides, they highlighted that the ex-post default frequency used for model calibration is a very bad proxy for ex-ante default probability. By recalculating implied credit spreads based on ‘structural models’, they found that only short-term spreads show significant discrepancy between risk-neutral and historical values. At the same time, they replicate the historical long-term BBB-AAA corporate bond credit spreads with a maximum 20% error which can be considered fairly accurate.
2.2 The adaption of information in bond market credit spreads

Fama and French (1993) discover common risk factors in returns on stock and bond markets. They find that high-grade corporate bond returns are mainly influenced by debt maturity and default risk. However, the variation of low-grade corporate bond returns is better explained by stock market factors, such as firm size and book-to-market ratio.

Collin-Dufresne, Goldstein and Martin (2001) examine the determinants of credit spread changes. They claim that in modeling, structural model based fits nicely explain the level of spreads, but not the changes implied on them. They discover, that while firm-specific information, like leverage, asset volatility and interest rates determine the spread amount, the changes cannot be associated with such factors. Instead, they believe that aggregate (systemic) factors are much more important in determining credit spread changes. They name market specific supply-demand shocks, independent of their proxies of liquidity, as such factors. They discover that default rate and recovery rate effects are cross-correlated among individual issues, which also supports the fact that market-wide events have a strong impact on the evolution of credit spreads.

Gilchrist and Zakrajsek (2011) also find evidence on the connection between credit spreads and economic activity. They split the credit spread into a ‘predictable’ component determined by firm-specific losses from expected default and a ‘residual’ component that equals an excess bond premium. They show that excess bond premiums are efficient predictors on declines in economic activity and contraction in the supply of credit.

Blanco, Brennan and Marsh (2003) analyze weekly credit spread changes and compare them with changes in CDS spreads. They show that credit spread evolution of high-yield bonds is more sensitive to market variables (slope of the yield curve, individual’s equity return, market-wide equity volatility) than investment grade bonds’ credit spread. They deduce that investment grade bonds more behave like Treasury securities, while high-yield bonds are more like equity. They find that price discovery (the incorporation of new information) is faster on CDS markets, meaning they are better integrated with short-term firm specific effects than bonds. At the same time, macro factors have a larger impact on bond markets.
2.3 The economics of distressed debt markets

Distressed debt can be described as a liability of an entity that is traded with a large discount against its face value. Distressed debt is usually referred to in terms of corporate defaults and bankruptcies, as a result of financial distress of issuer firms. Many authors, such as Altman (2014) use the distinction for distressed debt of a credit premium level higher than 1000 bps compared to riskless government debt with a comparable duration.

**High-yield Bonds, Junk Bonds, Distressed Bonds**

It is important to clarify the common properties and differences of the three categories. ‘High-yield bonds’ are carrying a rating below BBB from S&P and below Baa from Moody’s. They are characterized by their higher (in average, 150-300 basis points) yield paid to debt investors, compared to investment grade bonds, due to higher risk of default of the issuer company (Investopedia). The phrase ‘high-yield’ is usually used for market separation and investment strategies of funds who hold high-yield bonds in their portfolio. Investing in high-yield bonds require well-diversified portfolios as idiosyncratic risk on these bonds is rather high and potential price drops (yield volatility) are highly probable during the investment horizon. High-yield bonds are in turn also good investment products for investors who seek risk on a middle investment horizon as their maturity usually ranges from 3 to 7 years (Investopedia). The high-yield bond market’s performance is also used as a proxy of the global economy’s performance.

Junk bonds are virtually the same as high-yield bonds. The term is often used in a sarcastic sense for issuers who are downgraded from investment grade for showing a bad financial performance, also called ‘fallen angels’. Some national governments are also rated as junk on the bond market and their treasury securities are priced low due to general mistrust in the government’s economic policy, even if state bankruptcies are very rare. Junk bonds are also relevant in relation of fund portfolios. Several retirement plans and mutual funds are banned from investing in junk bonds.

Distressed bonds are also high-yield and junk bonds but their issuers are widely regarded as unable to serve their obligations during the debt’s lifetime. The main reason for this is usually economic distress, which means a worsening operation earnings ratio. Another reason can be overleveraged company financing.
The notion of default

Asquith, Gertner and Sharfstein (1994) identify high interest expenses (21.4%), poor operating performance (56.2%) and industry downturn (22.2%) as the main drivers of financial distress. Distressed firms (bonds) often become defaulted firms (bonds) when they (their issuer) are unable to serve their promised obligations. The term ‘default’ is described in many ways, as it covers the event when the issuer fails to serve its obligations. One clear way of default is the liquidation of the company, when the company’s assets are sold and stakeholders receive proportions of the proceeds from the sale, according to the absolute priority rule. Company liquidation is called Chapter 7 in the U.S. Bankruptcy Code. This kind of association of default conforms with the conception in the banking sector about nonperforming loans.

Default or nonperforming has gained importance since credit derivatives markets have expanded in the global economy. The protection leg of credit derivatives (for instance, Credit Default Swaps) can be called in case of ‘credit events’ that are defined by the International Swaps and Derivatives Association (ISDA) in the 2014 ISDA Credit Derivatives Definitions. The document defines the following credit events. (1) Failure to pay or deliver, (2) Bankruptcy filing (Chapter 11 of the U.S. Bankruptcy Code), (3) Restructuring, (4) Repudiation, (5) Moratorium, (6) Obligation Acceleration and (7) Obligation Default, which means the failure to comply with any claims fixed in the credit agreement. International credit rating agencies have borrowed the ISDA terms into their rating process. Both Moody’s and S&P apply ‘Defaulted’ rating to issuers who fail to pay an interest, go bankrupt or carry out a distressed exchange with creditors. In this sense, the credit agencies merge the notions of 'default event' and 'credit event'. They rate issuers suffering credit events 'partly-defaulted', 'selective-defaulted' or 'defaulted' based on the type of nonperforming.

The different types of risk faced by different types of distressed debt investors

Default or credit events have a huge importance on distress debt markets. Investors take it for granted that their purchased debt asset would not yield its promised fixed income until maturity. I collected the most important sources of credit risk in Figure 1 and highlighted in yellow the possible losses an investor should expect. Among the classical threats are (1) skipped coupon payments during bankruptcy protection (2) loss in PV of
the debt as a result of debt restructuring (3) dip in the market price of the bond due to loss of confidence in the market (4) low recovery rate on liquidated debt under Chapter 7. Blue boxes indicate states of the world in the flow chart, while the red square tells that the classical notions of PD and LGD can most easily be connected to liquidation of the company.

*Figure 1. The diverse risk types borne by distressed bond investors. (Self-made)*
A bankruptcy process does not mean straightforward bad news for bondholders. Altman (2014) writes that a company can successfully complete its Chapter 11 reorganization by reemerging as a going concern (with a new structure of its liabilities) or by being acquired by another corporation. Asquith, Gertner and Sharfstein (1994) write that bankruptcy itself gives firms the time to develop a consensual restructuring with creditors while preserving firm value. During Chapter 11 protection, management can continue their work, debt payments are stayed, secured creditors cannot take possession of their collateral. The bankruptcy is extended until the reorganization plan is agreed on or the company is liquidated (which is Chapter 7). Davydenko and Rahaman (2008) state that opting for this protection can mean redemption for distressed companies. They calculate that 80% of the firms with a Tobin Q ratio under 1 underperform their industry median competitors. Although Asquith, Gertner and Sharfstein (1994) prove that bankruptcy itself is costly, due to administrative expenses, that sum up to 3.1% of corporate value, this amount is dwarfed by a 16.8% asset value loss in 3 years, compared to competitors in case of excessive continuation (Davydenko and Rahaman, 2008).

Despite the theoretical optimality of the decision for Chapter 11 filing, the majority of the firms still seek to avoid exit. Davydenko and Rahaman (2008) estimate that only 26% of firm management decide to give up on their financial freedom. They often liquidate working capital or initiate debt restructuring. Davydenko and Strebulaev (2004) point out that debt restructuring, if successful, is ex-post likely to create corporate value as in case of co-operation between management and creditors, renegotiations would facilitate the operations of the company and afterwards it is more likely to serve its obligations. Creditors, however, fear the possibility of a strategic debt service in these situations, carried out by the bond issuer’s management. A strategic default is a case where the firm fails to pay the amount stipulated in the debt contract even though it possesses resources to do so. It is usually a consequence of equityholders’, notably management equityholders’ decision. This is a detrimental decision for bondholders who bear high exposure to such events during negotiations.

