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THE LINK BETWEEN DEFAULT AND RECOVERY RATES A GLOBAL STUDY

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ABSTRACT

Applying the same methods and definitions as in Altman, Resti and Sironi (2005) this thesis seeks to empirically explain the relationship between default and recovery rates in the global corporate bond market. Findings in this thesis show that global default rates explain as much as 80 percent of the annual variation in associated recovery rates when results are based on the same time frame (1982-2001) as in Altman, Resti and Sironi (2005), and around 66 percent when most recent observations (1982-2012) are included to the analysis. This thesis supports the findings in Altman, Resti and Sironi (2005) of a significant and negative link between default and recovery rates. Findings of a negative relationship between default and recovery rates have important implications for credit-risk-related models treating the recovery rate independent of the default rate, or probability of default. This thesis also analyzes the univariate and multivariate relationship between recovery rates and other market and macro based variables. Results from these tests shows that the bond default rate, in comparison to these variables, undoubtedly explains the highest degree of variation in recovery rates. On a univariate basis the supply of defaulted securities significantly explains from 20 to 60 percent of the variation in recovery rates, however, when added to the multivariate models, results are divergent and the supply of defaulted bonds show no significant explanatory contribution. The latter results differ from the central thesis in Altman, Resti and Sironi (2005), where the multivariate regression models assign a key role to the supply of defaulted bonds.

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1. INTRODUCTION

Risks have a central role in financial markets, and the Risks related to credit are as old as lending itself dating back to Babylon some 1800 BCE[1]. As in ancient Babylon, lenders still face the element of uncertainty regarding the borrower's ability to repay a particular loan. But as financial innovations have progressed credit risk has changed in many ways. Due to dramatic economic, political and technological change around the world, credit risk has grown exponentially. In all, credit risk has grown more complex, accordingly the need for accurate and reliable credit risk models are important. The field of credit risk management came to the world as the first banks where organized in Florence some 700 years ago, and has since then formed the core of their expertise[2]. Today financial economists, bank supervisors and regulators, and financial market practitioners devotes much attention to the measurement, pricing and management of credit risk, as virtually all financial contracts are affected by it[3].

To assess the credit risk related of a financial asset, three main variables must be considered: (i) the probability of default, (ii) the recovery rate and (iii) the exposure at default. While a significant portion of the literature on credit risk has been devoted to the estimation of default probabilities, less attention has been devoted to the estimation of recovery rate and the association between default and recovery[3]. Jankowitsch, Nagler and Subrahmanyam (2014) argue that it is important to better understand the stochastic nature of recovery rates as credit risk models fails to explain observed yield spreads.

With the aim at empirically explain the variation annual aggregate recovery rates Altman, Resti and Sironi (2005) study the link between default and recovery rates in the U.S. corporate bond market, and successfully find a significant and negative link between these two variables. Applying the same methods and definitions as in Altman, Resti and Sironi (2005), I have empirically analyzed whether this relationship is present in the global corporate bond market. My economic univariate models show that global default rates

[1] Homer, S., & Sylla, R. (1991). "*A history of interest rates*." Third edition
[2]Altman, Edward I., Andrea Resti, and Andrea Sironi, eds. *Recovery risk: The next challenge in credit risk management*. Risk Books, 2005.
[3] Altman, Resti and Sironi (2005)

explains a significant portion of the annual variation in associated recovery rates across all seniority levels.

1.1 RESEARCH QUESTION

As the main purpose of this thesis is to empirically analyze and explain the relationship between default and recovery rates in the global corporate bond market, and to see if the findings in Altman, Resti and Sironi (2005) also apply in this market, I attempt to clarify the following main and sub issues:

Is there a significant and negative relationship between default and recovery rates present in the global corporate bond market?

Are there other variables that better explain the variation in recovery rates than default rates?

Are global bond recovery rates a function of the supply and demand for defaulted securities and the default rates?

1.2 STRUCTURE

The paper is organized as follows: Section 2 reviews the literature. Section 3 gives a detailed overview of the definitions, explanatory variables and empirical evidence in Altman, Resti and Sironi (2005). Section 4 provides details of the data and explanatory variables used in my analysis. Section 5 presents the descriptive analysis and the results of the regression models. Section 6 provides a comparison between findings in Altman, Resti and Sironi (2005) my study. Section 7 examines the robustness of the regression models. Section 8 presents implications. Section 9 addresses weaknesses. Section 10 concludes.

2. LITERATURE REVIEW

As the majority of research on the association between aggregate default and recovery rates are embedded in credit risk modeling, it seems appropriate to start this literature review by presenting how the different credit risk models treat the default and recovery rates, and then subsequently present the most acknowledged, as well as the most recent contributions. The literature review and review of credit risk models is based on a detailed discussion of these subjects presented in Altman, Resti and Sironi (2001).

2.1 CREDIT RISK

The credit risk of a financial asset is affected by three main variables: (i) the probability of default; (ii) the "loss given default" (equals one minus the recovery rate); and (iii) the exposure at default. In the following part I will present how different credit models treat the default and recovery rate.

A significant portion of the literature on credit risk has been devoted to the estimation of default probabilities, while less attention has been devoted to the estimation of recovery rate and the association between default and recovery rates. Altman, Resti and Sironi (2001) find that this is a consequence of two related factors. First, since it is the systematic risk components of credit risk that attract risk premia, credit pricing models and risk management applications tend to focus it. Second, traditional credit risk models assumes that the recovery rate depend on individual features like collateral or seniority, which do not respond to systematic factors. During the past decade an increased number of studies have been dedicated to the subject of recovery rate estimation and the association between default and recovery rates. Altman, Resti and Sironi (2001) argues that this increase has partly revised the traditional focus on defaults, and is a consequence of the observed negative correlation between default and recovery rates in the U.S. market during the 1999-2002 period.

2.2. DEFAULT AND RECOVERY RATES IN CREDIT RISK MODELING

Credit risk models can be divided in to two main categories; (a) credit pricing models, and (b) portfolio credit value-at-risk (VaR) models. Credit pricing models can in turn be divided into three main approaches; (I) "first generation" structural-form models, (II) "second generation" structural-form models, and (III) reduced-form models (Altman, Resti, & Sironi, 2001).

2.2.1(I) FIRST GENERATION" STRUCTURAL-FORM MODELS

These models was first introduced by Merton (1974) adapting the principles of option pricing (Black & Scholes, 1973). The basic framework from this model is that the process of default is driven by the value of the company's assets and liabilities. More precisely, Merton's intuition behind the model is that; defaults occur when a firms' asset value is less than the value of its liabilities. In practice this means that the payment/recovery to bondholders at maturity equals the face value if the firms' asset value is greater than face-value of debt, and vice-versa.

Under structural form models relevant credit risk elements, including default and recovery, are a function of the structural characteristics of the firm: business risk and financial risk. In these models the payoff/recovery to bondholders is a function of the firm's residual assets value, thus treating the recovery rate as an endogenous variable. In Merton's theoretical structural-form framework the default probability and recovery rate are inversely related; if the firms value decreases, then its probability of default increases while the expected recovery rate at default decreases. On the other hand: if firm asset volatility decreases, its probability of default will decrease while the expected recovery rate will increase (Altman, Resti and Sironi (2001)).

Jones, Mason and Rosenfeld (1984) provide evidence that a Merton-type model, even aimed at companies with very simple capital structures, is no better at pricing investment-grade corporate bonds than a naive model assuming no default risk. The lack of success has been attributed to three different factors. First of all, a firm can only default at maturity of the debt. Second, the structure of debt seniority needs to be specified when valuating default-risky debt of firms with more than one class of debt in its capital structure. Third and lastly, Merton's framework also assumes that, in the event of default, the absolute-priority rules are adhered, meaning that the payoff to bondholders is paid off in the order of their seniority.

2.2.2 (II) "SECOND GENERATION" STRUCTURAL-FORM MODELS

These models adopt Merton's original framework concerning the default process, but remove the assumption that defaults only occur at the maturity of debt. Instead, "second generation" structural-form models implements that default can occur at any time between the issuance and maturity of debt (Altman, Resti, and Sironi, 2001)..

In the event of default, these models treat the recovery rate as an exogenous variable, independent from firm asset value and defined as a fixed ratio of outstanding debt, thus independent from the default probability. In these models the recovery rate is generally defined as a fixed ratio of the outstanding debt value.

By observing the historic default and recovery rate for various classes of debt, Longstaff and Schwartz (1995) reason that, one can estimate a reliable recovery rate, given firms are comparable. In their model they allow for correlation between defaults and interest rates and a stochastic term structure of interest rates. Compared to first generation models, this approach is somewhat simpler, since it, first, exogenously specifies the cash-flows to risky debt in the event of default, and second, defines default by some exogenously specified boundary of the underlying asset value (Altman, Resti, and Sironi, 2001).

By empirically testing both first-and second generation structural-form models, Eom, Helwege and Huang (2001) find that almost all these models, on average, predict spreads that are too high relative to those observed in the bond market. The only exception is Merton's model where the predicted spreads are too low. Concerning the second generation models, they find that low prediction accuracy is a problem since the models tend to severely overstate the credit risk of firms with high leverage or volatility. Altman, Resti and Sironi (2001) argue that the poor performance is caused by three main drawbacks. First, these models require unobservable estimates for firm asset value parameters. Second, it is not possible to incorporate changes in credit-rating. This is viewed as a drawback since most corporate bonds undergo credit downgrades before they actually default. They also address that any credit risk model should take into account the uncertainty associated to changes in credit rating as well as uncertainty concerning default. Lastly, the majority of structural-form models assume that firm value is modeled continuous in time, implying that a default can be predicted just before it happens, and consequently, there are no sudden surprises as the default probability of a firm are known with certainty.

2.2.3 (III) REDUCED-FORM MODELS

These modes were introduced in the mid-1990s and primarily differ from reduced-and structural-form models in the way that defaults are treated. While defaults in structural-form models are conditioned on some measure of the firm's asset value, no such assumptions are made in reduced-form models. In the reduced-form models the dynamics of default are exogenously specified by the default rate. Consequently, the price on credit sensitive debt can be calculated as if they were risk free by applying the risk free rate adjusted by the default rate. In reduced form models the recovery rate is also exogenously specified and independent from the default probability.

Regarding how the recovery rate is parameterized, Altman, Resti and Sironi (2001) find that reduced-form models are somewhat different from each other. For instance, they find that while Jarrow and Turnbull (1995) in their model assume that the recovery at default equals an exogenously specified fraction of a corresponding default-free bond, while other reduced-form models assume that the recovery rates for bonds of the same issuer, seniority, and face value, is the same regardless of time until maturity. Jarrow, Lando and Turnbull (1997) allow different debt seniorities to translate into different recovery rates for a given firm, while Zhou (2001) attempt to combine the advantages in structural and reduced-form models, and links the recovery rate to the firm value at default so that the variation in the recovery rate is endogenously generated (Altman, Resti, and Sironi, 2001).

2.2.4 VALUE AT RISK (VaR) MODELS

Developed by both banks and consultant firms[4], and aim at measuring the potential loss a credit portfolio can suffer, given a predetermined confidence level and time horizon. In these models the recovery rate is typically regarded as an exogenous and constant parameter or a stochastic variable independent from the default probability, and thus, treating the recovery rate independent of the default probability (Altman, Resti and Sironi (2001)).

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[4] J.P. Morgan's CreditMetrics® (Gupton, Finger and Bhatia [1997]), McKinsey's CreditPortfolioView® (Wilson [1997a, 1997b and 1998]),

2.3 RECENT CONTRIBUTIONS AND ACKNOWLEDGED STUDIES

In the following section I will present both well established and recent literature concerning the behavior of recovery rates and its relationship with defaults.

Both Finger (1999) and Gordy (2000) propose conditional models where defaults are driven by one systematic factor, namely the state of the economy, rather than a multitude of correlation parameters, and where recovery rates are affected by the same economic conditions. Thus, these models assume that the same economic conditions causing defaults to increase that cause recovery rates to decrease. Further, they provide evidence that recovery rates fluctuates with the intensity of defaults (Altman, Resti, and Sironi, 2001).

Frye (2000a and 2000b) propose a model where both the probability of default and the recovery rate depends on the state of a systematic factor. In this model the recovery rate and default probability are mutually dependent on the systematic factor, accordingly the correlation between the two variables derives from this common relationship. The simple intuition behind this theoretical model is that, when a debtor defaults on a loan, a bank's recovery may be determined by the collateral loan value, which again depends on the economic conditions. This means that if the economy is in a downturn, recoveries may decrease just as defaults tend to increase, yielding a negative correlation between recovery and default rates. In Frye's original model[5] recovery rates are implied from an equation that determines the collateral value. Recovery rates in Frye (2000b) are calculated directly, allowing him to use U.S bond market data to empirically test the relationship between default and recoveries. Results from this analysis show a strong negative correlation between the two variables. This empirical analysis allows Frye to draw the conclusion that in a severe economic recession, bond recoveries might decline 20-25 percentage points from their normal average.

Jarrow (2001) presents a novel approach for estimating recovery rates and default probabilities which are implicit in both debt and equity prices (Altman, Resti, and Sironi, 2001). Jarrow (2001), as in Frye (2000a and 2000b), assume that recovery rates and default probabilities are correlated and dependent on the state of the economy. The difference is that Jarrow's methodology separates the identification of recovery rates and

[5] Frye (2000a)

default probabilities by explicitly incorporating equity prices into the analysis. Due to the high variability in the yield spread between U.S. treasury securities and risky debt, Jarrow also includes a liquidity premium in the estimation procedure.

Carey and Gordy (2001) analyze loss-given-default (LGD[6]) measures and their correlation with default rates using four different datasets. They find that estimates of simple default rate-LDG correlation are close to zero, and suggest that a weak or asymmetric relationship may be influenced by different components of the economic cycle. They conclude that the basic intuition behind Frye's model may not adequately describe the link between recovery rates and defaults (Altman, Resti, and Sironi, 2001).

Through a comprehensive analysis of various assumptions regarding the association between aggregate default probabilities and the loss given default on corporate bonds and bank loans, Altman, Resti and Sironi (2001) seek to empirically explain the relationship between defaults and recoveries. They find that aggregate recovery rates basically is a function of supply and demand for the securities, and provide evidence of a significant negative correlation between aggregate default rates and recovery rates on corporate bonds. They also argue that their economic univariate and multivariate time series models describe a considerable share of the variance in bond recovery rates aggregated across all seniority and collateral levels.

Jokivuolle and Peura (2000) propose a rather different approach where the collateral value is correlated with the default probability, and where the option pricing framework is applied for modeling risky debt. In this model the borrowing firm's total asset-value determines the event of default, and the collateral value is assumed to be the only stochastic element determining the recovery rate. Due to the latter assumption, there is no need to estimate the firm asset value parameters since the model can be implemented using an exogenous default probability (Altman, Resti, and Sironi, 2001). From this study Jokivuolle and Peura find that the expected recovery rate is a decreasing function of the collateral volatility, and that defaults are driven by the correlation between collateral and firm value. A rather counterintuitive result is that the expected recovery rate increases when the default probability increases. Altman, Resti and Sironi (2001) argues that the

[6] Loss given default = 1 – recovery rate

findings from this model are rather unrealistic since it assumes that the asset value chosen as collateral tends to be uncorrelated with the borrower's prospect, and that not all loans are fully collateralized.

Based on an analysis of approximately 2,000 defaulted bonds and loans, Hanson and Schuermann (2004) provide evidence on the impact of seniority and industry affiliation on the recovery rate. These results are in line with Altman and Kishore (1996), which conclude that that the highest average recoveries come from public utilities and chemical, petroleum and related products, and that original bond ratings have little or no effect on recovery, once seniority is accounted for. Furthermore, Hanson and Schuermann study the empirical distribution of recovery rates and provide evidence that recoveries are lower during economic downturn.

Altman, Resti and Sironi (2005) examine the link between aggregate default rates/probabilities and recovery rates on U.S. corporate bonds, from both a theoretical and an empirical standpoint. They suggest that the literature on credit-risk-management models and tools appears somewhat simplistic and unrealistic, as recovery rates usually are treated as a function of the historic average recovery rates and independent from default rates. Examining the recovery rate on corporate bond defaults over the period 1982-2001, they find that recovery rates are a function of the supply and demand for defaulted bonds and the default rates, where the default rate plays a pivotal role. They do recognize a systematic relationship between macroeconomic performance measures and expected default rates. However, they conclude that these variables are less important as their explanatory power is considerable lower. Definitions, explanatory variables and empirical evidence applied in Altman, Resti and Sironi (2005) is presented in detail in section 3.