In the decision process over bankruptcy, private and secured debt holders – most notably banks – play a pivotal role. Carey and Gordy (2016) show that banks make high efforts to set the endogenous asset value threshold below which the debtor companies declare bankruptcy, in order to protect their recovery rates. They do so by using control rights granted by loan-covenants. Several bankruptcy processes end up being unsuccessful with
the corporation being liquidated (Chapter 7). When standing in line for the return on liquidated assets, senior and secured debt holders usually enjoy higher recoveries than unsecured creditors.

Another choice to avoid bankruptcy is being acquired by another company. It is not a very popular decision however by the management, as only 8% of the distressed firms decide to be acquired (Davydenko and Rahaman, 2008), as acquirers wait until long to reach a bargain price for the distressed company.

All the above-mentioned researchers agree that the probabilities and expected losses linked to different outcomes of a distressed situation, are highly dependent on the structure of debt and the collateral behind the company’s liabilities. The likeliness of bankruptcy is reduced by a large proportion of public to private debt, long-term to short-term debt, unsecured to secured debt and a small number of debtholders. Besides, ‘firms with more substantial assets have a better chance of moving ahead in the bankruptcy reorganization process than do smaller entities.’ (Altman, 2014, p. 104). Higher private debt share entails higher ultimate recoveries and recoveries are also strongly influenced by the industry the issuer company operates in (Altman and Kishore, 1996).

**Investors and investment strategies on the distressed debt market**

Creditholders of ailing companies can be divided into two main groups. The first of them, accidental creditors are original credit investors, who lent money to the debtor company during the time its financial position was still solid. On bond markets, mutual funds are usually among such creditors: they can run a sector bond portfolio (for instance, of energy sector bonds in mid-2016) or a cross-sector high yield bond portfolio and face negative financial developments from their debtors.

The other group, who are subsequent investors experienced in distressed debt investing, are called vulture funds. They are mostly hedge funds, private equity firms, banks with proprietary trading desks and other non-traditional lenders (Harner, 2008). Vulture funds attract capital to partly invest in and gain profit on undervalued or underutilized debt of financially distressed companies. They hope reaching significant profit from three sources: by reselling the debt, through recoveries on the debt (even full repayment from the debtor) in the restructuring process or by converting the debt into an equity position in the reorganized debtor (Harner, 2008). Jiang, Li and Wang (2012) find that these funds
are observably involved in 90% of Chapter 11 cases. Harner (2008) writes that these investors often act secretly, purchase positions in multiple tranches of the company’s debt and engage in activist investment strategies. She finds that two-thirds of them invest into distressed debt to try to influence board or management decisions. Altman (2014) lists several channels of their influence: (1) directly and indirectly acting as a member of the Creditors Committee, (2) direct impact on the corporate governance of the debtor through owning a significant amount of the post-restructured equity of the emerged entity, (3) loan-to-own strategy.

Vulture funds provide liquidity on the demand side of the distressed debt market. Original creditors can often monetize their slice of debt before the bankruptcy filing (or the restructuring process), and this makes the market more efficient. Harner (2008) writes that this merit manifests in banks and insurance companies tending to utilize the secondary market to remove distressed debt from their books.

The bond market’s reaction to financial distress

Altman (2014) points out the fact that financial distress does not shy away investors from buying the debt of a company, but in the contrary. Trading volume in individual issues is shown to hike up around the time of credit events of the issuers, by Friewald, Jankowitsch and Subrahmanyam (2013). Defaulted securities, after credit events, tend to stay on markets and become even more liquid, unlike before financial distress of their issuers.

In case of distressed bonds, the credit risk premium is largely influenced by the deviation of expected recovery rates conditional on default. Altman (2014) distinguishes two types of recovery rates: a real-world one that is received by creditors after the rather long (25 month) bankruptcy process or after the distressed exchange, and a market-implied one that is present in the market price of the bond and reflects actual expectations of market participants. The two values frequently differ from each other as the changing of market sentiment about a distressed issuer largely involves the changing of the expected recovery.

Davydenko, Strebulaev and Zhao (2011) discover a typical negative jump in the market value of debt and equity together, upon default announcement. The proportion of loss to firm value ranges from 12.8% in case of bond renegotiations to 28.8% in case of bankruptcy. Jankowitsch, Nagler and Subrahmanyam (2013) show that official default
dates on average indicate the lower bound of bond price histories. They also show that trading volume increases before the default date and peaks on the default date.

Guo, Jarrow and Lin (2009) define the market-implied recovery rate as a risk-adjusted discounted expectation across all possible realized ultimate recovery scenarios at the default date. They find that the price on the official default date is probably not the real market-implied recovery rate, as on many occasions, market prices are on a rising trend when the issuer officially proclaims default. This can be due to information leakage, about pre-bankruptcy bargaining or restructuring negotiations between equity holders and bondholders, that are likely to improve the performance of the distressed firm later. Therefore, the authors introduce the notion of the economic default date that is the first time that risky debt is priced as if default has happened. It is the first day before the official default date when the bond’s market value is smaller than the discounted present value of the bond price on the official default date. The authors limit the discrepancy of the two dates in 180 days. They find that thus the economic default date is approximately 2-3 months before the real default date.

This market pattern has been addressed by Gregory (2010) who writes that since the expansion of the CDS market, naked CDS protection buyers have surged in numbers. When ‘the total outstanding CDS protection on the reference entity is large compared with the amount of outstanding debt, a delivery squeeze can be created. In a delivery squeeze, the bond prices will increase to reflect a lack of supply and in turn the CDS prices will decline’ (Gregory, 2010, p. 144). Delivery squeezes are common on less liquid debt markets.

The subtle network of stakeholder interests and the diverse researcher opinion on typical market patterns make it extremely difficult to separate distinctive risk factors present in distressed bond credit spreads. Instead of trying to distinguish and calculate the risk premium on credit risk, liquidity, and the sensitivity to micro and macro variables, I restrict my research to single information discovery in credit spreads: do credit spreads give a trustworthy sign about whether and when the issuer is going to default on its obligation? I use statistical tests on a large sample to infer statements about the empirical connection between credit spreads and default events.
3. Methodology and Data

My first task to analyze the effectiveness of the distressed bond market via credit spreads, is to obtain the credit spreads belonging to observed bond prices. My definition of credit spread is the yield to maturity premium over the identical riskless fixed-income asset, namely Treasury securities. Due to the fact, that most of the junk bond issuers need to offer higher-than-average interest payments to their credit investors, these companies usually incorporate American call options in the bonds they issue. To include the influence of embedded options on credit spreads, I rely on the provided analytics by Bloomberg.

3.1 Independence test

Credit spreads are believed to include information on the probability of default. Feldhütter and Schaefer (2014) prove that lower-rated bond credit spreads dominantly incorporate risk premium for credit risk and this amount is also effectively describable with credit risk models. Hull, Predescu and White (2004) also highlight that the lower the rating the smaller the gap between risk-neutral and real-world credit spreads. In a representative sample of distressed bonds, one would expect that generally larger credit spreads are assigned to bonds whose issuers default. Here, the notion “default” can refer to nonperforming in case of credit events listed in ISDA definitions or liquidation.

From a statistical point of view, one can validate this hypothesis by looking at the ex-post relationship of the credit spread and the empirical outcome of the bond’s life. For this, I separate the issues in my sample into two subgroups: one in which the bonds survived during the observation period and another in which their issuers defaulted. Subsequently, the research question in the previous paragraph turns into the following: ‘can we tell the two subsets apart from each other based on their average credit spreads?’ As the observed companies had to disclose financial and operating details to the public, due to their security’s listing on the exchange, one would expect that the market could distinguish between hopeless and temporarily endangered companies.

To find out whether there exists a statistical evidence behind this instinct, I turn to a classical method. I run an independence t-test between the two subsets. The test compares the two means and tells if their differences could have occurred by random chance. The test uses the following hypotheses. (For details, see Appendix A)
\begin{align*}
H_0: \tilde{h}_{\text{defaulted},t} - \tilde{h}_{\text{non-defaulted},t} &= 0 ; \quad H_1: \tilde{h}_{\text{defaulted},t} - \tilde{h}_{\text{non-defaulted},t} \neq 0
\end{align*}

3.2 Using implied default intensities in panel data regressions

While the previous testing method refers to the level of credit spreads and their connection to credit events, the next test also takes the dynamics of credit spreads into consideration. When one examines the signaling ability of the credit spread on credit risk, its forecasting power of the timing of the default event is an obvious aspect for testing. In a panel regression, using market-implied default intensities, I seek to explain the variance of the bond’s empirical time to default with its market-implied ‘distance to default’. I will elaborate on the details in the following.