Through a comprehensive analysis of industry-wide distress and its relation to recovery rates at default, Acharya et al. (2007) argue that when defaulting firms operate in an industry witnessing industry-wide distress, debt recovery is 10% to 15% less on average. They believe that the main mechanism causing this effect is that defaulting firm, which operate in a distressed industry experience a lower ability to sell their assets to competitors. They also document that aggregate default rates have a negative effect on the recovery rates of individual issues, and provide some evidence that balance sheet ratios are of importance. Focusing on the modeling of the ultimate recovery rate distribution for defaulted bonds and loans, Altman and Kalotay (2012) provide further evidence these industry-driven effects.

Examining default event type Bris, Welch and Zhu (2006) and Davydenko and Franks (2008) find that the reorganization practices and the differences in creditors' rights are reflected in the level of recovery and default resolution. In these studies defaults across different countries, jurisdictions, and different bankruptcy procedures[7] are compared. Discussing distressed exchanges Altman and Karlin (2009) provide further evidence on the importance of the default event type, finding that recoveries at default are higher in distressed exchanges compared to other default event types.

Based on a comprehensive set of traded prices and volumes around various types of default events, Jankowitsch, Nagler, and Subrahmanyam (2012) examine the recovery on US corporate bonds over the time period 2002 to 2010. A detailed study on the microstructure of trading activity allows them to assess the liquidity of defaulted bonds, and to estimate reliable market-based recovery rates. They find that 64% of the total variance in the recovery rates across bonds is explained by quantifying the relation between these recovery rates and a comprehensive set of bond characteristics, firm fundamentals, macroeconomic variables and liquidity measures. They also find that transaction costs metrics of liquidity along with balance sheet ratios motivated by structural credit risk models, and macroeconomic variables are particularly important determinants of the recovery rate. Furthermore, they provide evidence that the type of default event, the bond seniority, and the industry in which the firm operates are of importance, in explaining the recovery rate.

My thesis extends the existing literature by empirically testing whether the findings in Altman, Resti and Sironi (2005) holds for the global corporate bond market. Accordingly, I will in the following section present a more thorough summary of the practical and theoretical framework applied in Altman, Resti and Sironi (2005).

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[7] Chapter 7 versus Chapter 11bankruptcy filing

3. ALTMAN, RESTI AND SIRONI (2005) - DEFINITIONS, EXPLANATORY VARIABLES AND EMPIRICAL EVIDENCE

In this section the definitions, explanatory variables and empirical evidence applied in Altman, Resti and Sironi (2005) is presented

3.1 DEPENDENT VARIABLE - ANNUAL AGGREGATE RECOVERY RATE

The aggregate annual bond recovery rate (BRR), as well as its logarithm (BRRL), is measured by the weighted average recovery on all corporate bond defaults over the period 1982-2001 in the U.S. Bond market. The weights used are based on the market value of defaulting debt issues of publicly traded companies. The market value of defaulted debt is measured as the closing "bid" levels on or as close to the default date as possible.

$$\mathrm{BRR_T} = \frac{\sum_{i=n}^{N} \text{Bid Level on Defaulted Bond}_n}{\sum_{i=n}^{N} \text{Face Value of Defaulted Bond}_n} \;\;\&\;\; \mathrm{BLRR_T} = \ln(\mathrm{BRR_T})$$

3.2 DATA, AND SAMPLE SIZE

The speculative-grade bond market is used as the population base, since practically all public corporate bond defaults most immediately migrate to default from the non-investment grade segment of the market. Data is gathered from a database constructed and maintained by NYU Salomon Center, and contains both quarterly and annual averages from about 1,300 defaulted bonds.

3.3 EXPLANATORY VARIABLES

In this section the variables which Altman, Resti and Sironi (2005) argues that could explain the variation in aggregate recovery rates, are presented. The expected effect of these variables on recovery rates is indicated by a plus or minus sign. The first five variables relates to the corporate bond market, while the last five are macroeconomic variables.

BDR (-) & BLDR (-): The bond default rate is defined as the weighted average default rate, on bonds in the high-yield bond market. The weights are based on the face value of all U.S. high-yield bonds outstanding each year and the size of each defaulting issue within a particular year. The high-yield or non-investment grade segment of the market is used as population base, as virtually all public defaults most immediately migrate to default from this segment. The value of a bond at default is assumed to equal the par-value. A variable measuring the distressed but not defaulted proportion of the high-yield bond market is excluded from Altman's analysis due to the lack of observations. They define distressed issues as bonds yielding more than 1,000 basis points over the 10-year risk-free treasury rate*.* It is assumed that an increase in defaults has a negative effect on the recovery rate.

$$\mathrm{BDR_T} = \frac{\sum_{i=n}^{N} \text{Par value of High Yeld Bond Default}_n}{\text{Face Value of All Outstanding High Yield Bonds}_{\mathrm{T(mid\ year)}}} \ \&\ \mathrm{BLDR} = \ln(\mathrm{BDR})$$

BDRC (-): The 1-year change in bond default rate (BDR). The intuition behind the negative effect is that; if default rates increases from one year to another, recovery rates will decrease.

$$\mathrm{BDRC_T} = \mathrm{BDR_T} - \mathrm{BDR_{T-1}}$$

BOA (-): Measured at midyear and in trillions of dollars, BOA is defined as the aggregate amount of U.S. high-yield bonds outstanding for a particular year. This amount represents the potential supply of defaulted securities. Due to yearly growth in the outstanding amount of high yield bonds over the sample period applied by Altman, Resti and Sironi (2005), the BOA variable picks up a time-series trend as well as representing a possible supply factor.

$$\mathrm{BOA_T} = \text{Total Amount of High Yield Bonds Outstanding at Midyear}_\mathrm{T}$$

BDA (-): As an alternative to BOA, the more directly related value of the bond defaulted amount is also examined.

GDP (+): The annual U.S. GDP growth rate.

GDPC (+): The change in annual GDP growth-rate from the previous year.

$$GDPC_\mathrm{T} = \text{GDP growth rate}_\mathrm{T} - \text{GDP growth rate}_{\mathrm{T}_{\mathrm{T}-1}}$$

GDPI (-): Applied as a dummy variable, taking the value of 1 when GDP growth is less than 1.5% and 0 when the GDP growth rate is greater than 1.5%.

SR (+): Annual percentage return on the S&P 500 stock index.

$$SR_{\mathrm{T}} = \frac{\text{S\&P 500}_{\mathrm{T}} - \text{S\&P 500}_{\mathrm{T-1}}}{\text{S\&P 500}_{\mathrm{T-1}}}$$

SCR (+): The change in the annual return on the S&P 500 stock index.

$$SCR_{\mathrm{T}} = SR_{\mathrm{T}} - SR_{\mathrm{T-1}}$$

3.4 THE DEMAND AND SUPPLY OF DISTRESSED SECURITIES

Altman, Resti and Sironi (2005) describe the logic behind their demand/supply analysis as both intuitive and important. Important, since most credit risk models fails to statistically and formally consider this relationship. The intuition behind their demand/supply analysis is grounded on the relationship between defaults and recoveries on a macroeconomic level, where it is the same forces that cause defaults to rise during economic downturn which also cause the value of assets of distressed companies to depreciate. Declining asset values will most likely lower the value of the distressed companies' financial securities. Although the economic logic behind this intuition is clear, Altman, Resti and Sironi (2005) argue that macroeconomic variables such as GDP has failed to statistically describe a significant relationship with recovery rates. Hence, they hypothesized that; "if one drills down to the distressed firm market and its particular securities, one can expect a more significant and robust negative relationship between default and recovery rates"(Altman, Resti and Sironi (2005)). The demand-side is driven by the principal purchasers of defaulted securities.

Based on periodic calculations in Altman and Jha (2003), Altman, Resti and Sironi (2005) finds that the supply of defaulted U.S. securities grew enormously during the economic downturn in 1990-01, to some $300 billion in face value, and then fell to much lower levels during the 1993-98 period and then grew to $940 billion USD in the turbulent 2001-02 period. They also find that price levels on new defaulting securities are relatively lower during these economic downturns. The ratio between the supply- and the demand side is around 10 to 1 in both these economic downturns.

3.5 FINDINGS FROM UNIVARIATE AND MULTIVARIATE REGRESSION

In their analysis of the relationship between default and recovery rates, Altman, Resti and Sironi (2005) apply both univariate and multivariate regression models. In the following section I will present findings from these models.

3.5.1 FINDINGS - UNIVARIATE MODELS (APPENDIX 1 A & B)

In the univariate regression both the recovery rate (BRR) and its natural logarithm (BLRR) is applied as dependent variables. Results are obtained regressing the BRR and BLRR against the all aforementioned explanatory variables. Results from the univariate regressions is presented in appendix 1 A and B. Examining the univariate relationship between BRR and bond default rate (BDR) for the period 1982-2001 they find that 51% of the variation in annual recovery rates is explained by the level of default rates. Logarithmic and power regressions yield an explanatory power of 60% or greater. These findings underpin their basic thesis; that the rate of default is an important indicator for the likely average recovery rate among corporate bonds. Regarding the other univariate results, they all show the expected sign for each coefficient, but not all of the relationships are statistically significant. With very significant *t*-ratios, the 1-year change in BDR (BDRC) is, as expected, highly negatively correlated with recovery rates, however, the *t*-ratios and R^2 values are not as significant as those for the logarithm of the bond default rate (BLDR). As they expected, both the supply (BOA) and demand (BDA) variables are negatively correlated with the recovery rate, with BDA being most significant. Test results regarding the macroeconomic variables, show that these variables do not explain as much of the variation in recovery rates as the corporate bond market variables. The weak performance of the macro variables, relative to the bond market variables, is further confirmed by the presence of some heteroscedasticity and serial correlation in the regression's residuals, implying one or more omitted variables.

3.5.2 FINDINGS - MULTIVARIATE MODELS

Analyzing the correlation between the different variables Altman, Resti and Sironi (2005) find a relatively strong link[8] between BDR and GDP, signifying that the default rate correlates with macro growth variables. Consequently, they expect that the significance of results will be blurred if the GDP variable is added to the BDR/BRR relationship. In their multivariate- linear and loglinear regression analysis they find that the basic structure (regression 1-6, appendix 2) of their most successful models is

$$\text{BRR} = f(\text{BDR}, \text{BDRC}, \text{BOA}, \text{or BDA})$$

[8] Correlation, between GDP and BDR between 1982-2001, of -.56

They find that the model with the highest explanatory power and the lowest "error" is the power model (regression 4, appendix 2) with the following structure:

$$\text{BLRR} = b_0 + b_1 \times \text{BLDR} + b_2 \times \text{ BDRC} + b_3 \times \text{BOA}$$

Giving the following structure for the BRR:

$$\text{BRR} = \exp[\ b_0] \times BDR^{b1} \times \exp[b_2 \times \text{BDRC} + b_3 \times \text{BOA}]$$

In this model all variables show the expected sign, and are significant at the 5-and 1 percent level, with BLDR and BDRC being the most significant variables, explaining more than 78 percent (adjusted R^2) of the variation in the BRR, showing that level and change in defaults are very important explanatory variables for recovery rates. The explanatory power of the model increases by 6-7 percent by adding the BOA variable, measuring the size of the speculative grade bond market. By replacing the BDA with the BOA (regression 5 and 6, appendix 2) they find that the explanatory power of the model weakens, however, they point out that the expected sign is correct and that BDA is more significant than the BOA in the univariate basis (regression 7-10, appendix 2).

Altman, Resti and Sironi (2005) are rather surprised by the low contribution from the macro variables (regression 7-10, appendix 2). When they including the GDP variable to the existing multivariate structures (regression 7 and 8, appendix 2) they find that it is not significant and does not show the expected sign. Subsequently, they argue that the GDPC variable, although not reported, leads to similar results as the GDP measure. They state that the strong negative correlation between the BDR and the GDP variables reduces the possibility of including both variables in the multivariate structure.

To account for the fact that the BRR is bounded between zero and one, they include logistic regressions to their multivariate analysis (regression 11-15, appendix 2). Results from the logistic regression models are similar to existing models, measured by R^2 and t-ratios.

3.6 ROBUSTNESS CHECK

Altman, Resti and Sironi (2005) perform various robustness checks with the aim at verifying how results change given different modifications to their approach.

Since one may argue that models based on an ex-post analysis of default rates are conceptually different from an ex-ante (probabilities of default) analysis of default rates, they analyze the validity of their results given an ex ante estimate of the default rate. They find that both specifications are of importance for different purposes, but argue that applying an ex-ante default probability in a regression analysis of recovery rates may be limited by the bias and the empirical evidence the ex-ante default probabilities are estimated from. Assessing the relationship between ex-ante default probabilities and recovery rates (BRR) by utilizing global issuer-based default probabilities generated by Moody's, they find that the ex-ante specification is significantly negative correlated with recovery rates, although the explanatory power is considerably lower compared to their multivariate models, all variables show the expected sign.

Given that annual data is applied in their main analysis, they utilize quarterly observations to analyze whether higher frequency data also confirms the existence of a link between default and recovery rates. On a univariate basis they find that the BDR still has the correct sign and is strongly significant, however, the explanatory power of the quarterly data is lower relative to the annual (R^2 drops from 23.9% to 51.4%). Arguing that the fall in the explanatory power is due to quarterly data being more volatile, they estimate a new model based on a four quarter moving average issuer weighted recovery rate (BRR4W) and the bond default rate (BDR), its lagged value (BDR-1) and its square ($BDR^{0.5}$). This model gives a much better R^2 (72.4%) and show that the association between default and recovery rates are rather "sticky".

Based on the logic that risk-free rates are fundamental in the pricing of bonds, they include an analysis of the association between the risk-free rate and the recovery rate. This analysis is conducted by adding the 1-year and 10-year U.S. Treasury rates, as well as the spread[9] between them to their best performing models. They find the results from this analysis as disappointing, given that none of these variables ever is statistically significant at the 10% level.

With the aim at analyzing how the "equilibrium price" is influenced by a possible link between the return experienced in the defaulted bond market and the demand for distressed securities, Altman, Resti and Sironi (2005) include a variable measuring the 1-

[9] Difference between 10-year and 1-year U.S. Treasury rate

year return on the Altman-NYU Salomon Center Index of Defaulted Bonds (BIR) to their univariate and multivariate models. On a univariate basis they find that the BIR shows the expected sign and explains around 35 percent of the variation in the recovery rate. Including the BIR in their multivariate models gives the expected signs. However, the significance is usually under 10 percent.

Attempting to circumvent the problem that the GDP growth variable lacks statistical significance and shows a counterintuitive sign in the multivariate models, Altman, Resti and Sironi (2005) includes a dummy variable for GDP growth variable. This dummy variable, GDPI, takes the value of 1 when the GDP grows at less than 1.5 percent and 0 otherwise. In the univariate analysis the GDPI variable shows a significant relationship with the expected sign. When including the variable in the multivariate analysis it shows the right sign, however, the tests show no statistical significance. To check whether the state of the economy cause a structural change in the relationship between default and recovery rates, they remove recession[10] years from their analysis. Results from this analysis, however not reported, confirm their basic models findings (regression 1-4, appendix 2), and suggest that their findings is not affected by recessions.

Lastly, they consider recovery rates broken down by the original bond- rating and seniority. They find that the link between default and recovery rates stay statistically significant in all cases; however, showing a weaker link for junk issues and subordinate bonds. They suggest that the reason why investment grade and senior class bonds shows a stronger link may be because these defaults are generally larger and are therefore causing asset prices to fall, which again causes recovery rates to fall.

3.7 CONCLUSION AND IMPLICATIONS FROM FINDINGS

As stated in the literature review, Altman, Resti and Sironi (2005) conclude that there exists a strong and significant negative correlation between default and recovery rates. Based on results from their univariate and multivariate regression models, they also conclude that the supply of defaulted bonds (BOA) explains a substantial portion of the variance in aggregate bond recovery rates.

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[10] Altman, Resti and Sironi (2005) defines it as *"years showing a negative real GDP growth rate"*

Additionally they address the implications the presence of a significant and negative correlation between default and recovery rates has for both VaR models and the procyclicality of capital requirements. First, given that most credit VaR models keep the recovery rate independent from the default probabilities; they compare the performance of two credit VaR models[11] both with and without the negative and stochastic correlation between recovery rates and default probabilities. Results indicate that credit VaR models vastly understates both the expected and unexpected losses if one assumes no relationship between default probabilities and default rates. Based on these findings they reason that neglecting this negative correlation might result in unnecessary shocks to financial markets as the expected losses on bank reserves are systematically misjudged. Lastly, they address the implications their findings have on procyclicality capital requirements, such as the internal ratings-based (IRB) proposed by the Basel Committee. They reason that the negative link between default and recovery rates might amplify cyclical effects, since periods of economic stress would cause default rates to increase which again would cause recovery rates to decrease resulting in higher credit losses. As a consequent capital requirements would increase causing the supply of bank credit to the economy to decrease, resulting in an amplification of the recession. Addressing that these same mechanisms also are at place when the economy is booming, they find that, although the use of the long-term average recovery rates would lower the cyclicality effect on IRB requirements, it would on the other hand cause that banks maintained a less updated picture of their risk, and as a result trade precision for stability.

[11] CREDITRISK+® and CreditMetrics®

4. MY APPROACH – A GLOBAL STUDY

In this section I will present the data, definitions and explanatory variables applied in the global study of the link between default and recovery rates. Differences in methodology, data and definition will be addressed. I have analyzed to different samples sizes in order to make results more robust and to analyze to what extent results vary over time. Sample 1 has the same time frame as in the U.S. study (1982-2001), while sample 2 includes the most recent observations (1982-2012). In the succeeding sections the study performed by Altman, Resti and Sironi (2005) is also referred to as *the U.S. study*.

4.1 DATA

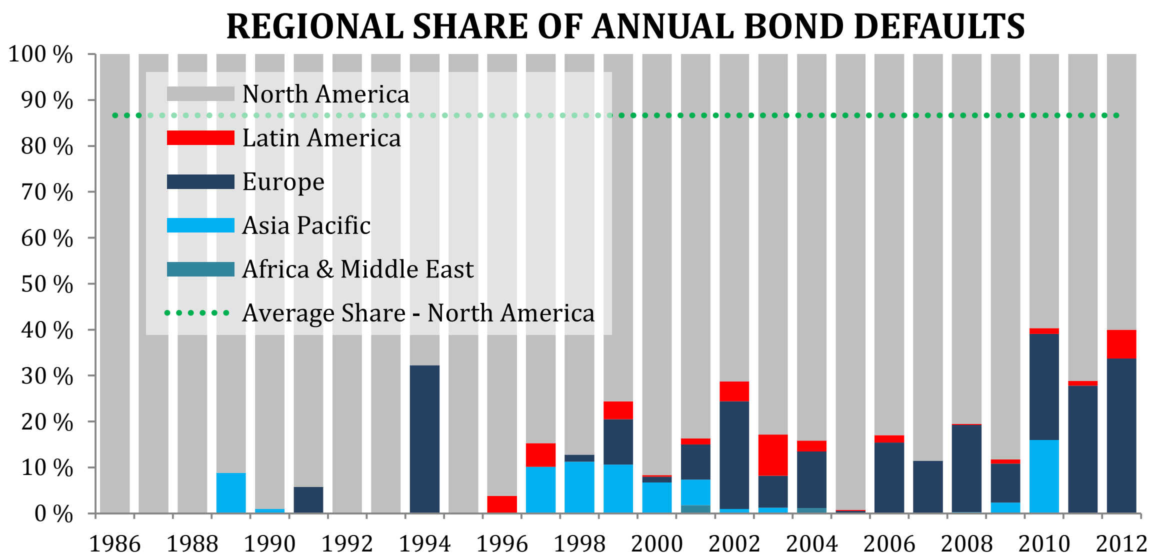

FIGURE 1 – GLOBAL DISTRIBUTION OF DEFAULTS

This thesis relies on several data sources that I combine to analyze recovery rates in the global corporate bond market. Data on defaults and recoveries is collected from Moody's annual report[12] on corporate default and recovery rates. In their annual study Moody's update statistics on defaults, credit loss, and rating transition experience for most the current year, in this case 2012, as well as for the historical period since 1920. In Moody's dataset the North American share global corporate bond defaults averages approximately 87% percent. This means that there, by construction, are some correlation between Moody's global dataset and the U.S. dataset applied by Altman, Resti and Sironi (2005)[13].

[12] Annual Default Study: Corporate Default and Recovery Rates, 1920-2012

[13] The Altman-NYU Salomon Center Corporate Bond Default Master Database

CORRELATION BETWEEN U.S. AND GLOBAL DATA SETS, 1982-2001

	BRR	BLRR	BDR	BLDR	BDRC	BOA	BDA
BRR	.81						
BLRR		.84					
BDR			.93				
BLDR				.90			
BDRC					.83		
BOA						.90	
BDA							.99

NOTE: Altman=>Column, Moody's=>Row. Number of Obs. 20.

In the table above the correlation between the global data set, provided by Moody's, and the U.S. data set, applied in Altman, Resti and Sironi (2005), is compared. From the correlation matrix we get that the correlation between the main variables in the two datasets is quite strong for all variables. One reason why the correlation between the two BDRC variables is relatively lower may be that the BDRC in the global dataset is set to zero in 1982. The correlation between the two recovery rates (BRR) is, relative to the correlation between the other variables, the weakest one. A reason for this relatively weak correlation may be that the BRR is volume weighted in Altman, Resti and Sironi (2005) while it is issuer-weighted in Moody's publication. Although the BRR is obtained using different weights, the 20 year average BRR is the same, approximately 42 percent, in both samples.

CORRELATION AMONG MAIN VARIABLES - U.S. DATA SET, 1982-2001

	BDR	BOA	BDA	GDP	SR	BRR
BDR	1.00	.33	*.73*	*-.56*	-.30	*-.72*
BOA		1.00	*.76*	.05	-.21	*-.53*
BDA			1.00	-.26	-.49	*-.64*
GDP				1.00	-.02	.29
SR					1.00	.26
BRR						1.00

NOTE.- The table shows the correlation between the different U.S. variables. Values greater than .5 are italicized. Number of observations is 20. Values from Altman et al. (2005)

CORRELATION AMONG MAIN VARIABLES - GLOBAL DATA SET, 1982-2001

	BDR	BOA	BDA	GDP	MSCIW	BRR
BDR	1.00	.44	.85	-.35	-.60	-.87
BOA		1.00	.74	.07	-.29	-.46
BDA			1.00	-.19	-.55	-.75
GDP				1.00	.14	.18
MSCIW					1.00	.58
BRR						1.00

NOTE.- The table shows the correlation between the different variables. Values greater than .5 are italicized. Number of observations is 20.

Comparing the correlation among the main variables in the two datasets, given an identical time-span of 20 years (1982-2001), shows that the correlations are quite similar, with the same sign in all cases, except for the correlation between GDP and MSCIW. All in all, the variables tend to correlate stronger in the global analysis.

CORRELATION AMONG MAIN VARIABLES - GLOBAL DATA SET, 1982-2012

	BDR	BOA	BDA	GDP	MSCIW	BRR
BDR	1.00	-.02	*.84*	*-.56*	-.37	*-.71*
BOA		1.00	.37	-.09	-.20	.20
BDA			1.00	*-.64*	-.30	-.46
GDP				1.00	.09	.41
MSCIW					1.00	.40
BRR						1.00

NOTE.- The table shows the correlation between the different variables. Values greater than .5 are italicized. Number of observations is 20.

The BRR and BDR show approximately the same correlation when variables are based on the U.S. and second global sample, while this correlation is surprisingly high in sample 1. Contrary to correlations in sample 1 and the U.S study, the BOA variable in sample 2 shows a counterintuitive correlation with the BOA, GDP and BRR variable. In sample 2, BRR correlates quite strongly with GDP. In both global samples the performance of the stock market (MSCIW) correlates quite strongly with the BRR.

4.2 DEPENDENT AND EXPLANATORY VARIABLES IN GLOBAL STUDY

In the following section, a detailed overview of all the variables included in the analysis as well as a clarification on how they may differ with the ones applied in Altman, Resti and Sironi (2005), is presented. The explanatory variables BLDR, BLRR, GDPC and MSCIWC are not given a detailed description since they, by construction are, identical to the ones applied in the U.S. study. Both the dependent and the independent variables are expected to have the same sign as in the U.S. study.

4.2.1 DEPENDENT VARIABLE – THE RECOVERY RATE (BRR & BLRR)

$$\mathrm{BRR_T} = \sum_{\mathrm{i=n}}^{\mathrm{N}} \frac{\text{Bid Level on Defaulted Bond}_\mathrm{n}}{\text{Face Value of Defaulted Bond}_n} * \frac{1}{\mathrm{N}} \text{ \& } \mathrm{BLRR_T} = \ln(\mathrm{BRR_T})$$

The aggregate annual global recovery rate is measured as the issuer-weighted (N) recovery on all corporate bonds defaults covered by Moody's. Moody's database[14] comprises more than 5100 observation on recovery rates. The bond recovery rate is measured as the "bid" quote 30 days after default. In their study[15] of trading prices as predictors of ultimate corporate bond and loan recovery rates, Moody's find that ultimate[16] recoveries on average are 3 percent higher than the trading-price-based recovery rates, with highest and most significant difference for senior secured bonds and loans. Despite the difference between ultimate and trading-price-based recovery rates, Moody's argue that trading price closely tracks average ultimate recovery over time.

4.2.1.1 DIFFERENCE IN METHODOLOGY

While Altman, Resti and Sironi (2005) use the "bid" level on, or as close to, the default date as possible, as the recovery rate, Moody's find that "bid" prices 30 days after default explain more of the variation in ultimate recoveries, since there are more observations available after 30 days, compared to prices closer to default. In the global study the weights for the annual aggregate recovery rate is issuer based, while it is value based in the U.S. study. However, it is not believed that this will weaken the study, as value- and issuer based weights are quite similar over time[17].

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[14] See Appendix 6 for more on Moody's database on defaults
[15] Moody's Investors Service, "Trading Prices as Predictors of Ultimate Corporate Recovery Rates", New York: Moody's, 2012
[16] The ultimate recovery rate is a realization of the recovery rate once a company emerges from bankruptcy
[17] Moody's Investors Service, "Moody's Dollar Volume-Weighted Default Rates" ", New York: Moody's, 2003

4.3 EXPLANATORY VARIABLES

4.3.1 – THE DEFAULT RATE (BDR & BLDR)

"A debt instrument can experience a loss only if there has been a default" Schuermann (2004). Banks, corporations, legislators, investors and credit rating agencies etc. often use different definitions of what constitutes a default. There is no standard definition of what constitutes a default, and different definitions may be used for different purposes.

Moody's definition of default consists of four types of credit events[18]:

1. "missed or delayed disbursement of a contractually-obligated interest or principal payment (excluding missed payments cured within a contractually allowed grace period), as defined in credit agreements and indentures;
2. a bankruptcy filing or legal receivership by the debt issuer or obligor that will likely cause a miss or delay in future contractually-obligated debt service payments;
3. a distressed exchange whereby 1) an obligor offers creditors a new or restructured debt, or a new package of securities, cash or assets that amount to a diminished financial obligation relative to the original obligation and 2) the exchange has the effect of allowing the obligor to avoid a bankruptcy or payment default in the future; or
4. a change in the payment terms of a credit agreement or indenture imposed by the sovereign that results in a diminished financial obligation, such as a forced currency re-denomination (imposed by the debtor, himself, or his sovereign) or a forced change in some other aspect of the original promise, such as indexation or maturity.

Bond defaults is in the NYU Salomon Center database applied by Altman, Resti and Sironi (2005) is defined as: "bond issues that have missed a payment of interest and this delinquency is not cured within the “grace-period” (usually 30 days), or the firm has filed for bankruptcy under reorganization (Chapter 11) or liquidation (Chapter 7), or there is an announcement of a distressed restructuring. The latter typically involves a tender for an equity for debt swap, where the creditors accept a lower-priority security in-lieu of the bond (usually common equity), or a lower coupon rate payment or an extension to repay the bond is proposed."[19]

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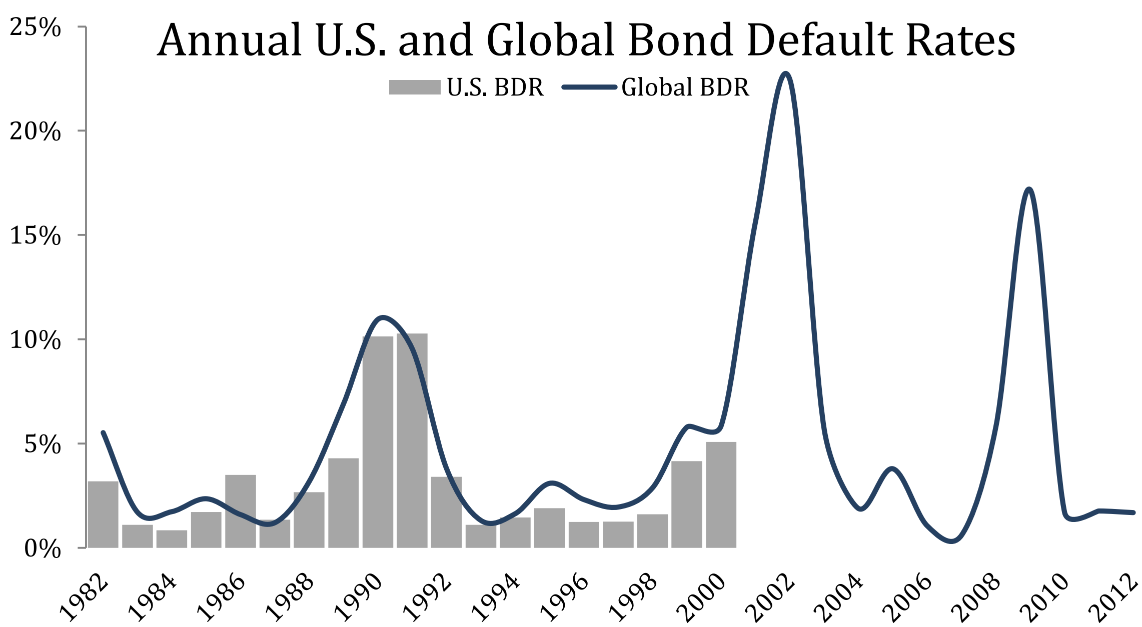
[18] Moody’s Investors Service, “Moody’s rating symbols and definition,” New York: Moody’s, 2014
[19]Edward Altman, "About Corporate Default Rates"

Although Moody's definition is more thorough, the two definitions of defaults are quite similar. The correlation between default rates in the U.S. and the global data-set is high (0.93) and potential differences are not believed to impose any weaknesses to the analysis.

The BDR variable applied in the global study is measured as the annual aggregate default rate in the speculative grade bond segment, as defined by Moody's. The BDR is, as in Altman, Resti and Sironi (2005), volume weighted. Prior to 1994 Moody's did not report volume-weighted default rates, so the BDR's from 1982 till 1993 is gathered from a revision of volume-weighted default rate published by Moody's[20]. Mathematically, Moody's 12-month trailing speculative bond default rates are calculated as:

$$\mathrm{BDR_T} = \frac{\sum_{t=-11}^{0} v_t^i}{B_{t-11}^i}\ , for\ t = -11, .., 0\ and\ i = Ba1, Ba2, .., Ca, C\ , \&\ \mathrm{BLDR_T} = \ln(\mathrm{BDR_T})$$

From the formula above we have that the BDR_T for the 12-months ending at time *t* is the sum of the monthly defaulted bonds measured at face value and defined by rating *i*, in this case the speculative or high yield bond segment, divided by dollar volume, also measured at face, of bonds outstanding at the beginning of that 12-month period. The BDRC is defined as the one year change in the default rate ($BDRC_T$=BDR_T- BDR_{T-1}).