Obtaining the hazard rate estimate from the credit spread

The interpolation of PD from the credit spread has been theoretically approached in versatile ways. In the following, I will use a simple mathematical framework to obtain statistical variables that would help me estimate a ‘distance to default’. Concerning theoretical background, I rely heavily on Mosconi (2015) and on Hull, Predescu and White (2004).

My first assumption is that default (where default means liquidation primarily, but can also refer to ISDA-defined credit events or distressed exchange) is described by a time homogenous Poisson process which is an exogeneous jump process. Per Mosconi (2015), this is equivalent to: “Default is not triggered by basic market observables but has an exogeneous component that is independent of all the default-free market information. Monitoring the default-free market does not give complete information on the default process, and there is no economic rationale behind default.” (Mosconi, 2015, p.7.) While a large proportion of this conditional background can be argued, it helps one to gain a mathematical toolkit for modeling.

In mathematical models called ‘reduced form’ or ‘intensity’ models, default is associated with a random time marked by \( \tau \). \( \tau \) is the first jump time of a Poisson process in the current context. The notion of ‘hazard rate’ – also called ‘default intensity’ – is widely used as a measure of instantaneous credit spread. Mosconi (2015) defines the hazard rate as the
probability that a company defaults in the infinitesimal interval \([t, t + dt)\) having not defaulted before \(t\):

\[
P(\tau \in [t, t + dt] | \tau \geq t, \text{market info up to } t) = h(t)\, dt \tag{1}
\]

Mosconi (2015) uses the hazard rate defined in formula (1) to derive a formula for the probability of the bond issuer’s survival up to time \(t\) (for details, see Appendix A):

\[
S(t) = e^{-H(t)} = e^{-\int_{0}^{t} h(u)\, du} \tag{2}
\]

Equation (2) can be simplified by using the time homogenous Poisson assumption. In time homogenous Poisson process models the hazard rate is a constant \(\lambda\) value over time. In such a Poisson process, where \(M(t)\) means the increments of the process up to time \(t\) and the default time is modeled as the first jump of the process, the survival probability up to time \(t\) is simplified as:

\[
P(M_t = 0) = S(t) = e^{-\int_{0}^{t} \lambda \, du} = e^{-\lambda t} \tag{3}
\]

A further implication is that the number of jumps between two points in time follow the Poisson Law and the number of jumps in a time interval is independent of the history of the process before the start of the interval, so the process is memoryless. This Poisson distribution assumption also yields the consequence that times between subsequent jumps – and the time until the first jump – are independent and identical exponentially distributed variables with parameter \(\lambda\).

By using equations (2) and (3), one can use survival probabilities with the same structure as discount factors and the default intensity in the role of the credit spread. Duffie and Singleton (1999) lay down the theory behind this connection. They represent the values of corporate bonds along with a corresponding credit default swap’s premium and protection legs as expectations under the risk-neutral measure. Following their theory, I repeat the pricing formula of a risky (defaultable) fixed-coupon bond with maturity \(T\):

\[
CB(c, RR, T) = E \left[ c \cdot \int_{0}^{T} e^{-\int_{0}^{t} r_s + \lambda_s + \gamma_s \, ds} \, dt \right] + E \left[ e^{-\int_{0}^{T} r_t + \lambda_t + \gamma_t \, dt} \right] + E \left[ RR \cdot \int_{0}^{T} \lambda_t \cdot e^{-\int_{0}^{t} r_s + \lambda_s + \gamma_s \, ds} \, dt \right] \tag{4}
\]
where \( r(t) \) is the annual risk-free rate, \( \lambda(t) \) is the hazard rate at time \( t \), \( \gamma(t) \) is the non-default related (mostly liquidity) premium at time \( t \) and \( RR \) is the expected recovery rate.

Using the non-stochastic assumption on the hazard rate over time results in the formula of the hazard rate derived from the credit spread and the recovery rate, suggested by Hull, Predescu and White (2004):

\[
h = \frac{s}{1 - RR} = \frac{y - r}{1 - RR} \quad (5)\]

where \( RR \) is the expected recovery rate on the bond, \( y \) is its annualized yield to maturity and \( h \) is the probability of default in a year, conditional on no earlier default. For obtaining the intensity, I use a constant recovery estimation of 40%. Per Hull, Predescu and White (2004) this amount is commonly used among industry members (traders and modelers), although in general it is not realistic as a constant value (see Altman and Kishore, 1996).

The annualized measure \( h \) in equation (5) can be converted into the instantaneous (now daily) probability of default (\( \lambda \)) by dividing it with the number of days in a year. I choose this amount to be 365 days as I use the hazard rate for ‘distance to default’ estimation and my comparison benchmark is given in calendar days.

**Estimating ‘distance to default’**

Having obtained a daily default intensity from equation (5), I use the former assumption about the exponential distribution of the default event to estimate the market-implied ‘distance to default’. In this context, the reciprocate of the default intensity is the expected value of the distribution. It means that \( 1/\lambda \) is the expected number of days that the bond is expected to ‘survive’. I call this value the ‘distance to default’, which has the dimension of calendar days.

This estimation should be more accurate for liquidation (Chapter 7) events, as those are the events when the bond issuer indeed fails to serve its obligations to its creditors. However, credit derivatives such as CDSs are triggered by ISDA-defined credit events, and Moody’s also considers distressed exchanges as default events. Therefore, I use the market-implied distance to default as a proxy to explain the variance of real-world distances to other default events as well.
Regressor variables

My goal in the second round of statistical tests is to analyze the relationship of market-implied and real-world ‘distances to default’. I conduct panel regressions on two types of datasets. First, I pick the real-world time to liquidation as the dependent variable and my primary independent variable is the market-implied distance to default. In the second case, the dependent variable is the real-world time until the default announcement (which could be a bankruptcy filing, a distressed exchange announcement or a missed interest payment). I also conduct some regressions where the primary variable is changed to the credit spread.

Credit spreads are non-linearly connected to empirical time to default (see Figures 2 and 3), while market-implied distances only seem to be in linear connection with the time to default in liquidation cases (see Figures 2 and 3 again). To improve the explanatory power of the models, I introduce some additional variables in the panel regression. $C_i$ is the coupon of the $i^{th}$ bond (in percent of face value); $IsSecured_i$ is a binary dummy on whether the $i^{th}$ bond is secured; $Time to maturity_{i,t}$ is the remaining time to the maturity of the $i^{th}$ bond at time $t$ (in calendar days); $Type of default_i$ is the type of default (in credit event cases) used as a factor variable. (Factor $= 0$ means bankruptcy, factor $= 1$ means distressed exchange, factor $= 2$ means missed coupon payment.) $IsEmerging_i$ is a binary dummy on
whether the $i^{th}$ bond was issued by a company headquartered in an emerging country; 

$\text{IsEnergy}_i$ is a binary dummy on whether the $i^{th}$ bond was issued by a company operating in the energy sector. (This variable was included because a significant proportion of the sample was issued from this sector, and because I can measure industry effect on the credit event.) $\text{Stock price}_{i,t}$ is the closing price of the $i^{th}$ bond issuer’s stock on day $t$; $\text{Stock return since 2014H2}_{i,t}$ is the relative level of the stock price of the bond issuer, proportionate to the price level on 30th June 2014. (As the sample observation period starts in December 2014, all the default events happened and most of the distressed periods started through 2015-2016. It means that a benchmark price from Q2 2014 was reasonable.) $\text{IsInBankruptcy}_i$ is a binary dummy on whether the $i^{th}$ bond was already in bankruptcy at time $t$ (in liquidation cases).

The panel regression models

As I have observations across entities (ISINs or issues) and time (days), I expand the usual OLS linear regression framework using the characteristics of panel regression. My dependent variable is in all cases the empirical time to liquidation / default (measured in calendar days):

$$\tau_i = \text{default day of the } i^{th} \text{ bond}$$

$$y_{it} = \tau_i - t$$

I plot the heterogeneity across individuals in Figure 4 to discover that there is a large time-invariant entity effect in the dependent variable. (Figure 10 in Appendix B shows...
the same for the primary independent variable.) To control for individual effects, I use fixed individual effects models. The model’s formula is the following:

\[ y_{it} = \sum \beta_k x_{it,k} + \mu_i + \epsilon_{i,t} \] (6)

Where

\( \mu_i \) is the individual effect invariant over time, \( \beta_k \) is the coefficient of the \( k \)th independent variable, \( x_{it,k} \) is the value of the \( k \)th independent variable linked to the \( i \)th entity at time \( t \), \( \epsilon_{i,t} \) is the error term. ‘\( t \)’ goes from 1 to \( T \) (the number of periods, here: days) and ‘\( i \)’ goes from 1 to \( N \) (the number of individuals, here: bonds).

In R, I use the “within” transformation to replicate equation (6), which demeans the variables to eliminate individual effects. In case of fixed individual effects models, independent variables cannot include bond-specific time-invariants. It means the dummy variables and the coupon value of the bond are excluded in this framework from the regressors.

After I looked at the daily deviation of credit spreads across entities during the observation period, I decided to create time fixed effects models as well, where I control for the entity-invariant global effects. A wide consensus among academic researchers is
also present about the strong effect of the business cycle on the bond market, especially its lower-graded submarket (see Gilchrist and Zakrajsek, 2011 in Section 2). Moreover, I can measure the effect of properties assigned to bond individuals (listed above) on credit events. The model looks like the following in credit event and liquidation cases, respectively:

\[
y_{it} = \sum \delta_k x_{it,k} + \mu_t + \gamma_1 * C_i + \gamma_2 * D_{secured}^i + \gamma_3 * D_{emerging}^i + \gamma_4 * D_{energy}^i + \gamma_5 * D_{default type}^i + \varepsilon_{i,t} \quad (7)
\]

\[
y_{it} = \sum \delta_k x_{it,k} + \mu_t + \gamma_1 * C_i + \gamma_2 * D_{under bankruptcy}^i + \varepsilon_{i,t} \quad (8)
\]

The panel regression framework only works ex-post, since the bonds included in the sample are all liquidated / defaulted at the time of sample selection. However, it is still interesting to know in retrospect, how well the market anticipated the remaining ‘life’ of bonds.

### 3.3 Logistic regression on quarterly default events

Binary logistic regression is a common tool in banking to predict the possibility of client bankruptcy. Since my former two models work only ex-post, I run logistic regression on my sample to acquire ex-ante (or predictive) results from credit spreads. Another advantage of this framework is that it does not exclude non-defaulting firms from the sample. Thus, the analysis is less biased.

In this context, my dependent variable \( Y \) is a binary variable (0 = no default, 1 = default), later turned into a linear variable, the logit. The connection between the dependent and independent variables is estimated using maximum likelihood method. During the tests, I rely on the theoretical summary of Ferenci (2015).

I use credit spreads (level or dynamic value) and in some tests, stock price levels (relying on Fama and French, 1993) from the market to estimate a default possibility for every issue at the end of every quarter. To infer a 1-0 prediction from the default probability (1 meaning default is likely, derived from a default probability), one must carry out classification into groups. This classification is based on a cut-off point: a probability level, above which I predict default and below which I predict survival. I use a certain
partition of the data for creating a risk model, and another as a holdout or validation sample.

3.4 Data

For the mentioned statistical tests, I collected the panel data of credit spreads from Bloomberg. Unfortunately, Bloomberg offers Data and Analytics linked to fixed-income trading platforms for only the past 2 years. I collected data from the Terminal twice: on 13th January 2017 and on 14th March 2017. This resulted in a 2-month shift between the time horizons of observed analytics series of the first and second groups of the observed securities.

I only work with publicly registered and traded bonds. I excluded sovereign debt, so only corporate bonds are in my sample. My primary rule of picking a security in my data set was linked to the definition of distressed bonds I related to earlier: the bond’s government spread had to reach 1000 basis points during the observation horizon. I also targeted large issuer companies in my selection, to analyze the most liquid securities.

The securities I further excluded were assigned to either of the following: (1) defaulted before the start of the observation period, (2) not denominated in USD or EUR, (3) securities not traded on an American or Eurozone or UK exchange, (4) issues of banks. I ended up with a rather heterogenous sample of 84 issues from 75 different issuers. Most of the issuers were large multinational companies, with an average yearly revenue of $2100M, before financial distress. 15 of the 75 issuers were headquartered in an emerging country, mostly Brazil. The domination of the Brazilian issuers was due to the recession in the Brazilian economy along the fall of commodity prices during the years 2015-2016. The commodity bear market resulted with several energy sector issuers in the sample. 37 issuers were doing business in at least one of the following industries: oil and gas, mining, coal, steel, electricity, renewable energy. 28 issues were secured bonds, meaning that the issuer company or its holding company provided collateral for the case of bankruptcy to pay back its obligation to creditors.
Among the bonds 16 were short-term (0-2 years to maturity), 60 were medium-term (3-7 years to maturity) and 8 were long-term (over 7 years to maturity). 72 bonds were callable.

Figure 5 indicates the numbers of data points per day (blue area) along the corresponding daily quantiles (25-50-75%) and averages of credit spreads in the whole sample. Note that average spreads are highly biased by extreme spread values on certain days. The average number of data points per bond was 347 days (1.36 years) in the sample.

61 bonds defaulted, 23 survived during the whole observation window. Among the defaulted bonds, 43 cases were related to the filing of Chapter 11 bankruptcy, 16 cases to missing an interest payment and 9 cases to out-of-court distressed exchange (debt restructuring) with the bondholders, several followed by bankruptcy filings. From the aspect of liquidation, only 6 issuers were liquidated during the window, which resulted in a much smaller sample for statistical tests on liquidation. (All the liquidated issuers went bankrupt earlier.) I collected the dates of credit events (for instance, bankruptcy filings) and liquidations from Moody’s Credit Rating database (at https://www.moodys.com/credit-ratings) and from online business newspapers.

When I included stock prices from Yahoo! Finance, I also had to exclude some issuers (i.e. for being privately owned) and I could observe stock price effect analysis on liquidation event statistics, since most of the issuers were not publicly owned by the time they were liquidated.
4 Empirical results

This section contains the most important results from the several tests I run on my distressed bond dataset. One additional table elaborates the results in Appendix C.

4.1 Results of the independence t-tests

Figure 6 indicates the credit spread evolution of bonds, marked by a binary code of defaulted/non-defaulted during the observation window. The upper half of Figure 6 considers only liquidation cases, while the lower half considers the ISDA-termed credit events as well as out-of-court debt restructuring exchanges. In the upper half, the red subgroup consists of 6 issuers with 76 issuers in the green subgroup. Time series are plotted along the whole observation window, except for liquidated issuers, whose bond spread evolution is stopped at liquidation. In the lower half, the red subgroup frequently changes in terms of group size. As an issuer announces a credit event, its time series is terminated. There are on average 37.6 bonds in the red subgroup and 19 bonds in the green subgroup.

Note that the paths in red are seemingly not isolated from the dense zone of green lines. Moreover, credit spreads of surviving firms even surpassed premiums of later liquidated / defaulted ones temporarily, before returning to lower zones. It is also visible that the whole sample represents a substantially high zone of credit spreads. Within this extreme yield domain, a company could end up in liquidation at 10000 and at a million basis points of credit risk premium as well. These magnitudes imply a bond price equal to just a few percent of face value. It is remarkable though, that tapping into the region of 10000 bps of credit spread is common for distressed bonds, without having to file for liquidation under Chapter 7.

Credit spreads also experience large volatility. Before liquidation, liquidity possibly dries out from the market of the distressed (then, usually already under bankruptcy protection) bonds, as several trading days pass without quoted prices. In the case of Sabine Oil & Gas Corporation for instance, between the company’s filing for bankruptcy under Chapter 11 and for liquidation under Chapter 7, the average time between two quoting of a new price
on the bond exchange was 9.44 trading days, almost two weeks. In contrast, Radioshack’s bondholders traded the security every day between bankruptcy protection and liquidation. Its credit risk premium’s standard deviation along this period was, however, more than 56000 basis points. As holding these securities practically has the only reason of hoping for a share in debt recovery from asset sales of the issuer, referring to distressed bonds

Figure 6. The two plots indicate the credit spread paths across the whole dataset. The upper plot separates liquidated (red) from not liquidated (green) bonds. The lower plot separates defaulting (red) from non-defaulting (green) bonds. Note that the two plots use different scales on y-axis, though both logarithmic. (Self-made)
before liquidation as fixed income securities is rather unreasonable. Their market patterns more preferably resemble that of equities, as Figure 11 in Appendix B shows as well. This is in line with the cited publications by Fama and French (1993), Blanco, Brennan and Marsh (2003) and Hull, Predescu and White (2004).