**U.S. default rates from Altman et al. (2005), Global default rates from Moody's annual corporate bond default report*

FIGURE 2 – U.S. AND GLOBAL DEFAULT RATES

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[20] Moody's Investors Service, "Moody's Dollar Volume-Weighted Default Rates" ", New York: Moody's, 2003

4.3.1.1 DIFFERENCE IN METHODOLOGY

In the global study the annual aggregate default rate is weighted by the dollar amount of bonds outstanding at the beginning of the period, while it is weighted by the dollar amount outstanding mid-year in Altman, Resti and Sironi (2005). The correlation between the two BDR's is high, and this difference in methodology is not believed to weaken the analysis.

4.3.2 TOTAL AMOUNT OF DEFAULTED BONDS (BDA)

The annual total dollar par-value of defaulted corporate bonds in the global speculative grade bond market (BDA) is gathered from Moody's report - Annual Default Study: Corporate Default and Recovery Rates, 1920-2012. For the same reasons as in Altman, Resti and Sironi (2005), the Texaco's 1987 default[21] is excluded[22].

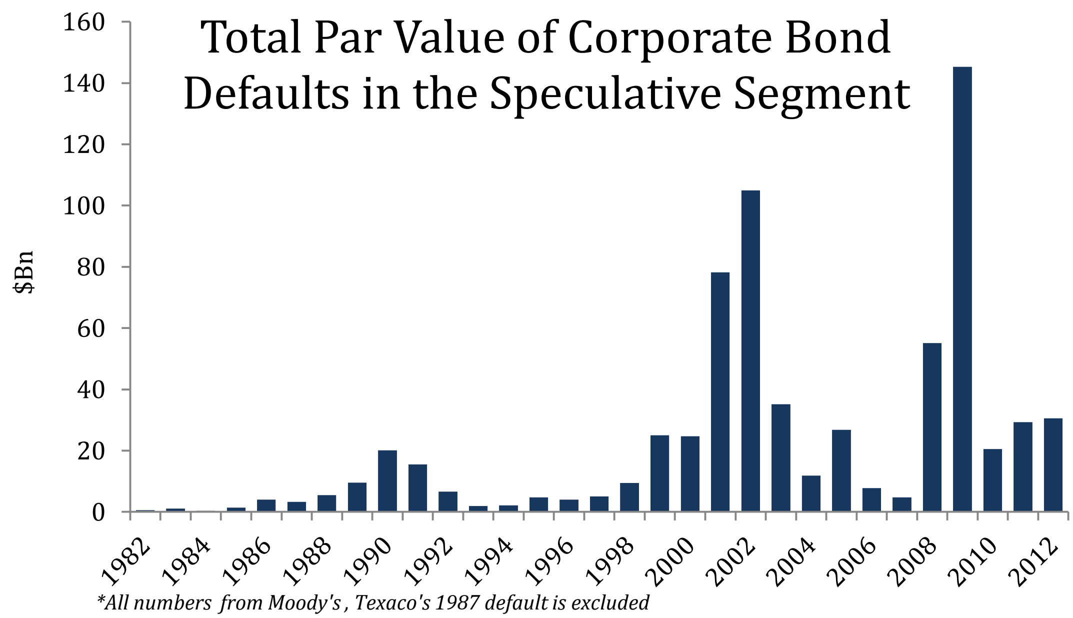


FIGURE 3 – HISTORIC PAR VALUE OF CORPORATE BOND DEFAULTS

4.3.2.1 DIFFERENCE IN METHODOLOGY

There are no differences other than what might comprise or define a bond default. Obviously there are bond defaults in the global speculative market which is not recorded in Moody's dataset. The correlation between the U.S. and the global BDA variable is very high (.99).

[21] 1,841.7 mUSD – Altman & Kishore (1994) – "Defaults and Returns on High Yield Bonds – Through 1994"

[22] The default was motivated by a lawsuit which was considered frivolous, resulting in a strategic bankruptcy filing and a recovery rate (price at default) of over 80%.(Altman, Resti and Sironi (2005))

4.3.3 TOTAL AMOUNT OF BONDS OUTSTANDING (BOA)

Obtaining a reliable measure of the global amount of bonds outstanding in the speculative grade segment proved to be a difficult task. Consequently, the BOA is estimated by dividing the dollar amount of default bonds[23] in the speculative bond market (BDA) on the previously described global bond default rate (BDR)..

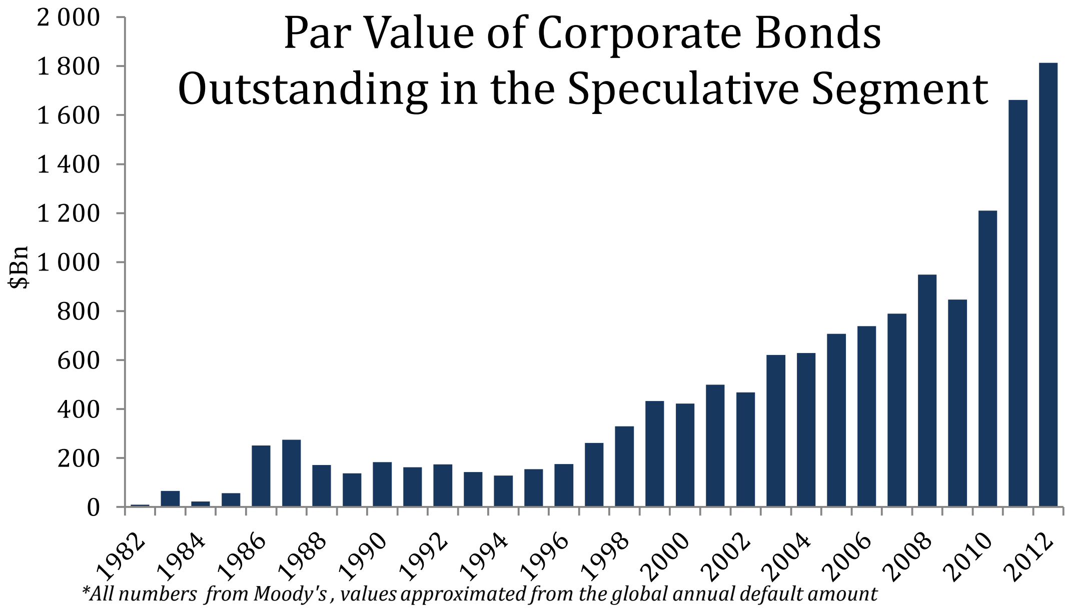


FIGURE 4 – PAR VALUE OF CORPORATE BONDS OUTSTANDING

4.3.3.1 DIFFERENCE IN METHODOLOGY

While the BOA in Altman, Resti and Sironi (2005) is measured mid-year and excludes defaulted issues, the BOA in the global analysis is an approximation based on a default rate weighted by the year start face amount of outstanding corporate bonds in the speculative market.

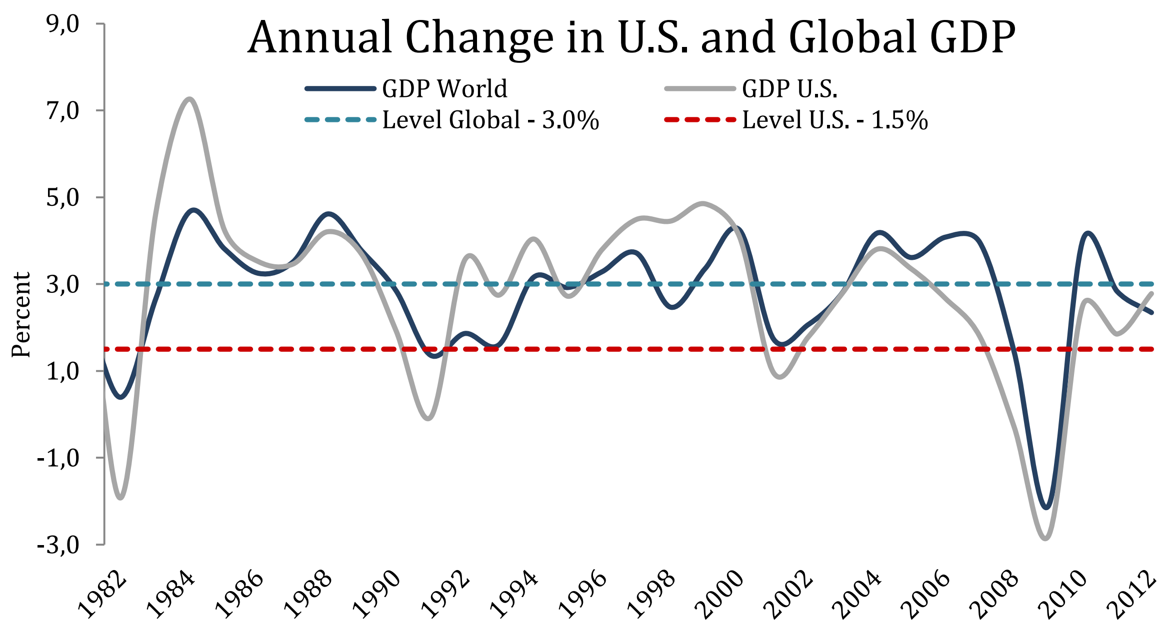
$$BOA_T = {BDA_T} \Big/ \frac{\sum_{t=-11}^{0} v_t^i}{B_{t-11}^i} \quad for\ t = -11, .., 0\ and\ i = Ba1, Ba2, .., Ca, C$$

Furthermore, the BOA variable applied in the global analysis does not exclude defaulted issues. Even though the global BOA variable is somewhat different by construction, the U.S. and the global BOA variable are surprisingly highly correlated (.90), indicating that the estimation may be satisfactory.

[23] Reported in Moody's report - Annual Default Study: Corporate Default and Recovery Rates, 1920-2012

4.3.4 GDP GROWTH RATE AND RELATED VARIABLES (GDP, GDPC & GDPI)

The world GDP growth rate has been selected as the GDP variable in the global analysis. This rate is collected from The World Bank[24], and is the dollar denominated annual rate based on constant 2005 U.S. dollars. The GDPC is the yearly change in the GDP growth rate. The GDPI is a dummy variable, with the aim at measuring if the economy is in a recession or not. The variable takes the value of 1 if the economy is in a recession and 0 otherwise.



**All numbers from The World Bank, correlation in period is .81, Levels indicate the state of economy (GDPI)*

FIGURE 5 – ANNUAL CHANGE IN U.S. AND GLOBAL GDP

4.3.4.1 DIFFERENCE IN METHODOLOGY

To better reflect when the global economy is in a downturn the threshold for when the GDPI dummy variable takes the value of 1 has been increased from 1.5 percent in the U.S. analysis till 3.0 in the global analysis. This is since the International Monetary Fund considers a global recession as a period where gross domestic product (GDP) growth is at 3% or less[25].

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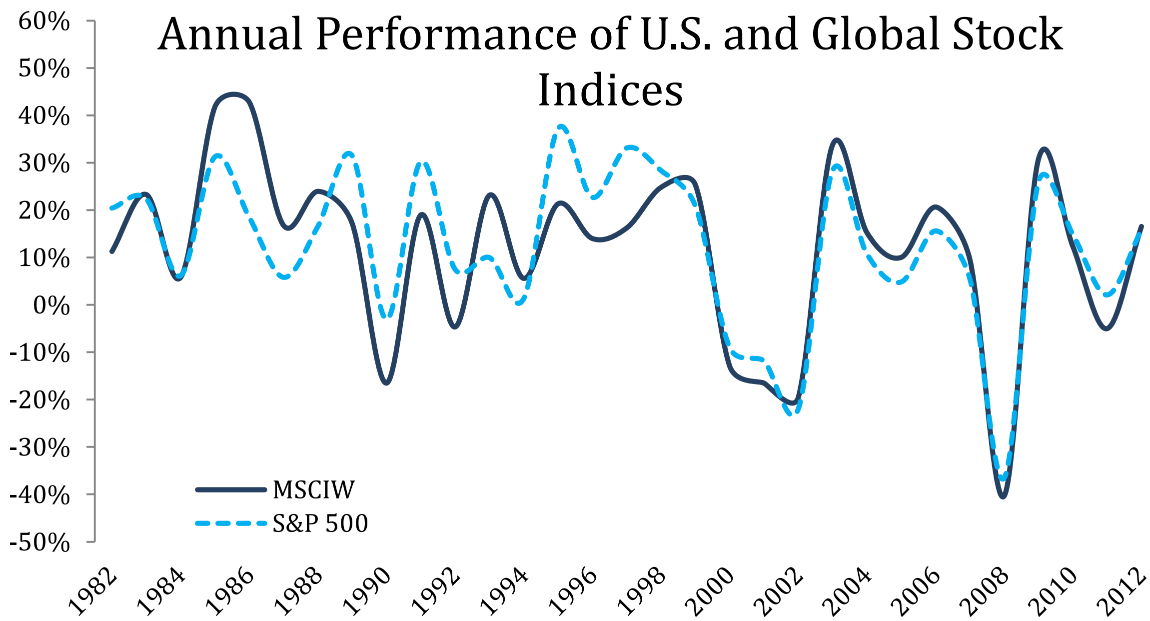
[24] For methodology: http://data.worldbank.org/about/data-overview/methodologies

[25]Definition from Investopedia: http://www.investopedia.com/terms/g/global-recession.asp

4.3.5 THE RETURN IN THE STOCK MARKET (MSCIW & MSCIWC)

In the global study the annual return on the MSCI World Index (MSCIW) has been selected as the variable measuring the performance of the global stock market. The MSCIW measures the total return, gross dividend taxes, of 23[26] developed country stock indices. The MSCIWC variable measures the yearly change in the MSCIW.



**MSICW returns from msci.com, S&P 500 returns produced by Aswath Damodaran, correlation of .86*

FIGURE 6 – PERFORMANCE OF THE U.S. AND GLOBAL STOCK MARKET

4.3.5.1 DIFFERENCE IN METHODOLOGY

There are no apparent differences between the two variables, other than what they measure. Although the MSCIW does not include all countries, it is believed that it is a good indicator for the performance of the global stock market. As assumed, the correlation between the two indices is high (.86), as the U.S. stock market is the largest market in the world measured by the market capitalization[27], and therefore, by construction, highly affects the fluctuation in the MSCIW.

[26] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States

[27] http://www.world-exchanges.org/

5. FINDINGS FROM THE GLOBAL STUDY

In the following section findings from the global study of the link between default and recovery rates is presented. The univariate and multivariate regressions discussed, is calculated using both the recovery rate (BRR) and its natural logarithm (BLRR) as dependent variables. In the tables summarizing the regressions the dependent variable is signified with an X in the corresponding row. As this thesis aims at testing the findings in Altman, Resti and Sironi (2005), the same statistical methods and goodness of fit measures are applied in order to make results as directly comparable as possible. I have not included a discussion or presentation of the statistical methods applied; however, I have included a brief presentation of the different goodness of fit measures used to determine the best models.

The statistical regression models applied in this thesis has been obtained by, first, writing a statistical script that reproduces the findings in Altman, Resti and Sironi (2005), and then rewriting this script for the global data (unreported). Obtaining the same results as in the U.S. study, makes me confident that the statistical methods and goodness of fit measures applied in the global study align with the statistical methods and goodness of fit measures applied in Altman, Resti and Sironi (2005).

The first sample analyzed has the same time-span as in the U.S. study, comprise 20 observations and contain data ranging from 1982 until 2001 (denoted "sample 1"). The second sample analyzed comprises 31 observations and contains data ranging from 1982 until 2012 (denoted "sample 2).

5.1 GOODNESS OF FIT MEASURES

5.1.1 T-RATIO

The t-ratio is the estimated regression line coefficient divided by the standard error. A large t-ratio indicates that it is unlikely that estimates are obtained due to sampling error. As a rule of thumb, a t-value higher than two is a good indicator of significance for a test at the 5 % significance level. The t-ratio is an important measure in order to validate whether a regression variable has any significant explanatory contribution to the regression model.

5.1.2 COEFFICIENT OF DETERMINATION (R^2)

R^2 is often referred to as the amount of variability in the data accounted for or explained by the regression model, and is therefore often used to judge the adequacy of a regression model. A R^2 close to one indicates that the independent variable/-s explain a high degree of the variation in the dependent variable. Since R^2 increases as more variables are added to the regression model, it can be difficult to know if the increase is telling us anything useful. Consequently, the adjusted R^2 is applied as it only increases if the variable added reduces the error mean square.

5.1.3 F-STATISTICS

The F-ratio and its exceedance probability is used to determine if the residual sum of squares is significantly less than the total sum of squares. Although R^2 tells us how much better a model with independent variables explains observed data, we do not know if the model with independent variables is significantly better. Therefor the F-ratio and its exceedance probability are used to test the significance of all the independent variables taken together. An exceedance probability close to zero indicates that the model is significant. In a simple univariate regression model the F-ratio equals the square of the t-ratio of the independent variable.

5.1.4 SERRIAL CORRELATION (BREUSCH-GODFREY LM TEST)

The Breusch-Godfrey LM test is applied to validate the null hypothesis of no autocorrelation within the regression model. Large test values, with probability close or equal to zero, indicate that there exists higher-order autocorrelation within the regression model. Consequently, the null hypothesis of no autocorrelation should be discarded. In this thesis, as in Altman et al (2005), the lag is of second-order.

5.1.5 HETEROSCEDASTICITY (WHITE'S TEST)

White's test is used to examine the characteristics of the regression residual variance, and consequently to determine the presence of heteroscedasticity. The null hypothesis is that the regression residuals are homoscedastic. The closer the p-value is to zero, the more likely it is that heteroscedasticity is present, and consequently the null hypothesis of constant variance in regression residuals is rejected.

5.2 RESULTS FROM THE GLOBAL STUDY – SAMPLE 1 (1982-2001)

5.2.1 RESULTS FROM UNIVARIATE ANALYSIS

Results from the univariate regression analysis are presented in table 1A and B, where table A summarizes the performance of the market variables, and B the macro variables.

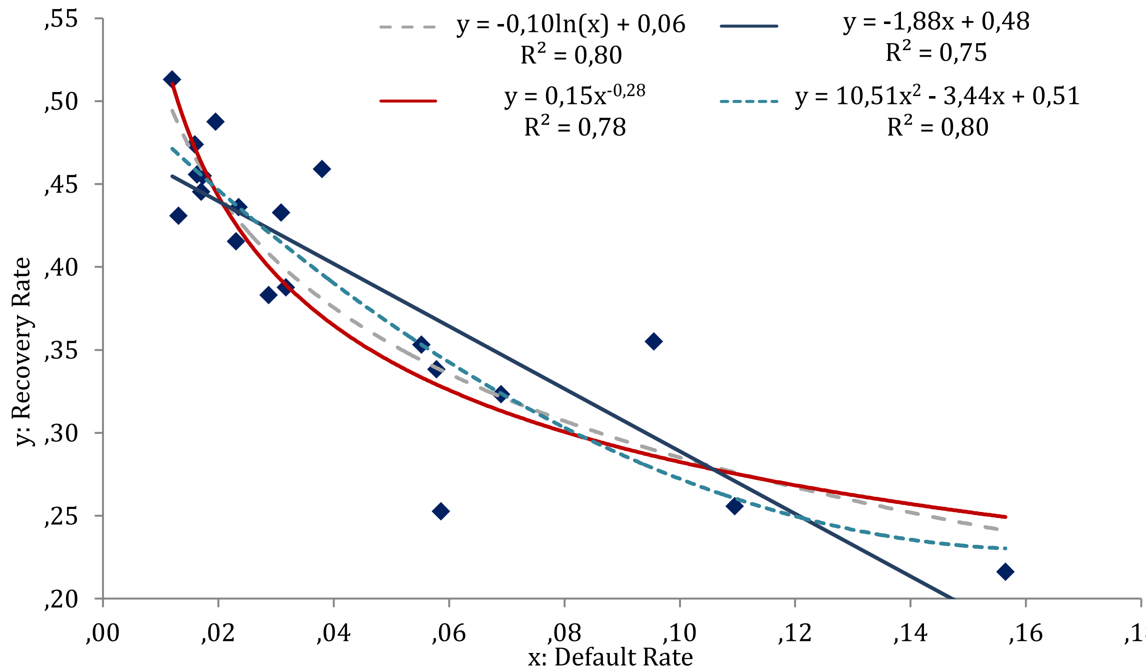


FIGURE 7- LINK BETWEEN BDR/BLDR AND BRR/BLRR, (1982-2001)

As expected there exists a strong and significant link between default rates and recovery rates for the period 1982-2001. The linear model (presented in regression 1 in table 1A) show that the default rate explains around 75 percent of the annual variation in recovery rates, while the power and logarithmic models (presented in regression 3 and 4) explain as much as 80 percent of the variation in the annual recovery rate. All the coefficients in regressions 1 through 4 are significant at the 1 percent level, there are some heteroscedasticity, though not significant given an alpha of 5 percent, and consequently the null hypothesis of constant variance is accepted. Also, the Breuch-Godfrey test shows there are no significant serial correlation in these first four regressions. Thus, the basic thesis in Altman, Resti and Sironi (2005) that default rates are an important indicator of the likely annual recovery rates is backed by the global analysis.

The remaining market variables (regression 5 through 10) all show the expected sign for each coefficient; however, the relationship between the dollar amount of bonds outstanding (BOA) and the recovery rate (BRR), (regression 7 and 8), is not significant as the p-value from the F-statistics is greater than the 1 percent threshold. Also, the Breuch-Godfrey test shows that there is a significant amount of serial correlation in the regression residuals in regression 7 and 8. The link between the total annual dollar amount of bond defaults (BDA) and the recovery rate (BRR), (regression 9 and 10), is stronger than expected, with annual BDA explaining more than 60 percent of the annual variation in BRR.

Although all the macro variables show the expected sign for each coefficient, regression results (presented in Table 1 B) show that these variables explain less of the variation in the recovery rate compared to the market variables. The annual performance of the global stock market (MSCIW), (regression 17 and 18), is the only macro variable which is significant at the 1 percent level, and surprisingly explains almost 40% percent of the annual variation in the recovery rate.

5.2.2 RESULTS FROM MULTIVARIATE AND LOGISTIC REGRESSION ANALYSIS

Results from the multivariate regression analysis is presented in table 2A and B, where table A summarizes the regression variables, the coefficients and the respective t-ratios, and table B summarizes the performance of each multivariate regression model. Regression 11 through 15 is logistic regression models with Gaussian family and with a logit identity. The logistic regression modes are, as in Altman, Resti and Sironi (2005), included in the analysis to account for the fact that the recovery rate is bound between zero and 1.

The six first multivariate regressions are based on the market variables. Results show that these models explain as much as 81 percent (adjusted R^2, regression 6) of the variation in recovery rates, and all variables, except the BDA variable in regression 5, show the expected sign. The BDR and BLDR are significant at the 1 percent level in all these regressions. However, the BDRC, BOA and BDA are not significant at the 10 percent level or less based on their t-ratios. These models also show some signs of heteroscedasticity, though not significant given an alpha of 5 percent.

In regression 7 through 10, macro variables are added to the basic multivariate regression models (regression 1 through 4). As in the basic models the BDR and BLDR are significant at the 1 percent level, and all coefficients show the expected sign. The best performing model explains as much as 83 percent of the variation in recovery rates, and is obtained when the MSCIW is included to the basic structure (regression 10). In this model the BDRC and MSCIW is significant at the 10 percent level. The GDP variable gives no significant contribution to the existing multivariate structures, and does not show the expected sign (regression 7 and 8). The logistic regressions (regression 11 through 15), gives similar results as the linear and log models, with the BDR being the only significant variable.

5.2.2.1 ADDITIONAL REGRESSION

Given the significant and strong univariate relationship between the amount of bonds outstanding and the recovery rate found in the univariate analysis (table 1A, regression 9 and 10), I ran a multivariate regression with BLDR and BDA as dependent variables. Results from this regression-model are summarized below, and show that by including the BDA variable, the explanatory power significantly increases with around 4-8 percent (measured by the adjusted R^2) compared with the univariate relationship between default and recovery rate (regression 1-4, table 1 A).

```
Call:
lm(formula = BLRR ~ BLDR + BDA)

Residuals:
     Min       1Q   Median       3Q      Max
-0.24167 -0.03259 -0.01363  0.04777  0.18426

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.59546    0.16815  -9.488 3.32e-08 ***
BLDR        -0.20264    0.04433  -4.571 0.000272 ***
BDA         -4.59702    1.89984  -2.420 0.027027 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1018 on 17 degrees of freedom
Multiple R-squared: 0.8364,     Adjusted R-squared: 0.8172
F-statistic: 43.47 on 2 and 17 DF,  p-value: 2.071e-07

Serrial correlation LM, 2 lags (Breusch-Godfrey)  3.345
(p-value)                                         0.188
Heteroscedasticity (White, Chi square)            6.617
(p-value)                                         0.158
```

TABLE 1A Univariate Regressions, 1982-2001: Variables Explaining Annual Recovery Rates on Defaulted Corporate Bonds

	A. Market Variables									
Regression number	1	2	3	4	5	6	7	8	9	10
Dependent variable										
BRR	X		X		X		X		X	
BLRR		X		X		X		X		X
Explanatory variables: coefficients & (t-ratios)										
Constant	.477	-.712	.058	-1.907	.402	-.931	.451	-.775	.433	-.837
	(32.25)	(-18.04)	(1.43)	(-15.69)	(28.30)	(-23.64)	(14.51)	(-8.96)	(28.53)	(-21.24)
BDR	-1.883	-5.518								
	(-7.38)	(-8.11)								
BLDR			-.099	-.279						
			(-8.47)	(-7.99)						
BDRC					-1.759	-5.239				
					(-3.91)	(-4.20)				
BOA							-.284	-.897		
							(-2.21)	(-2.51)		
BDA									-3.524	-10.802
									(-4.75)	(-5.60)
Goodness of fit measures										
R^2	.752	.785	.800	.780	.459	.495	.213	.259	.556	.635
Adjusted R^2	.738	.773	.788	.768	.429	.467	.169	.218	.531	.615
F-Statistic	54.490	65.741	71.800	63.861	15.250	17.625	4.878	6.284	22.534	31.377
(p-value)	.000	.000	.000	.000	.002	.001	.041	.022	.000	.000
Residual tests										
Serrial correlation LM, 2 lags (Breusch-Godfrey	.085	.051	.623	1.149	3.546	3.993	5.872	6.783	1.177	.828
(p-value)	.959	.975	.732	.563	.170	.136	.053	.034	.555	.661
Heteroscedasticity (White, Chi square)	1.923	3.065	1.37	3.022	1.068	.533	1.592	1.841	2.625	4.311
(p-value)	.382	.216	.504	.221	.586	.766	.451	.398	.269	.116
Number of observations	20	20	20	20	20	20	20	20	20	20

TABLE 1 A - UNIVARIATE REGRESSIONS, 1982-2001, MARKET VARIABLES

TABLE 1B

	B. Macro Variables									
Regression number	11	12	13	14	15	16	17	18	19	20
Dependent variable										
BRR	X		X		X		X		X	
BLRR		X		X		X		X		X
Explanatory variables: coefficients & (t-ratios)										
Constant	.354	-1.062	.394	-.956	.413	-.905	.353	-1.083	.394	-.956
	(6.55)	(-6.83)	(23.38)	(-19.82)	(16.62)	(-12.68)	(17.15)	(-19.18)	(21.00)	(-17.98)
GDP	1.322	3.517								
	(.77)	(.71)								
GDPC			3.066	8.834						
			(2.25)	(2.27)						
GDPI					-.042	-.117				
					(-1.15)	(-1.10)				
MSCIW							.287	.891		
							(3.00)	(3.40)		
MSCIC									.071	.265
									(.79)	(1.03)
Goodness of fit measures										
R^2	.032	.028	.220	.222	.068	.063	.333	.391	.034	.056
Adjusted R^2	-.022	-.026	.176	.179	.016	.011	.296	.357	-.020	.004
F-Statistic	0.60	0.51	5.07	5.14	1.32	1.22	9.00	11.54	0.62	1.07
(p-value)	.451	.485	.038	.036	.267	.285	.008	.004	.440	.315
Residual tests										
Serrial correlation LM, 2 lags (Breusch-Godfrey)	10.639	11.856	9.153	9.387	9.947	11.439	.922	1.28	6.181	6.345
(p-value)	.005	.003	.01	.009	.007	.003	.631	.527	.045	.042
Heteroscedasticity (White, Chi square)	.442	.256	.539	.355	.055	.404	4.407	5.652	5.275	3.553
(p-value)	.802	.880	.764	.837	.815	.525	.110	.059	.072	.169
Number of observations	20	20	20	20	20	20	20	20	20	20

NOTE: Global data set, 1982-2001

TABLE 1 B - UNIVARIATE REGRESSIONS, 1982-2012, MACRO VARIABLES

TABLE 2A **Multivariate Regressions, 1982-2001**

	Linear and Logarithmic Models										Logistic Models				
Regression number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Dependent variable															
BRR	x		x		x		x		x		x	x	x	x	x
BLRR		x		x		x		x		x					
Explanatory variables: coefficients and (t-ratios)															
Constant	.477	-.702	.126	-1.654	.470	-1.581	.508	-1.656	.460	-1.585	.054	.050	.095	-.025	.127
	(21.00)	(-11.97)	(2.37)	(-11.06)	(25.85)	(-9.36)	(10.43)	(-10.73)	(14.03)	(-10.87)	(.87)	(.55)	(1.31)	(-.13)	(.98)
BDR	-1.636	-4.645			-1.739		-1.844		-1.453		8.899	7.715	7.247	8.210	6.891
	(-4.42)	(-4.86)			(-3.42)		(-3.89)		(-3.23)		(6.97)	(4.84)	(3.29)	(4.13)	(3.68)
BLDR			-.083	-.222		-.196		-.228		-.188					
			(-5.88)	(-5.59)		(-4.36)		(-4.88)		(-4.45)					
BDRC	-.298	-.921	-.460	-1.552	-.409	-1.093	-.113	-1.458	-.373	-1.689		1.742	1.800	1.230	2.176
	(-.65)	(-.78)	(-1.31)	(-1.56)	(-.85)	(-.99)	(-.21)	(-1.34)	(-.79)	(-1.80)		(.94)	(.94)	(.56)	(1.13)
BOA	-.048	-.218	-.059	-.256			-.039	-.252	-.041	-.211		.244		.213	.214
	(-.56)	(-.98)	(-.82)	(-1.27)			(-.44)	(-1.20)	(-.47)	(-1.10)		(.70)		(.59)	(.60)
BDA					.242	-3.326							2.382		
					(.20)	(-1.45)							(.42)		
GDPG							-.830	-.625						2.084	
							(-.72)	(-.25)						(.45)	
MSCIW									.057	.284					-.257
									(.74)	(1.77)					(-0.83)

TABLE 2 A - MULTIVARIATE REGRESSIONS, 1982-2001

TABLE 2 B - GOODNESS OF FIT MEASURES, 1982-2001

TABLE 2B	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Goodness of fit measures															
R^2 (Pseudo - R^2)	.767	.811	.836	.842	.763	.846	.774	.842	.775	.869	.771	.793	.789	.796	.802
Adjusted R^2	.723	.775	.805	.812	.718	.817	.714	.800	.715	.834	.758	.755	.750	.742	.750
F-stat	17.52	22.86	27.20	28.32	17.14	29.26	12.88	20.01	12.90	24.86	60.665	20.480	19.959	14.645	15.226
(p-value)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Residual tests															
Serrial correlation LM, 2 lags (Breusch-	.971	1.339	2.020	1.875	.379	4.017	.557	1.696	1.582	2.256	0.085	0.971	0.379	0.557	1.582
(p-value)	.615	.512	.364	.392	.828	.134	.757	.428	.453	.324	0.959	0.615	0.828	0.757	0.453
Heteroscedasticity (White, Chi square)	9.703	10.146	9.460	9.865	11.465	11.128	12.417	10.406	12.961	12.349	2.298	10.200	11.237	12.791	11.635
(p-value)	.138	.119	.149	.130	.075	.084	.134	.238	.113	.136	.317	.116	.081	.119	.168
N. of observations	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

NOTE - The logistic regression family is Gaussian with a logit identity. Regressions are based on 1982-2001 data. Pseudo Rsquared for logistic regressions. Regarding the White's-test, the degree of freedom is set to two times the number of explanatory variables in the respective regression.