Concerning the discrepancy between the red and green subgroups of either plot, one cannot tell the credit spread levels easily from one another. On the long run, red credit spread paths show a more positive drift than green lines. However, since the independence t-test only refers to the average level of the credit spreads, I decided to only run the test on the credit-event-type of distinction (indicated in the lower half of Figure 6). In the case of Chapter 7 filings (upper half), my finding was that instead of credit spreads, bond prices are better features of groups: I show a more distinctive depiction in Figure 11 in Appendix B. It is important to note, however, that the small subset of liquidated companies in my sample is by far not representative and from a larger subset, perhaps clearer market patterns could be inferred. By contrast, in the lower half of Figure 6, the two subsets are closer to each other in terms of size than the previous groups based on liquidation. Therefore, they are more representative of the corresponding properties and their inferred differences may be the same as their populations’. It is worth to run an independence t-test on the two subgroups.

Figure 7 shows the most important time series of the independence test. One can clearly glean from the chart that the null hypothesis can be rejected on a relatively low confidence level during most of the observation period, as the confidence level associated with the p-value of the test fluctuates between 0 and 1, rather hectically. Notably, on a 90% confidence level, the null hypothesis is rejected in 81.3% of the days in the observation window. Hence, independence of the two subgroups – defaulted and served bonds – is hardly robust. The second grey line represents the same confidence level measure, after filling in for missing quotes with the previous quotes on the market. The slightly observable difference between the grey lines mean that this modification cannot improve the robustness of the test significantly.

Another possible explanation of the weakness of the tests would be the regular change in the size of the defaulted subgroup, since after default events, certain securities disappear from the subgroup. However, confidence levels (or alternatively, p-values of the test) are changing in trends, resembling of regimes. A sudden disappearing of a sample member
would rather imply a single jump or drop and then a relative standstill in the time series but not a gradual move. Instead, a gradual change in the market should be linked with an underlying economic process.

I tried to track the underlying causes of regimes in the distressed bond market. My hypothesis was that investors start to punish low quality bonds – by assigning a larger credit spread – in times of turbulences, i.e. high volatility regimes on the stock market. The stock market’s volatility is connected to investors’ mood and economic development as well.

Figure 8 uses the VIX index (left plot) and the rolling standard deviation of the S&P 500 index on a yearly basis, to symbolize the volatility on the stock market. The VIX index represents an expected level of volatility in the upcoming 30 days, while the S&P 500 rolling volatility is a data from the past. In general, the plot shows that the credit premiums on defaulted bonds increase significantly above the credit premiums of not defaulted bonds when the volatility measure is on a higher level. In case of the VIX index, the
connection is non-linear and rather weak. The rolling yearly volatility of the S&P index implies a stronger effect on the robustness of average credit spread difference, also a nearly linear one. This means distressed bond investors’ risk aversion strengthens in uncertain periods; however, they rather react to past events than to expectations.

Another takeaway from Figure 7 is that the high-yield bond market is assumedly able to predict a default-intensive credit cycle. During my observation period, the times of bankruptcy filings were approximately uniformly distributed in time, except for a peak between May 2016 and August 2016. The most significant independence between the “defaulting” and “non-defaulting” subgroups emerged before this period and was stable. Linking this insight with the connection between stock market volatility and credit spread independence shown before, I conclude that stock market turbulences, risk aversion on distressed bond markets and rising default rates on distressed bond markets are simultaneous. For vulture funds, such periods are suitable opportunities to acquire a determining part of the company’s debt and hope for a market rebound later.

One could argue that the binary defaulting / non-defaulting property used for separation is inconsistent, as some of the companies in the subgroup “non-defaulting” may announce default after the end of the observation horizon. To control for this uncertainty, I repeated the independence test with a different grouping process. I only regarded the following 90 / 180 calendar days to separate defaulting bonds from non-defaulting ones, every day. Thus, the two subgroups became consistently complementary. My results showed that this modification did not change the robustness of the test. This also supports the inference
that underlying economic factors are stronger influencing powers in this test than sampling effects.

4.2 Results of the panel regressions

To explain the variation of the real-world time to default, I create multiple panel data models. Again, there are two separate approaches to the notion of default. As I mentioned in Section 2, the credit risk incorporated in bond credit spreads represent the risk of the issuer’s failure to serve its obligations. That literally only happens in the case of liquidation. When a company is liquidated, its obligations ‘vanish’, its creditors retrieve recovery value from the sold assets. Cases of credit events, most notably a bankruptcy filing, entails different risks that I also listed in Section 2. In my interpretation, credit risk, borne by bondholders, should show better in the first approach: I expect the market-implied distance to default to be a good approximation of the real-world time to liquidation. Nonetheless, as other default events are likewise as important for market participants, I also expect the market-implied distance to default to be a good proxy for the time to credit events, with a weaker economic significance.

Time to liquidation models

Table 1 shows the results of fixed individual effects models whose dependent variable is the real-world time to liquidation. The difference between the adjusted R-squared values of regressions “1” and “2” in Table 1 indicates that the explanatory power of the market-implied distance to liquidation is superior to that of the credit spread. Although, the coefficients of the variables are highly significant in both cases. Regression “1” tells that a day increase in the risk-neutral (market-implied) distance to liquidation is expected to cause a 0.8 day increase in real-world time to liquidation in average, having controlled for individual effects. There seems to be a 20% discrepancy which could be due to any of the supplementary risk factors listed in Section 2.1. Regression “2” tells that a 10000 basis points increase in credit spread is expected to decrease the real-world time to liquidation by 23 days in average, having controlled for individual effects. While the finding of “1” is easily interpretable as an almost-unequivocal relationship between risk-neutral and real-world times to liquidation, the latter finding is rather confusing. It suggests that ‘large’ credit spread changes, in the magnitude of 1000 points, only imply weak effects on the time to liquidation, ceteris paribus. In my opinion, this oddity is down to the clearly non-linear connection between the variables in “2”.

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I also show the results of the corresponding log-log models. In case of the market-implied distance to liquidation, if it rises by 1%, the real-world time to liquidation rises by 0.84%, ceteris paribus.

Table 5 in Appendix C shows fixed time effects models on the time to liquidation. When controlling for fixed time effects, the model yields counter-intuitive results, as the coefficient of the market-implied distance to liquidation has a negative sign. Introduction of other variables does not change the sign of the coefficient. In case of a log-log model, the adjusted R-squared value even turns negative.

**Time to default models**

In case of regressions run on the real-world time to default, the market-implied distance to default is again superior to the credit spread in almost all cases as a regressor variable. As expected, the explanatory power of these models is inferior to those of the liquidation models, when controlling for either individual or time fixed effects. I realized that I could improve the effectiveness of the model by excluding multiple issues from the same bond issuer companies. I believe this step reduced cross-correlation between independent variables. As shown in Table 2, model “1” almost reached the adjusted R-squared value of model “1” in Table 1. The improved model suggests that a 100 day increase in the risk-

<table>
<thead>
<tr>
<th>Fixed individual effect</th>
<th>y = time to liquidation (in days)</th>
<th>y = Log (time to liquidation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor</td>
<td>&quot;1&quot;</td>
<td>&quot;2&quot;</td>
</tr>
<tr>
<td>Credit Spread (in 10000 bps)</td>
<td></td>
<td>-25.8428 (2.894e-05)</td>
</tr>
<tr>
<td>Implied Distance (in days)</td>
<td>0.80502 (1.715e-05)</td>
<td></td>
</tr>
<tr>
<td>Log (Credit Spread)</td>
<td></td>
<td>-1.10434 (2.554e-07)</td>
</tr>
<tr>
<td>Log (Implied Distance)</td>
<td></td>
<td>0.843390 (&lt; 2.2e-16)</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>58.64%</td>
<td>31.55%</td>
</tr>
<tr>
<td>N</td>
<td>2131</td>
<td>2131</td>
</tr>
</tbody>
</table>

*Table 1. The numbers in the boxes show the coefficient of the linear panel regression assigned to the particular independent variable (upper value) and the p-value assigned to the coefficient, after a heteroscedasticity consistent, Arellano-type computation of robust standard error for the coefficient (lower value). Table is self-made*
neutral distance to defaul is expected to cause an 11 day increase in the real-world time to default in average, having controlled for individual effects.