5.3 RESULTS FROM THE GLOBAL STUDY – SAMPLE 2 (1982-2012)

5.3.1 RESULTS FROM UNIVARIATE ANALYSIS, 1982 - 2012

Results from the univariate regression analysis are presented in table 3A and B, where table A summarizes the performance of the market variables, and B the macro variables.

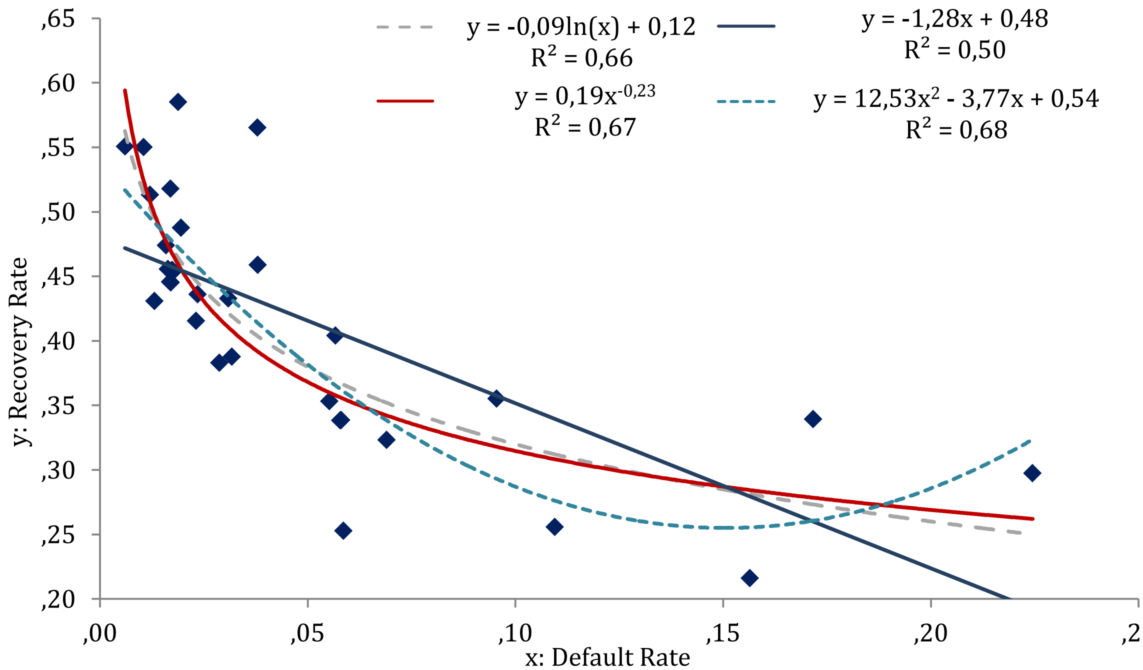


FIGURE 8 - LINK BETWEEN BDR/BLDR AND BRR/BLRR, (1982-2012)

Univariate regression results based on sample 2 shows that the BDR and BLDR (regression 1 through 4) explains 50 to 66 percent of the annual variation in recovery rates. Even though these regressions are significant at the 1 percent level, the Breusch-Godfrey test indicates that there is a significant (alpha of 5 percent) amount of serial correlation in the regression residuals. This is however the case in all the univariate regression models. The amount of bonds outstanding (BOA), unexpectedly, show the wrong sign, and almost no explainable power, the BDA on the other hand explains up to 20 percent of the variation in recovery rates, and is significant at the 1 percent level.

The macro variables perform surprisingly well, with regression 11 through 18 being significant at the 5 percent level. On a univariate basis both recessions (GDPI) and the performance of the global stock market (MSCIW) explains around 20 percent (regression 15 and 18) of the annual variation in recovery rates. With exception of regression 19 all the macro variables show the excepted sign.

5.3.2 RESULTS FROM MULTIVARIATE ANALYSIS - 1982 - 2012

Results from the multivariate regression analysis are presented in table 4 A and B, where table A summarizes the regression variables, the coefficients and the respective t-ratios, and table B summarizes the performance of each multivariate regression model.

In the extended sample there is a positive correlation between BOA and the recovery rate. This is reflected in the multivariate analysis, where the coefficient for the BOA variable counterintuitively shows a positive sign in all models. The six first multivariate regression models are based on the market variables. Results show that these variables explain as much as 68 percent (adjusted R^2, regression 6) of the variation in recovery rates, and all variables, except the BOA, show the expected sign. The BDR and BLDR are significant at the 1 percent level in all these regressions. However, the BDRC and BOA are not significant at the 10 percent level, or less, based on their t-ratios. These models show some signs of heteroscedasticity, with the heteroscedasticity being significant, given an alpha of 5 percent in regression 1 and 2. In regression 5 and 6 the BDA variable is added to the basic model, with regression 5 nearly being significant at the 5 percent level, and regression 6 almost being significant at the 10 percent level. Regression 6 is the model with the highest explanatory power and greatest F-statistics, with almost all coefficients significant at the 10 percent level, and with no significant serial correlation or heteroscedasticity.

In regression 7 through 10, macro variables are added to the basic multivariate regression models (regression 1 through 4). As in the basic models the BDR and BLDR are significant at the 1 percent level, and all coefficients show the expected sign. The best performing model explains as much as 68 percent (adjusted R^2) of the variation in recovery rates, and is obtained when the MSCIW is included to the basic structure (regression 10). However, in this model only the constant term and BLDR show significant coefficients. The GDP variable gives no significant contribution to the existing multivariate structures, and does not show the expected sign in regression 8. The logistic regressions (regression 11 through 15) explain less of the annual variation in recovery rates in comparison to the multivariate linear and log models.

5.3.3.1 ADDITIONAL REGRESSION

Applying the extended dataset and running the same model as in section 5.2.2.1 gives the following results:

```
Call:
lm(formula = BLRR ~ BLDR + BDA, data = THELINK)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.32356 -0.06445 -0.01455  0.07606  0.36546 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.82318    0.16101 -11.324 5.78e-12 ***
BLDR        -0.26020    0.04107  -6.335 7.46e-07 ***
BDA          1.31945    1.10998   1.189    0.245    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1432 on 28 degrees of freedom
Multiple R-squared: 0.683,	Adjusted R-squared: 0.6604 
F-statistic: 30.17 on 2 and 28 DF,  p-value: 1.034e-07

Serial correlation LM, 2 lags (Breusch-Godfrey)    6.819
(p-value)                                          0.033
Heteroscedasticity (White, Chi square)             3.677
(p-value)                                          0.004
```

Adding the BDA variable slightly increases the explanatory power. However, the BDA variable is not significant and tests indicate that there is a significant amount of serial correlation and heteroscedasticity in regression residuals.

TABLE 3A Univariate Regressions, 1982-2012: Variables Explaining Annual Recovery Rates on Defaulted Corporate Bonds

	A. Market Variables									
Regression number	1	2	3	4	5	6	7	8	9	10
Dependent variable										
BRR	x		x		x		x		x	
BLRR		x		x		x		x		x
Explanatory variables: coefficients & (t-ratios)										
Constant	.480	-.734	0.121	-1.677	.416	-.906	.397	-.947	.446	-.823
	(28.43)	(-17.26)	(2.97)	(-16.00)	(27.77)	(-23.51)	(16.27)	(-14.82)	(24.00)	(-17.14)
BDR	-1.280	-3.436								
	(-5.39)	(-5.74)								
BLDR			-.0864	-.226						
			(-7.51)	(-7.62)						
BDRC					-.832	-2.243				
					(-3.07)	(-3.22)				
BOA							.041	.095		
							(1.10)	(0.96)		
BDA									-1.320	-3.580
									(-2.79)	(-2.93)
Goodness of fit measures										
R^2	.501	.532	.660	.667	.246	.263	.040	.031	.211	.229
Adjusted R^2	.483	.516	.648	.656	.220	.238	.007	-.002	.184	.202
F-Statistic	29.07	32.96	56.32	58.09	9.44	10.37	1.20	.92	7.76	8.60
(p-value)	.000	.000	.000	.000	.005	.003	.282	.344	.009	.007
Residual tests										
Serrial correlation LM, 2 lags (Breusch-Godfrey)	6.711	6.444	7.950	6.722	7.462	8.266	12.943	14.725	12.882	13.892
(p-value)	.035	.040	.019	.035	.024	.016	.002	.001	.002	.001
Heteroscedasticity (White, Chi square)	1.963	6.439	1.283	3.458	.947	1.599	9.276	5.112	2.125	3.749
(p-value)	.375	.040	.527	.177	.623	.450	.010	.078	.346	.153
Number of observations	31	31	31	31	31	31	31	31	31	31

TABLE 3 A - UNIVARIATE REGRESSIONs, 1982-2012, MARKET VARIABLES

TABLE 3B

Regression number	11	12	13	14	15	16	17	18	19	20
	B. Macro Variables									
Dependent variable										
BRR	X		X		X		X		X	
BLRR		X		X		X		X		X
Explanatory variables: coefficients & (t-ratios)										
Constant	.388	-1.089	.416	-.903	.457	-.807	.393	-.973	.417	-.903
	(9.30)	(-11.30)	(26.71)	(-22.21)	(21.27)	(-14.17)	(20.89)	(-20.42)	(24.18)	(-20.13)
GDP	.028	.065								
	(2.40)	(2.14)								
GDPC			.023	.059						
			(2.56)	(2.51)						
GDPI					-.083	-.198				
					(-2.68)	(-2.42)				
MSCIW							.203	.597		
							(2.35)	(2.72)		
MSCIC									-.006	.036
									(-.10)	(.21)
Goodness of fit measures										
R^2	.166	.137	.184	.178	.199	.168	.159	.204	.000	.002
Adjusted R^2	.137	.107	.0156	.150	.171	.140	.130	.176	-.034	-.033
F-Statistic	5.77	4.59	6.55	6.30	7.18	5.87	5.50	7.41	.01	.044
(p-value)	.023	.041	.016	.018	.012	.022	.027	.011	.926	.836
Residual tests										
Serrial correlation LM, 2 lags (Breusch-Godfrey)	16.903	18.706	15.002	16.103	15.189	17.401	6.2	6.373	14.336	14.868
(p-value)	.000	.000	.001	.000	.001	.000	.045	.041	.001	.001
Heteroscedasticity (White, Chi square)	1.781	.351	1.046	.459	.954	.014	3.453	4.97	4.802	3.569
(p-value)	.410	.839	.593	.795	.329	.907	.178	.083	.091	.168
Number of observations	31	31	31	31	31	31	31	31	31	31

NOTE: Global data set, 1982-2012

TABLE 3 B – UNIVARIATE REGRESSIONS, 1982-2012, MACRO VARIABLES

TABLE 4 Multivariate Regressions, 1982-2012

	Linear and Logarithmic Models										Logistic Models				
Regression number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Dependent variable															
BRR	X		X		X		X		X		X	X	X	X	X
BLRR		X		X		X		X		X					
Explanatory variables: coefficients and (t-ratios)															
Constant	.456	-.791	.140	-1.616	.475	-1.785	.448	-1.606	.435	-1.603	.044	.137	.063	.171	.225
	(20.66)	(-14.17)	(3.05)	(-13.71)	(26.78)	(-11.46)	(9.72)	(-13.51)	(16.40)	(-14.02)	(.63)	(1.51)	(.86)	(.86)	(2.03)
BDR	-1.137	-3.038			-1.807		-1.109		-1.036		6.304	5.639	8.518	5.499	5.203
	(-4.07)	(-4.30)			(-4.22)		(-3.45)		(-3.64)		(5.25)	(4.25)	(3.35)	(3.59)	(3.90)
BLDR			-.078	-.202		-.245		-.218		-.186					
			(-6.00)	(-6.06)		(-6.10)		(-5.75)		(-5.52)					
BDRC	-.231	-.648	-.241	-.720	-.302	-.965	-.226	-.795	-.173	-.554		.896	1.070	.889	.600
	(-.89)	(-.98)	(-1.18)	(-1.37)	(-1.21)	(-1.85)	(-.85)	(-1.48)	(-.67)	(-1.07)		(.86)	(1.08)	(.84)	(.57)
BOA	.036	.079	.021	.040			.036	.031	.045	.067		-.130		-.132	-.173
	(1.32)	(1.16)	(.92)	(.70)			(1.31)	(.52)	(1.63)	(1.15)		(-1.21)		(-1.20)	(-1.57)
BDA					1.337	1.851							-5.712		
					(2.04)	(1.68)							(-2.02)		
GDPG							.002	-.020						-.009	
							(.19)	(-.87)						(-.19)	
MSCIW									.099	.258					-.405
									(1.37)	(1.68)					-1.31

TABLE 4 A - MULTIVARIATE REGRESSIONS, 1982-2012

TABLE 4 B - GOODNESS OF FIT MEASURES, 1982-2012

Goodness of fit measures															
R^2 (Pseudo - R^2)	.547	.572	.687	.695	.582	.718	.548	.703	.577	.725	.533	.573	.606	.573	.599
Adjusted R^2	.497	.525	.652	.661	.536	.687	.478	.658	.512	.682	.517	.525	.563	.507	.537
F-stat	10.864	12.035	19.77	20.48	12.54	22.97	7.87	15.41	8.876	17.10	33.158	12.055	13.859	8.727	9.714
(p-value)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Residual tests															
Serrial correlation LM, 2 lags (Breusch-Godfrey)	3.342	2.942	4.403	3.852	1.689	3.516	3.515	3.070	3.188	2.450	6.711	3.342	1.689	3.515	3.188
(p-value)	.188	.230	.111	.146	.430	.172	.172	.215	.203	.294	.035	0.188	0.430	.172	.203
Heteroscedasticity (White, Chi square)	15.548	12.806	11.639	10.585	10.856	5.459	18.656	10.271	16.274	13.714	2.500	15.114	11.952	18.511	17.160
(p-value)	.016	.046	.071	.102	.093	.486	.017	.247	.039	.090	.286	.019	.063	.018	.028
N. of observations	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31

NOTE - The logistic regression family is Gaussian with a logit identity. Regressions are based on 1982-2012 data. Pseudo Rsquared for logistic regressions. Regarding the White's-test, the degree of freedom is set to two times the number of explanatory variables in the respective regression.

6. COMAPRISON BETWEEN THE GLOBAL AND U.S. FINDINGS

In the following section results from the global study is compared with the findings in Altman, Resti and Sironi (2005). The univariate and multivariate regression results in Altman, Resti and Sironi (2005) is presented in appendix 1 A and B.

6.1 UNIVARIATE MODELS

6.1.1 SAMPLE 1, 1982-2001

The results from the global study of the univariate relationship between the market variables (regression 1 through 10, table 1 A) and the recovery rate are surprisingly similar to the findings in the U.S. study. All the market based univariate regression models shows the expected and same sign as in the U.S. study, and is, with the exception of regression 7 and 8, significant at the 1 percent level. The natural logarithm of the annual default rates (BLDR) is, as in in U.S. study, the variable with the highest explanatory power (regression 3 and 4). While the BLDR explains 65 percent (R2) of the annual variation in recovery rates in the U.S. study, it explains around 80 percent in the global study. The macro variables (regression 11 through 20, table 3 B) show similar relationships with the BRR as in the U.S. study, with the same sign in all cases. Contrary to findings in the U.S. study, recessions (GDPI) show no explanatory power in the global study (regression 15 and 16, table 1B). While the performance of the stock market show no explanatory power in the U.S. study, results from the global analysis shows that the performance of the stock market (regression 17 and 18, table 1B) explains around 39 percent of the variation in BRR.

6.1.2 SAMPLE 2, 1982-2012

Contrary to the U.S. study, almost all regression variables in the extended global study show a significant amount of serial correlation in regression residuals. Results from the global univariate relationship between the BDR and BLDR variable and the BRR (regression 1 through 4, table 3 A) is surprisingly similar to the findings in the U.S. study. In both studies these variables explain around 50 to 65 percent of the variation in annual recovery rates. Although significant at the 1 percent level, the BDRC explains about half of the variation in BRR compared to the findings in the U.S. study. Whereas the BOA variable significantly explains almost 33 percent (regression 8, appendix 1A) of the variation in

BRR in the U.S. study, it shows no explanatory power in the global study. When sample 2 is applied the BDA variable significantly explains around 20 percent of the annual variation in the recovery rate, under half of the R2 found in the U.S. study. The macro variables (regression 11 through 20, table 3 B) perform similarly as in the U.S. study, with the same sign, except regression 19, in all cases. However, while the performance of the stock market (SR) and general economy (GDP) explains an insignificant and small portion of the variation in annual recovery rates in the U.S. study (regression 17 and 18, appendix 1B), results from the global study show that the GDP (regression 11 and 12, table 3 B) and stock market performance (regression 17 and 18, table 3 B) explains a significant part of the variation in recovery rates, with R2 of respectively .167 and .20. In the global study there is a significant amount of serial correlation in all regression residuals, whereas macro variables in the U.S. study show no significant serial correlation in regression residuals.

6.2 MULTIVARIATE MODELS

6.2.1 SAMPLE 1, 1982-2001

Comparing the performance of the multivariate models in the U.S. study (regression 1 through 15, appendix 2) with the performance of the multivariate models in the global study, show that the multivariate models in the latter study performs rather poorly. While the basic models (regression 1 through 4, appendix 2) in U.S. study shows significant coefficients and shows a significant increase in the explanatory power compared to the univariate modes, the basic models in the global study shows no significant increase in the explanatory power, with BDR and BLDR being the only significant variables. The GDP variable and the performance of the stock market (MSCIW and SR) give similar results in both studies and does not significantly explain any of the variation in recovery rates. The logistic models give similar results as the univariate models is both studies.

6.2.2 SAMPLE 2, 1982-2012

Contrary to results from the U.S. study, but in line with the findings from the multivariate regression analysis based on the sample 1 (table 3), the multivariate models based on sample 2 (table 4) also fails at significantly explaining an increased part of the annual variation in recovery rates. While the BOA variable performs quite well in the U.S. study, it shows the wrong sign and no significant explanatory power in the extended global study. In the global analysis based on sample 2, the GDP variable and the performance of the stock market (MSCIW and SR) show no significant explanatory power and accordingly gives similar results as in the U.S. study. As in the U.S. study the logistic models does not contribute with any significant explanatory power.

6.3 SUMMARY

In line with results from the U.S. study, univariate regression results from both global samples show that the annual aggregate default rates has a significant and negative relationship with recovery rates (regression 1 through 4, table 1 and 2 a). While regression results from sample 1 show that the BOA variable has, as in the U.S. study, a significant and negative effect on recovery rates, regression results (regression 7 and 8, table 1 A) from sample 2 show no such effects. Results from both global samples show, as in the U.S. study, that the annual amount of bond defaults (BDA) has a significant and negative impact on the recovery rate. Regarding the univariate models based macro variables, it is noteworthy that the GDP variable has a significant coefficient and explains around 16 percent of the variation in recovery (table 3B, regression 11 and 12). Contrary to findings in the U.S study, regression results from both global samples show that the performance of the stock market significantly explains up to 39 percent (R^2, regression 18 table 1B) of the variation in recovery rates. Univariate regression results from both global samples show that the MSCIW variable significantly explains more of the variation in recovery rates than the BOA variable.

While the univariate models based on the global samples significantly support many of the findings in Altman, Resti and Sironi (2005), the multivariate models does, however, not support the findings. In the global study none of the multivariate regression models give results where all coefficients are significant. While the BDR and BLDR variables are significant in all cases, the BDRC, BDA and BOA variables show no significant explanatory power. As in the U.S. study, the macro variables do not add any significant explanatory power to the BDR and BRR relationship.

While the additional multivariate regression model based on sample 1 (section 5.2.3.1), is in line with findings in the U.S. study, results from the additional multivariate regression model based on sample 2 is however not in line with the U.S. study. Given the diverging results, it is difficult to conclude whether the BDA variable adds any explanatory power to the BDR and BRR relationship.

7. ROBUSTNESS CHECK

I did not perform a robustness test on the data frequency, as I did not manage to obtain higher-frequency data on default and recovery rates. However, all the different sample sizes and frames (regression 1-4, table 1A, 3A and appendix 3) show a negative and significant relationship between default and recovery rates.

Since the BDA variable applied in the global sample only contains defaulted bonds in the speculative grade segment, I wanted to check whether the poor performance of the BDA variable was due to measurement error in supply of defaulted bonds. I therefore ran additional regressions applying a BDA variable that also included bond defaults in the investment grade segment. Regression results when the new BDA variable is applied show no significant contribution. The initial BDA variable shows almost a significant contribution, however showing a counterintuitive sign.

Performance of the BDA and BDA* Variables

Dependent variable	BRR	BRR	BRR
Explanatory variables:			
coef. and (t-ratios)			
Constant	.48	.484	.480
	(27.988)	(29.728)	(28.43)
BDR	-1.366	-1.952	-1.280
	(-4.227)	(-4.708)	(-5.39)
BDA		.001	
		(1.937)	
BDA*	.000		
	(.399)		
Goodness of fit measures			
R^2	.503	.560	.501
Adjusted R^2	.468	.528	.483
F-statistic	14.194	17.792	29.07
(p-value)	.000	.000	.000
N. of observations	31	31	31

NOTE: *Includes both investment and speculative grade bonds

TABLE 5- REGRESSAON WITH NEW BDA VARIABLE

To further examine the robustness of the negative relationship between default and recovery rates, I tested, as in the U.S. study, weather results would hold when recovery rates are broken down seniority. Results (present in table 5) from this test are similar as to those in the U.S. study, and confirm that secured bonds recover more than unsecured and subordinated bonds.

Data Broken Down by Seniority Status

Dependent variable	RR on Sr. Sec. Bonds*	RR on Sr. Unsec. Bonds	RR on Sr. Sub. Bonds	RR on Sub. Bonds**
Explanatory variables:				
coef. and (t-ratios)				
Constant	.654	.517	.44	.413
	(19.89)	(25.47)	(18.91)	(11.15)
BDR	-1.531	-1.353	-1.302	-1.066
	(-3.41)	(-4.73)	(-3.98)	(-2.08)
Goodness of fit measures				
R^2	.301	.436	.353	.134
Adjusted R^2	.276	.416	.33	.103
F-statistic	11.648	22.387	15.804	4.315
(p-value)	.002	.000	.000	.047
N. of observations	29	31	31	30

NOTE: *Year 1984 and 1993 not included since there are no recorded defaults these years. **Year 2007 not included since there are no recorded defaults this year

TABLE 6 - BRR BROKEN DOWN BY SENIORITY

Performance of the GDPI Dummy Variable

Dependent variable	BRR	BLRR	BRR	BLRR
Explanatory variables:				
coef. and (t-ratios)				
Constant	.488	-1.648	.480	-1.677
	(26.624)	(-12.251)	(28.43)	(-16.00)
GDPI	-.031	-.021		
	(-1.129)	(-.352)		
BDR	-1.148		-1.280	
	(-4.357)		(-5.39)	
BLDR		-.221		-.226
		(-6.499)		(-7.62)
Goodness of fit measures				
R^2	.522	.668	.501	.667
Adjusted R^2	.488	.645	.483	.656
F-statistic	15.31	28.23	29.07	58.09
(p-value)	.000	.000	.000	.000
N. of observations	31	31	31	31

NOTE: The GDPI takes the value of 1 if the global GDP rate is 3% or less, and 0 otherwise.

TABLE 7 – PERFORMANCE OF THE GDPI VARIABLE

The GDPI variable has, as in the U.S. study, been added to the global analysis to account for the high correlation between the BDR and the GDP variable[28]. In regressions based on the first sample (1982-2001) the GDPI variable shows no significant relationship with the recovery rate. However, when the extended sample (1982-2012) is applied, the performance of the GDPI variable drastically increases (regression 15 and 16, table 1B), and shows both the correct sign and is significant at the 5 percent threshold. Results from the univariate analysis based on data over the past 20 years (1993-2012), supports these findings (regression 5 and 6, B. macro variables, appendix 3), and shows a strong link between the GDPI variable and the recovery rate. The effect of adding the GDPI variable to the BDR and BRR relationship is summarized in table 7. Results show that the GDPI variable gives no significant contribution to the BDR and BRR relationship.

8. IMPLICATIONS

A negative link between default and recovery rates has import implication for a number of credit-risk-related conceptual and practical areas[29] (Altman, Resti and Sironi (2005)). In this thesis I have not included a thorough analysis of the various implications findings from the global study may have on various credit-risk-related areas. In section 3.7 a summary of the key areas which Altman, Resti and Sironi (2005) argues can be significantly affected when one considers that default rates are negatively correlated with recovery rates is presented. For further discussions on the implications: see Altman et al. (2001), and Altman, Resti and Sironi (2005). In general, evidence of a significant and negative relationship between global corporate bond default and recovery rates has important implications for all credit-risk-related models treating the recovery rate independent of default rates.

9. WEAKNESSES

The default and the recovery rate are calculated differently in the global study and U.S. study. This may cause that results are less comparable. There might be differences in the types of defaults included in the global analysis as data on defaults are defined by Moody's

[28] -.56 in both the U.S. and the global study based on sample 2

[29] Appendix 5 gives an overview over how the recovery rate are treated in different credit risk models

and not by the NYU Salomon Center, which is applied in the U.S. study. Univariate regression results based on sample 2 shows a significant amount of serial correlation in regression residuals and violates the ordinary least squares assumption that the residuals are uncorrelated. Numerous corporate bond defaults is presumably omitted in the global analysis as the BDA mainly comprise Moody's rated or listed bonds, affecting both the annual aggregate default and recovery rate. This also affects the BOA, as this size is implied from the amount of bonds outstanding and the default rate.

It was not possible to validate results in light of higher-frequency data, as it proved difficult obtaining data on quarterly or monthly default and recovery rates.

10. CONCLUSION

The global study supports the findings in Altman, Resti and Sironi (2005) of a significant and negative link between default and recovery rates. I find that global default rates explain 80 percent of the annual variation in associated recovery rates when results are based on the same sample size (1982-2001) as in the U.S. study, and around 66 percent when the sample also includes the most recent observations (1982-2012). Evidence of a negative relationship between default and recovery rates have important implications for credit-risk-related areas treating the important recovery rate independent from default rates. Results from the global study shows that the bond default rate, in comparison to the other variables, undoubtedly explains the highest degree of variation in recovery rates. Although default rates have the highest explanatory power in the global analysis, it is noteworthy that the performance of the global stock market explains as much as 39 percent of the variation in recovery rates. Univariate regression results shows that the performance of the global stock market explains more of the annual variation associated in recovery rates than the BOA variable. On a univariate basis the supply of defaulted securities significantly explains from 20 to 60 percent of the variation in global recovery rates, however, when added to the multivariate models, results are divergent and the supply of defaulted bonds show no significant explanatory contribution. The latter finding differs from results in Altman, Resti and Sironi (2005), where the multivariate regression models assign a key role to the supply of defaulted bonds. None of the multivariate models in the global study give results where all coefficients are significant.

APPENDIX 1A -UNIVARIATE RESULTS ALTMAN, RESTI AND SIRONI (2005)

*Table is copied from: Journal of Business, 2005, vol. 78, no. 6, page 2212

TABLE 2 Univariate Regressions, 1982–2001: Variables Explaining Annual Recovery Rates on Defaulted Corporate Bonds

A. Market Variables										
Regression number	1	2	3	4	5	6	7	8	9	10
Dependent variable										
BRR	X		X		X		X		X	
BLLR		X		X		X		X		X
Explanatory variables: coefficients and (t-ratios)										
Constant	.509	−.668	.002	−1.983	.432	−.872	.493	−.706	.468	−.772
	(18.43)	(−10.1)	(.03)	(−10.6)	(24.9)	(−20.1)	(13.8)	(−8.05)	(19.10)	(−13.2)
BDR	−2.610	−6.919								
	(−4.36)	(−4.82)								
BLDR			−.113	−.293						
			(−5.53)	(−5.84)						
BDRC					−3.104	−7.958				
					(−4.79)	(−4.92)				
BOA							−.315	−.853		
							(−2.68)	(−2.95)		
BDA									−4.761	−13.122
									(−3.51)	(−4.08)
Goodness of fit measures										
R^2	.514	.563	.630	.654	.560	.574	.286	.326	.406	.481
Adjusted r^2	.487	.539	.609	.635	.536	.550	.246	.288	.373	.452
F-statistic	19.03	23.19	30.61	34.06	22.92	24.22	7.21	8.69	12.31	16.67
(p-value)	.000	.000	.000	.000	.000	.000	.015	.009	.003	.001
Residual tests										
Serial correlation LM, 2 lags (Breusch-Godfrey)	1.021	1.836	1.522	2.295	1.366	2.981	1.559	1.855	3.443	2.994
(p-value)	.600	.399	.467	.317	.505	.225	.459	.396	.179	.224
Heteroscedasticity (White, Chi square)	.089	1.585	.118	1.342	8.011	5.526	2.389	1.827	.282	1.506
(p-value)	.956	.453	.943	.511	.018	.063	.303	.401	.868	.471
N. obs.	20	20	20	20	20	20	20	20	20	20

APPENDIX 1B, UNIVARIATE RESULTS ALTMAN, RESTI AND SIRONI (2005)

*Table is copied from: Journal of Business, 2005, vol. 78, no. 6, page 2213

B. Macro Variables

Regression #	11	12	13	14	15	16	17	18	19	20
Dependent variable										
BRR	X		X		X		X		X	
BLRR		X		X		X		X		X
Explanatory variables										
Constant	.364	−1.044	.419	−.907	.458	−.804	.387	−1.009	.418	−.910
	(7.59)	(−8.58)	(18.47)	(−15.65)	(15.42)	(−10.8)	(10.71)	(−11.3)	(16.42)	(−14.4)
GDP	1.688	4.218								
	(1.30)	(1.28)								
GDPC			2.167	5.323						
			(2.31)	(2.22)						
GDPI					−.101	−.265				
					(−2.16)	(−2.25)				
SR							.205	.666		
							(1.16)	(1.53)		
SRC									.095	.346
									(.73)	(1.07)
Goodness of fit measures										
R^2	.086	.083	.228	.215	.206	.220	.070	.115	.029	.060
Adjusted R^2	.035	.032	.186	.171	.162	.176	.018	.066	−.025	.007
F-statistic	1.69	1.64	5.33	4.93	4.66	5.07	1.36	2.35	.53	1.14
(p-value)	.211	.217	.033	.040	.045	.037	.259	.143	.475	.299
Residual tests										
Serial correlation LM, 2 lags (Breusch-Godfrey)	2.641	4.059	.663	1.418	.352	1.153	3.980	5.222	3.479	4.615
(p-value)	.267	.131	.718	.492	.839	.562	.137	.073	.176	.100
Heteroscedasticity (White, Chi square)	2.305	2.077	2.254	2.494	.050	.726	2.515	3.563	3.511	4.979
(p-value)	.316	.354	.324	.287	.823	.394	.284	.168	.173	.083
Number of observations	20	20	20	20	20	20	20	20	20	20

NOTE.—The table shows the results of a set of univariate regressions carried out between the recovery rate (BRR) or its natural log (BLRR) and an array of explanatory variables: the default rate (BDR), its log (BLDR), and its change (BDRC); the outstanding amount of bonds (BOA) and the outstanding amount of defaulted bonds (BDA); the GDP growth rate (GDP), its change (GDPC), and a dummy (GDPI) taking the value of 1 when the GDP growth is less than 1.5%; the S&P 500 stock-market index (SR) and its change (SRC).