I also introduced stock prices of the issuers as variables in models “3” and “4”. I had to diminish my sample size since not all the issuers were owned publicly from the sample. Still, I could run these regressions on a dataset of 7151 observations which I consider a large sample. The stock price as an independent variable brought impressive changes into the model’s explanatory power: it improved the adjusted R-squared value to over 60%. A percentage point increase in the relative stock price is expected to increase the real-world time to default by 4 days in average. One can also infer that the level of the stock price (even if demeaned by the “within” method) has less explanatory power than a relative stock level instead, measured against an older share price (on 30/06/2014). I assign this discovery to that the relative stock price also has information about the past state of the issuer company.

Table 3 shows variants of fixed time effect models, run on the dataset filtered for multiple bond issues. The table shows that in case of controlling for time fixed effects, the market-implied distance to default has a much weaker explanatory power of the real-word time to default than in the case of individual fixed effects models. On the other hand, this framework provides an opportunity to assess the effects of other, bond specific properties on the time of default. By far the most significant effect belongs to the dummy about a headquarter in an emerging economy. In case of original variables, issued by a company

<table>
<thead>
<tr>
<th>Fixed individual effect</th>
<th>y = time to default (in days)</th>
<th>y = Log (time to default)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor</td>
<td>“1”</td>
<td>“2”</td>
</tr>
<tr>
<td>Credit Spread (in 10000 bps)</td>
<td>-101.1774 (0.1757)</td>
<td>-0.992903 (7.818e-08)</td>
</tr>
<tr>
<td>Implied Distance (in days)</td>
<td>0.115017 (3.797e-14)</td>
<td>0.099303 (1.37e-08)</td>
</tr>
<tr>
<td>Stock price (in $)</td>
<td>2.434175 (0.01476)</td>
<td>0.105506 (0.0003959)</td>
</tr>
<tr>
<td>Relative stock price (proportion to price level on 31/06/2014)</td>
<td>402.105506 (0.0003959)</td>
<td></td>
</tr>
<tr>
<td>Log (Implied Distance)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>54.31%</td>
<td>8.16%</td>
</tr>
<tr>
<td>N</td>
<td>13500</td>
<td>13500</td>
</tr>
</tbody>
</table>

*Table 2. The numbers in the boxes are to be interpreted identically to Table 1. All models were run on the sample after the exclusion of multiple issues by the same issuer. Table is self-made*
with a headquarter in an emerging country, bonds in the dataset are expected to default in average 75–246 days earlier than those issued by a developed-economy-based company, ceteris paribus, having controlled for fixed time effects.

The attribute of belonging to the energy sector shows an insignificant but positive effect on survival of the bond first. After stock prices are incorporated, its coefficient turns negative and significant. This variable does not hold much economic idea in itself. The only real effect of belonging to the energy sector is a probable tangible-asset-weighed balance sheet, which increases the expected recovery rate. It does not reason, however,
why these issuers would move into bankruptcy earlier than others, unless they issue secured debt powered by asset-sale covenants.

The factors of different types of default also show insignificant effects. Type 1, which is out-of-court distressed exchange turns sign and turns significant after the introduction of stock prices. The direction of the effect is although vague in this case: is the ex-post default date earlier because out-of-court debt restructuring negotiations are usually more effective than pre-bankruptcy talks or because in case of bankruptcies the companies do not try to start talks as early as in case of out-of-court deals?

Time to maturity, a continuous variable, has both statistically and economically insignificant effect on the time to default. The level of coupon paid by the issuer to the bondholders shows always a negative effect, and turns highly significant after introducing stock prices. This effect is in line with my expectations as usually a higher interest obligation forces companies to default earlier, ceteris paribus.

The dummy variable on security shows versatile effects. Alone, it showed positive and insignificant effects (this version is not indicated in Table 3). In my opinion, that was counter-intuitive as cited research papers proved that secured creditors always push distressed companies towards an earlier bankruptcy to receive their guaranteed recoveries. I suspected this variable would interact with the market-implied distance, since secured bonds are expected to have smaller spreads as their expected recovery rates are much higher. This proved partly true as introducing an interaction variable reduced the p-value on security and changed its coefficient’s sign (Table 3, model “2”). A possible explanation for the empirical insignificance is the following. It is possible that those issuers whose secured bonds were selected in my database also issued unsecured bonds. Given that those unsecured bonds were purchased in large by professional distressed debt investors, those funds could influence restructuring negotiations in a way that bankruptcy was put off to their interest.

In case of fixed time effects models, the introduction of relative stock prices does not improve the explanatory power dramatically alone. However, when accompanied by other variables (as in model “5” in Table 3), it improves the adjusted R-squared value to over 50%, a similar result to individual effects model. It also improves the significance of almost all the other bond property factors, except for security, while it does not interfere.
with the magnitude of the effect from the market-implied distance to default. This is evidence that the stock price covers important information about the default event.

The magnitudes and significance levels of fixed effects were strong in all cases (see robustness checks below). The standard deviation in the individual fixed effects moved between 99 and 109 days, depending on the model. The time fixed effects were also economically significant, usually with around 90 days of absolute effect in average.

**Robustness checks**

Following Torres-Reyna (2007; 2010), I conducted several kinds of robustness tests on the panel data models. First, I executed the Hausman-test to find out whether the fixed effect model dominates the random effect model in model selection. It supported my decision to run a fixed effects regression on a 95% confidence level, except for the case when the credit spread was the independent variable and I controlled for individual fixed effects. I also run a global F-test to check out the significance of the fixed effects compared to an OLS regression. This test always proved that the fixed effect model was reasonable to use, on a 99% confidence level.

Robustness tests included the Breusch-Godfrey / Woolridge test for serial correlation in panel models. Unfortunately, all my models suffered from serial correlation on a 95% confidence level. This statistic was improved however, when I excluded multiple issues from the same issuer, and introduced stock price time series as a variable or when I run a log-log model. I also carried out the Breusch-Pagan LM test and the Pesaran CD test for cross-sectional dependence in panels. These tests always showed that the residuals across entities were correlated on a 99% confidence level. Again, it was improved when I used stock prices too and when I ran regression on the time to liquidation.

I carried out a global Breusch-Pagan test on homoscedasticity / heteroscedasticity in all cases. Heteroscedasticity turned out to be present in all my models on a 97.5% confidence level, except for the log-log model on time to liquidation, where my independent variable was the log of the implied distance. I also used the augmented Dickey-Fuller test to check the stationarity of the dependent variables. All series of dependent variables were stationary on a 95% confidence level.

Since these tests signaled a large bias and inconsistency in my regression estimations, I had to re-estimate standard errors for the variable coefficients that were robust to
heteroscedasticity, contemporaneous cross-sectional correlation and serial correlation. I applied Arellano’s method to estimate HC0-type robust covariance matrices and used the derived standard errors for the t-tests. The tables in the thesis contain p-values conforming these standard errors. I used the ‘sandwich’ package provided in R to carry out the estimations.

4.3 Results of the logistic regression

I collected data from 9 successive quarters of the distressed bond market that I load into the logistic regression. As this is a model typically used for ex-ante predictions, I separate the dataset (again a panel database, for now all the issues until default) into a training and a testing period. I use only the first 6 quarters as training period, as my sample does not contain many default events in the last quarters. I exclude multiple issues from the same issuers again.

As for independent variables, I use multiple selections, shown in Table 4. First, I only use the credit spread as a market predictor, supported by two bond properties: coupon and security (models “1-4”). Between the level of the spread at the beginning of the predicted quarter and the change of the spread during the previous quarter, the spread level turns out to be a more effective estimator on the training dataset. The introduction of the bond properties is, however, ineffective: the coupon level and the security dummy only slightly decrease the deviance of the model.

The inclusion of the stock price improves the explanatory power of the model, though the sample size is reduced to 133 data points (models “5-7”). The equity return of the last quarter and the relative equity level proportional to the mid-2014 level equivalently enhance the explanatory power. On basis of the AIC value, I select the relative stock price at the beginning of the quarter to be used for prediction.

The model based on the sole level of credit spread has a 20.8% McFadden pseudo-R-squared value, while the model expanded with the stock return leads to a higher 31.25% pseudo-R-squared.

Concerning the coefficients, one can deduce the following. A 1 percentage point increase in the credit spread level in the beginning of the quarter increases the odds ratio (PD/(1-PD)) by around 3% in average. In turn, a 1 percentage point increase in the relative equity level at the beginning of the quarter decreases the odds ratio by around 3.8% in average.
The classification of the predictions is based on a cut-off point in the (0,1) interval. Usually, 50% is used as such cut-off to separate non-default (0) from default (1). My models, however, are not able to predict any default events with such a high cut-off level within the test sample. When I reduce the cut-off point to 15%, the model is able to predict 1 out of 2 default events in the following quarters. The accuracy of the model is better though, with the cut-off set to 0.5: it yields an 80.6% accuracy, while the 0.15 cut-off point yields only a 75.7% accuracy.

When I include the stock return as an additional variable, I expect an improved performance from the model. At a 50% cut-off, it yields an 86.05% accuracy level, which is rather impressive. However, it still never predicts any default events and only deserves its accuracy thanks to the majority of non-defaulting events in the test sample. When I reduce the cut-off point again to 15%, the model gets worse. It predicts default events too often but still not in the right quarters. It yields a mere 65.11% accuracy level.

Although I only used the logistic model to validate my ex-post results in an ex-ante framework, I was surprised at the ineffectiveness of the model. Its accuracy is acceptable but almost no default events are correctly predicted. It is true that logistic regression

### Table 4. The fitting of the logistic regression of the 6-quarter-long training dataset.

Note that data points have a quarterly frequency. The upper values in the boxes indicate the coefficients of the independent variables of the logistic regression, while the lower values indicate the p-values of the Wald-test, assigned to the significance of the coefficients. N means the number of data points in the sample. The table is self-made

<table>
<thead>
<tr>
<th>Factor</th>
<th>&quot;I&quot;</th>
<th>&quot;I&quot;</th>
<th>&quot;I&quot;</th>
<th>&quot;I&quot;</th>
<th>&quot;I&quot;</th>
<th>&quot;I&quot;</th>
<th>&quot;I&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change of credit spread in last Q</td>
<td>0.1636 (0.228)</td>
<td>0.1650 (0.23145)</td>
<td>3.7158 (9.71e-09)</td>
<td>3.8538 (6.99e-09)</td>
<td>3.4969 (0.000122)</td>
<td>3.126 (0.000631)</td>
<td>2.8600 (0.00116)</td>
</tr>
<tr>
<td>Relative equity level at beginning of quarter (measured to 30/06/2014)</td>
<td>0.01404 (0.89461)</td>
<td>-0.1242 (0.32695)</td>
<td>-3.8376 (0.01044)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor: Is Secured?</td>
<td>0.04614 (0.91884)</td>
<td>0.4746 (0.35578)</td>
<td>N</td>
<td>314</td>
<td>314</td>
<td>314</td>
<td>314</td>
</tr>
<tr>
<td>Null deviance</td>
<td>227.71</td>
<td>227.71</td>
<td>227.71</td>
<td>227.71</td>
<td>105.445</td>
<td>105.445</td>
<td>105.445</td>
</tr>
<tr>
<td>Residual deviance</td>
<td>226.41</td>
<td>180.33</td>
<td>226.39</td>
<td>179.08</td>
<td>82.333</td>
<td>74.512</td>
<td>72.494</td>
</tr>
<tr>
<td>AIC</td>
<td>230.41</td>
<td>184.33</td>
<td>234.39</td>
<td>187.08</td>
<td>86.332</td>
<td>80.512</td>
<td>78.494</td>
</tr>
</tbody>
</table>

Note: Data points have a quarterly frequency. The upper values in the boxes indicate the coefficients of the independent variables of the logistic regression, while the lower values indicate the p-values of the Wald-test, assigned to the significance of the coefficients. N means the number of data points in the sample. The table is self-made.
models are very dependent on the selected variables; most probably, I did not select the correct predictor regressors.

On the other hand, I reached back to Guo, Jarrow and Lin (2009) who wrote about economic default dates prior to official default dates. In my sample, the distance between the economic default dates and the official default dates are distributed as shown in Figure 9. (See formula for economic default date in Appendix A.) A typical example on the phenomenon of economic default date is shown in Figure 12 in Appendix B.

The discrepancy could be caused by influential investors or managers who deliberately determined a bankruptcy / credit event date months later than the company started to destroy value by operating in a wasteful way, under financial distress. Also, as per Gregory (2010), CDS delivery squeeze can be a possible explanation, since most of the issuers in the sample had quite liquid CDS markets as well.

\[ \text{Figure 9. On the left, the histogram of the difference between the official and the economic default dates (defined by Guo, Jarrow and Lin) in my dataset. On the right, the left side of the same distribution broken down into finer intervals. The figures are self-made.} \]
5 Conclusion

In my thesis, I analyzed how well corporate bond credit spreads predict corporate default events. My analysis also serves as a measure of the information content in credit spreads on credit risk and as an efficiency test of the distressed bond market.

Measuring the accuracy of prediction was a highly complicated task in this special case. Not only credit spreads are known to contain additional risk premium over credit risk (see for instance Amato and Remonola (2003) and Feldhütter and Schaefer (2014), described in Section 2.1), but credit risk itself is complex concerning distressed debt (see Figure 1 and cited literature in Section 2.3) Due to the subtle system of credit exposure in this asset class, I chose not to carry out a credit spread attribution, but rather to observe statistical connections between credit spreads and default events. I separated cases of liquidation events from credit events (defined by ISDA and used by rating agencies), since both are used as conceptions of default.

My first test was an independence t-test on whether the average credit spreads in defaulting and non-defaulting sets of bonds are derived from different distributions. Although the test failed to prove strong independence before credit events, I detected some relevant facts. First, I found that bonds before liquidation behave rather as equity than as fixed-income assets. Second, I discovered that market conditions, most notably stock market volatility and default rates have a large impact on distressed bond credit spreads. These findings stand in line with the former results of Fama and French (1993), Gilchrist and Zakrajsch (2011), Blanco, Brennan and Marsh (2005) and Hull, Predescu and White (2004).

From my test results, I inferred that the corporate bond market is not very efficient to separate failing businesses from temporarily distressed firms. These results were, however, rather fragile, as they lacked strong statistical significance and assumptions of the test were also violated (see Appendix A). In case of liquidation events, I lacked the necessary size of liquidated firms in order to carry out a relevant test. Despite all, I believe with a larger sample and longer time horizon, the same test could provide more useful results on a weekly basis, both for credit events and for liquidation.

My second-round tests included a list of panel data regression models, covering the variance in the empirical time to default, explained by a market-implied distance to
default and some additional variables. I calculated market-implied distances to default by assuming a time homogenous Poisson process behind the credit events and using the theory of Duffie and Singleton (1999) to obtain intensities from credit spreads. Having obtained the independent variable, I ran fixed individual and fixed time effects parallelly. My results showed that the market-implied distance to default was a nice approximation for time to liquidation, when controlling for fixed individual effects and especially when introducing stock price as an additional variable. When using it as a proxy for time to default, the introduction of the issuer’s stock level as another variable again helped significantly improve the explanatory power of the model.

Time fixed effects models reached a consistently lower adjusted R-squared value than individual fixed effects models. However they opened the possibility to test the effect of bond properties on the timing of default. Among them, the headquarter of the company (in developed / emerging economy) turned out to be of utmost importance, beside the credit spread and the stock price.

My panel data models can be improved in several ways. First, Altman and Kishore (1996) point out the deviation of ultimate recovery rates across industries. In case of hazard rate estimation, such a distinction could provide further accuracy. So could the use of swap rates as risk-free rates. Further independent variables could be borrowed from the CDS market (which is more efficient than the bond market, stated by Blanco, Brennan and Marsh (2005)), company fundamentals (such as leverage) and the structure of the company’s debt (for instance, debt amount).

The last test I carried out was a logistic regression to predict default events in the following calendar quarter. Although these models had an accuracy over 60%, they could not predict the vast majority of the default events. After computing for the ‘economic default dates’ described by Guo, Jarrow and Lin (2009) I concluded that in my sample, the issuers usually reached their economic depths about two months before they reached the decision to announce default on their obligations. The weakness of the model’s prediction could be either due to this phenomenon or to a bad selection of regressor variables.

Potential further research in this area is manifold. Liquidity on the market is of pivotal importance in my opinion, to understand credit spreads. Individual stories of bankrupt and liquidated firms can serve with a lot of new discoveries as well. Lastly, I believe that
apart from the existing structural and reduced-form credit models, game theoretical modeling would be necessary to estimate risk measures to such securities, as the background network of stakeholder interests imply an almost unsolvable case for traditional stochastic financial modeling.
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https://en.wikipedia.org/wiki/VIX [downloaded: 22\textsuperscript{nd} April 2017]

http://www.investopedia.com/terms/h/high_yield_bond.asp [downloaded: 27\textsuperscript{th} April 2017]

http://www.investopedia.com/terms/j/junkbond.asp [downloaded: 27\textsuperscript{th} April 2017]
Appendix

A. Formulae

The independence t-test

For running the independence t-test, one does not need to know the mean and standard deviation of the underlying populations of the data sets. Some assumptions must be made however. First, two independent categorical groups should represent the subsets. In my case this category is a binary code on the incident of liquidation / a credit event. Second, the dependent variable – here the credit spread – should be approximately normally distributed, measured on a continuous scale. Accordingly, I manipulated my database: I replaced credit spreads higher than 15000 basis points with this value, in order to control for the negative skewness in the distribution. Third, the variances of the dependent variables should be equal. This assumption is violated to some extent, although only due to extreme yield members in the defaulting subgroup.

The value of the t-statistic is the following:

\[
t = \frac{\mu_A - \mu_B}{\sqrt{\left(\frac{\sum A^2 - (\frac{\sum A}{n_A})^2}{n_A} + \frac{(\sum B^2 - (\frac{\sum B}{n_B})^2)}{n_B}\right) \cdot \left(\frac{1}{n_A} + \frac{1}{n_B}\right)}}
\]

where ‘A’ refers to the elements of the first subset and ‘B’ refers to the elements of the second subset. \(\mu_x\) is the mean of dependent variable subset \(X\) and \(n_x\) is the size of subset \(X\).

The t-statistic then must be compared to the corresponding t-table value. One needs to set an alpha level (derived from the confidence level) and compute the degree of freedom to obtain the t-table value. The degree of freedom equals \(n_A + n_B - 2\). Finally, if the absolute value of the t-statistic is smaller than the t-table value then the null hypothesis can be rejected on a larger significance value (the p-value) than alpha.

I ran the independence test on every single day (\(t\)) in my time frame, obtaining a time series of t-statistics and corresponding p-values.
Derivation of the probability of survival to time t

Connecting the framework of Poisson processes with the survival function of Li (2000) we can obtain an estimation of the hazard rate. Mosconi (2015) provides the following derivation:

\[ F(t) = P(\tau < t), \text{where } t \geq 0, F(t) = 0, \]

\[ F \text{ denotes the cumulative distribution function of default time} \]

\[ F(t) = \int_{-\infty}^{t} f(u)du, \text{if } F \text{ is differentiable} \]

\[ S(t) := P(\tau \geq t) = \int_{t}^{\infty} f(u)du = 1 - F(t), S \text{ denotes the survival probability} \]

\[ h(t) := \lim_{d\to 0} \frac{P(t \leq \tau < t + dt)}{dt \cdot P(\tau \geq t)} = \frac{F(t + dt) - F(t)}{dt \cdot S(t)} = \frac{f(t)}{S(t)} \]

\[ = - \frac{S'(t)}{S(t)}, \text{where } h(t) \text{ is the hazard rate function} \]

\[ H(t) := \int_{0}^{t} h(u)du = - \int_{0}^{t} d\left(\ln(S(u))\right) \]

\[ = - \ln(S(t)), \text{where } H(t) \text{ is a cumulative hazard rate function} \]

\[ S(t) = e^{-H(t)} = e^{-\int_{0}^{t} h(u)du} \]

Derivation of the equation between the hazard rate, the credit spread and the recovery rate

A credit default swap ensuring the cash flow of the bond above has got a continuously paid premium. The present value of its premium leg is equal to

\[ P(s, T) = E[s \cdot \int_{0}^{T} e^{-\int_{0}^{t} r_s + \lambda_s ds} dt] \]

where

\[ r_t \text{ is the anualized risk-free rate at time } t \]

\[ \lambda_t \text{ is the hazard rate at time } t \]

\[ s \text{ is the premium of the CDS} \]
Meanwhile, the protection leg of the CDS is priced the following way:

\[
P(RR, T) = E[(1 - RR) \times \int_0^T \lambda_t e^{-\int_0^t r_s + \lambda_s ds} dt]
\]

Under no-arbitrage assumption, the present value of the two legs of the CDS contract must be equal. At the same time, Duffie and Singleton (1999) also show that the premium of the CDS must equal the credit spread of the bond. From this, the equation is trivial.

This formula presumes that upon default, a constant portion of the original debt is recovered to the creditors immediately. While this is not so in reality, original creditors indeed sell their share of debt to professional distressed debt investors (in case of a continuing concern) or official insolvency inspectors (in case of liquidation) who later liquidate assets of the defaulted company. The received value can be considered as a recovery.

**The economic default date**

Guo, Jarrow and Lin (2009) introduce the notion of the economic default date defined as the first date when the market prices the firm’s debt as if it has defaulted. In their formula they describe \( \hat{\tau} \) the economic default date as

\[
\hat{\tau} = \inf_{t < \tau^*} \left\{ t : B_t \leq B_{\tau^*} e^{-\int_t^{\tau^*} r_s ds} \right\}
\]

Where \( B(t) \) is the debt price at time \( t \), \( \tau^* \) is the official default date when the recovery payment is assumedly made to the creditors, \( B_{\tau^*} \) is the debt price on the official default date and \( r(t) \) is the risk-free rate at time \( t \).

To find the economic default date, one needs to start stepping back in time before the official default date. If there is a day before the official default date when the bond’s price was lower than the risk-free discounted present value of the official default date’s bond price, then that day should be called the economic default day until an earlier one takes away this title from it.

The authors arbitrarily drew a line at 180 days before the official default date as a minimum date for the economic default date. I followed this method.
For illustrative reasons, I added the plot of price and spread evolution of Ultra Petroleum Corporation’s senior unsecured bond during the observation period, to Appendix B.

B. Additional Figures

**Figure 10.** The heterogeneity of the market-implied distances to default across entities in the sample. The circles indicate the average implied distances in case of the particular bonds.

**Figure 11.** The price evolution of distressed bonds in the sample, along the observation window. In red, the credit spread paths of bonds whose issuers were liquidated during the window. In green, the credit spread paths of surviving bonds.
C. Additional Tables

<table>
<thead>
<tr>
<th>Factor</th>
<th>&quot;1&quot;</th>
<th>&quot;2&quot;</th>
<th>&quot;3&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Implied Distance to default (in days)</td>
<td>-0.34752 (0.04457)</td>
<td>-0.2189884 (0.01779)</td>
<td>-0.026513 (0.60220)</td>
</tr>
<tr>
<td>Factor: Is Under Bankruptcy Protection? (1)</td>
<td>-20.3830165 (0.56026)</td>
<td>160.974617 (4.439e-07)</td>
<td></td>
</tr>
<tr>
<td>Coupon</td>
<td>9.9228229 (0.22089)</td>
<td>12.696558 (0.02047)</td>
<td></td>
</tr>
<tr>
<td>Time to Maturity (in days)</td>
<td>0.0234973 (0.68789)</td>
<td>0.017316 (0.69617)</td>
<td></td>
</tr>
<tr>
<td>Factor: Is Brcy? (1) x Implied Distance</td>
<td>-0.301121 (1.897e-15)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>15.32%</td>
<td>25.36%</td>
<td>54.14%</td>
</tr>
<tr>
<td>N</td>
<td>2131</td>
<td>2131</td>
<td>2131</td>
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<tr>
<td>Balanced / Unbalanced panel data set</td>
<td>Unbalanced</td>
<td>Unbalanced</td>
<td>Unbalanced</td>
</tr>
</tbody>
</table>

*Table 5. Time fixed effects models on time to liquidation. For interpretation, see Table 1. Table is self-made*