APPENDIX 2, MULTIVARIATE RESULTS ALTMAN, RESTI AND SIRONI (2005)

*Table is copied from: Journal of Business, 2005, vol. 78, no. 6, page 2216 and 2217

TABLE 4 Multivariate Regressions, 1982–2001

	Linear and Logarithmic Models										Logistic Models				
Regression number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Dependent variable															
BRR	X		X		X		X		X		X	X	X	X	X
BLRR		X		X		X		X		X					
Explanatory variables: coefficients and (*t*-ratios)															
Constant	.514	−.646	.207	−1.436	.482	−1.467	.529	−1.538	.509	−1.447	−.074	−.097	.042	.000	.000
	(19.96)	(−11.34)	(2.78)	(−8.70)	(20.02)	(−6.35)	(11.86)	(−9.07)	(14.65)	(−8.85)	(−.64)	(−.92)	(.44)	(.00)	(.00)
BDR	−1.358	−3.745			−1.209		−1.513		−1.332		12.200	6.713	5.346	7.421	6.487
	(−2.52)	(−3.13)			(−1.59)		(−2.28)		(−2.33)		(4.14)	(2.82)	(1.55)	(2.59)	(2.64)
BLDR			−.069	−.176		−.167		−.222		−.169					
			(−3.78)	(−4.36)		(−2.94)		(−4.64)		(−4.17)					
BDRC	−1.930	−4.702	−1.748	−4.389	−2.039	−4.522	−1.937	−4.415	−1.935	−4.378		8.231	8.637	8.304	8.394
	(−3.18)	(−3.50)	(−3.39)	(−3.84)	(−3.03)	(−3.35)	(−3.11)	(−4.05)	(−3.09)	(−3.87)		(3.339)	(3.147)	(3.282)	(3.315)
BOA	−.164	−.459	−.141	−.410			−.153	−.328	−.162	−.387		.742		.691	.736
	(−2.13)	(−2.71)	(−2.12)	(−2.78)			(−1.86)	(−2.20)	(−2.03)	(−2.63)		(2.214)		(1.927)	(2.136)
BDA					−1.203	−3.199							8.196		
					(−.81)	(−1.12)							(1.064)		
GDP							−.387	−2.690						1.709	
							(−.43)	(−1.62)						(.473)	
SR									.020	.213					−.242
									(.192)	(1.156)					(−.56)
Goodness of fit measures															
R^2	.764	.819	.826	.867	.708	.817	.767	.886	.764	.878	.534	.783	.732	.786	.787
Adjusted R^2	.720	.785	.793	.842	.654	.782	.704	.856	.702	.845	.508	.742	.682	.729	.731
F-stat	17.250	24.166	25.275	34.666	12.960	23.752	12.320	29.245	12.168	26.881	20.635	19.220	14.559	13.773	13.876
(*p*-value)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Residual tests															
Serial correlation LM, 2 lags (Breusch-Godfrey)	3.291	2.007	1.136	.718	1.235	.217	3.344	.028	5.606	1.897	1.042	2.673	1.954	2.648	5.899
(*p*-value)	.193	.367	.567	.698	.539	.897	.188	.986	.061	.387	.594	.263	.376	.266	.052
Heteroscedasticity (White, Chi square)	5.221	5.761	5.049	5.288	12.317	12.795	5.563	4.853	6.101	6.886	.008	5.566	9.963	5.735	5.948
(*p*-value)	.516	.451	.538	.507	.055	.046	.696	.773	.636	.549	.996	.474	.126	.677	.653
Numbers of observations	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

APPENDIX 3, UNIVARIATE REGRESSIONS, 1993-2012

Table 1: Results, Univariate Regressions, 1993-2012

	Dependent variable: A. MArket Variables									
	BRR	BLRR	BRR	BLRR	BRR	BLRR	BRR	BLRR	BRR	BLRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.484***	−0.729***	0.132**	−1.654***	0.422***	−0.895***	0.396***	−0.963***	0.471***	−0.766***
	(0.023)	(0.059)	(0.056)	(0.144)	(0.021)	(0.054)	(0.040)	(0.105)	(0.026)	(0.067)
	$t = 20.832$	$t = -12.431$	$t = 2.343$	$t = -11.472$	$t = 20.206$	$t = -16.701$	$t = 9.770$	$t = -9.173$	$t = 18.202$	$t = -11.461$
	$p = 0.000$	$p = 0.000$	$p = 0.031$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
BDR	−1.177***	−3.141***								
	(0.296)	(0.746)								
	$t = -3.981$	$t = -4.209$								
	$p = 0.001$	$p = 0.001$								
BLDR			−0.085***	−0.221***						
			(0.016)	(0.040)						
			$t = -5.342$	$t = -5.473$						
			$p = 0.000$	$p = 0.000$						
BDRC					−0.751**	−2.015**				
					(0.318)	(0.816)				
					$t = -2.360$	$t = -2.470$				
					$p = 0.030$	$p = 0.024$				
BOA							0.042	0.109		
							(0.051)	(0.132)		
							$t = 0.833$	$t = 0.825$		
							$p = 0.416$	$p = 0.421$		
BDA									−1.543***	−4.045***
									(0.534)	(1.377)
									$t = -2.891$	$t = -2.937$
									$p = 0.010$	$p = 0.009$
Observations	20	20	20	20	20	20	20	20	20	20
R^2	0.468	0.496	0.613	0.625	0.236	0.253	0.037	0.036	0.317	0.324
Adjusted R^2	0.439	0.468	0.592	0.604	0.194	0.212	-0.016	-0.017	0.279	0.286

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1: Results, Univariate Regressions, 1993-2012, B. Macro Variables

	Dependent variable:									
	BRR	BLRR	BRR	BLRR	BRR	BLRR	BRR	BLRR	BRR	BLRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.327***	−1.115***	0.422***	−0.894***	0.472***	−0.780***	0.402***	−0.954***	0.423***	−0.893***
	(0.046)	(0.124)	(0.022)	(0.057)	(0.030)	(0.079)	(0.024)	(0.061)	(0.024)	(0.062)
	$t = 7.067$	$t = -9.021$	$t = 19.363$	$t = -15.732$	$t = 15.926$	$t = -9.846$	$t = 16.565$	$t = -15.549$	$t = 17.687$	$t = -14.401$
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
GDPG	0.034**	0.080*								
	(0.015)	(0.040)								
	$t = 2.313$	$t = 2.017$								
	$p = 0.033$	$p = 0.059$								
GDPGC			0.022*	0.055*						
			(0.011)	(0.030)						
			$t = 1.901$	$t = 1.850$						
			$p = 0.074$	$p = 0.081$						
GDPI3					−0.098**	−0.225*				
					(0.042)	(0.112)				
					$t = -2.332$	$t = -2.009$				
					$p = 0.032$	$p = 0.060$				
MSCIW							0.230*	0.660**		
							(0.117)	(0.296)		
							$t = 1.962$	$t = 2.229$		
							$p = 0.066$	$p = 0.039$		
MSCIWC									−0.007	0.029
									(0.087)	(0.226)
									$t = -0.084$	$t = 0.130$
									$p = 0.934$	$p = 0.898$
Observations	20	20	20	20	20	20	20	20	20	20
R^2	0.229	0.184	0.167	0.160	0.232	0.183	0.176	0.216	0.000	0.001
Adjusted R^2	0.186	0.139	0.121	0.113	0.189	0.138	0.130	0.173	-0.055	-0.055

Note: *p<0.1; **p<0.05; ***p<0.01

APPENDIX 4, MULTIVARIATE REGRESSIONS, 1993-2012

Table 1: Results: Multivariate Regressions, 1993-2012

	Dependent variable:									
	BRR	BLRR	BRR	BLRR	BRR	BLRR	BRR	BLRR	BRR	BLRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.459***	−0.795***	0.147**	−1.605***	0.474***	−1.933***	0.433***	−1.590***	0.436***	−1.611***
	(0.037)	(0.093)	(0.068)	(0.174)	(0.026)	(0.296)	(0.075)	(0.183)	(0.041)	(0.167)
	$t = 12.396$	$t = -8.539$	$t = 2.150$	$t = -9.224$	$t = 17.945$	$t = -6.535$	$t = 5.752$	$t = -8.706$	$t = 10.671$	$t = -9.639$
	$p = 0.000$	$p = 0.000$	$p = 0.048$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
BDR	−1.028**	−2.734***			−1.572**		−0.953**		−0.957**	
	(0.369)	(0.929)			(0.734)		(0.425)		(0.369)	
	$t = -2.787$	$t = -2.943$			$t = -2.142$		$t = -2.244$		$t = -2.596$	
	$p = 0.014$	$p = 0.010$			$p = 0.048$		$p = 0.041$		$p = 0.021$	
BLDR			−0.077***	−0.199***		−0.278***		−0.208***		−0.185***
			(0.019)	(0.048)		(0.071)		(0.055)		(0.047)
			$t = -4.052$	$t = -4.127$		$t = -3.892$		$t = -3.786$		$t = -3.942$
			$p = 0.001$	$p = 0.001$		$p = 0.002$		$p = 0.002$		$p = 0.002$
BDRC	−0.207	−0.573	−0.190	−0.565	−0.252	−0.842	−0.161	−0.684	−0.094	−0.252
	(0.332)	(0.837)	(0.270)	(0.687)	(0.330)	(0.677)	(0.361)	(0.765)	(0.341)	(0.690)
	$t = -0.623$	$t = -0.685$	$t = -0.702$	$t = -0.822$	$t = -0.764$	$t = -1.243$	$t = -0.446$	$t = -0.895$	$t = -0.275$	$t = -0.366$
	$p = 0.542$	$p = 0.504$	$p = 0.493$	$p = 0.424$	$p = 0.456$	$p = 0.232$	$p = 0.662$	$p = 0.386$	$p = 0.787$	$p = 0.720$
BOA	0.027	0.068	0.018	0.044			0.031	0.035	0.038	0.073
	(0.039)	(0.099)	(0.034)	(0.086)			(0.041)	(0.091)	(0.040)	(0.084)
	$t = 0.695$	$t = 0.692$	$t = 0.527$	$t = 0.513$			$t = 0.745$	$t = 0.384$	$t = 0.947$	$t = 0.870$
	$p = 0.498$	$p = 0.500$	$p = 0.606$	$p = 0.616$			$p = 0.468$	$p = 0.707$	$p = 0.359$	$p = 0.399$
BDA					0.973	2.633				
					(1.150)	(1.874)				
					$t = 0.846$	$t = 1.405$				
					$p = 0.411$	$p = 0.180$				
GDPG							0.007	−0.016		
							(0.018)	(0.038)		
							$t = 0.390$	$t = -0.405$		
							$p = 0.702$	$p = 0.692$		
MSCIW									0.129	0.351
									(0.107)	(0.228)
									$t = 1.201$	$t = 1.536$
									$p = 0.249$	$p = 0.146$
Observations	20	20	20	20	20	20	20	20	20	20
R^2	0.498	0.527	0.632	0.647	0.505	0.680	0.503	0.650	0.542	0.695
Adjusted R^2	0.404	0.438	0.563	0.580	0.412	0.620	0.371	0.557	0.420	0.613

Note: *p<0.1; **p<0.05; ***p<0.01

APPENDIX 5, TREATMENT OF LDG AND BDR IN CREDIT RISK MODELS

*Table is copied from: Altman, Edward I., Andrea Resti, and AndreaSironi.2001, page 26.

Table I.1 – The Treatment of LGD and Default Rates within Different Credit Risk Models

	MAIN MODELS & RELATED EMPIRICAL ST UDIES	TREATMENT OF LGD	RELATIONSHIP BETWEENRR AND PD
Credit Pricing Models			
First generation structural-form models	Merton (1974), Black and Cox (1976), Geske (1977), Vasicek (1984), Crouhy and Galai (1994), Mason and Rosenfeld (1984).	PD and RR are a function of the structural characteristics of the firm. RR is therefore an endogenous variable.	PD and RR are inversely related (see Appendix I.A).
Second generation structural-form models	Kim, Ramaswamy e Sundaresan (1993), Nielsen, Saà-Requejo, Santa Clara (1993), Hull and White (1995), Longstaff and Schwartz (1995).	RR is exogenous and independent from the firm's asset value.	RR is generally defined as a fixed ratio of the outstanding debt value and is therefore independent from PD.
Reduced-form models	Litterman and Iben (1991), Madan and Unal (1995), Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), Lando (1998), Duffie and Singleton (1999), Duffie (1998) and Duffee (1999).	Reduced-form models assume an exogenous RR that is either a constant or a stochastic variable independent from PD.	Reduced-form models introduce separate assumptions on the dynamic of PD and RR, which are modeled independently from the structural features of the firm.
Single systematic factor models	Frye (2000a and 2000b), Jarrow (2001), Carey and Gordy (2001), Altman and Brady (2002).	Both PD and RR are stochastic variables which depend on a common systematic risk factor (the state of the economy).	PD and RR are negatively correlated. In the "macroeconomic approach" this derives from the common dependence on one single systematic factor. In the "microeconomic approach" it derives from the supply and demand of defaulted securities.
Credit Value at Risk Models			
CreditMetrics®	Gupton, Finger and Bhatia (1997).	Stochastic variable (beta distr.)	RR independent from PD
CreditPortfolioView®	Wilson (1997a and 1997b).	Stochastic variable	RR independent from PD
CreditRisk+®	Credit Suisse Financial Products (1997).	Constant	RR independent from PD
KMV CreditManager®	McQuown (1997), Crosbie (1999).	Stochastic variable	RR independent from PD

APPENDIX 6 - MOODY'S BONDS AND LOANS DATABASE

Moody's database of corporate defaults covers more than 3,000 long-term bond and loan defaults by issuers both rated and non-rated by Moody's. Additional data sources, such as Barclay's Fixed Income Index data, supplemented Moody's proprietary data in the construction of the aggregate dollar volume-weighted default rates. Defaulted bond pricing data was derived from Bloomberg, Reuters, IDC, and TRACE. The majority of these market quotes represent an actual bid on the debt instrument, although no trade may have occurred at that price. Over the 1982-2012 period, the dataset includes post-default prices for approximately 5,000 defaulted instruments issued by over 1,700 defaulting corporations.

Source:
Moody's Investors Service, (2013), "Annual default study: corporate default and recovery rates, 1920-2012," New York: Moody's, https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_151031

APPENDIX 7 –VALUES IN THE GLOBAL STUDY

YEAR	BRR	BLRR	BDR	BLDR	BDRC	BOA	BDA	GDP	GDPC	GDPI	MSCIW	MSCIWC
1982	0,35	-1,04	0,06	-2,90	-	0,01	0,00	0,40	-1,66	1	0,11	0,15
1983	0,45	-0,81	0,02	-4,07	-0,04	0,07	0,00	2,66	2,27	1	0,23	0,12
1984	0,45	-0,79	0,02	-4,06	0,00	0,02	0,00	4,67	2,01	0	0,06	-0,18
1985	0,44	-0,83	0,02	-3,75	0,01	0,06	0,00	3,81	-0,87	0	0,42	0,36
1986	0,47	-0,75	0,02	-4,14	-0,01	0,25	0,00	3,25	-0,56	0	0,43	0,01
1987	0,51	-0,67	0,01	-4,42	-0,00	0,27	0,00	3,51	0,27	0	0,17	-0,26
1988	0,39	-0,95	0,03	-3,45	0,02	0,17	0,01	4,61	1,10	0	0,24	0,07
1989	0,32	-1,13	0,07	-2,67	0,04	0,14	0,01	3,76	-0,85	0	0,17	-0,07
1990	0,26	-1,36	0,11	-2,21	0,04	0,18	0,02	2,84	-0,92	1	-0,17	-0,34
1991	0,36	-1,04	0,10	-2,35	-0,01	0,16	0,02	1,36	-1,48	1	0,19	0,35
1992	0,46	-0,78	0,04	-3,27	-0,06	0,17	0,01	1,86	0,50	1	-0,05	-0,24
1993	0,43	-0,84	0,01	-4,34	-0,02	0,14	0,00	1,60	-0,26	1	0,23	0,28
1994	0,46	-0,79	0,02	-4,12	0,00	0,13	0,00	3,15	1,55	0	0,06	-0,18
1995	0,43	-0,84	0,03	-3,48	0,01	0,16	0,00	2,92	-0,23	1	0,21	0,16
1996	0,42	-0,88	0,02	-3,77	-0,01	0,18	0,00	3,28	0,36	0	0,14	-0,07
1997	0,49	-0,72	0,02	-3,94	-0,00	0,26	0,01	3,71	0,43	0	0,16	0,02
1998	0,38	-0,96	0,03	-3,55	0,01	0,33	0,01	2,47	-1,25	1	0,25	0,09
1999	0,34	-1,08	0,06	-2,85	0,03	0,43	0,03	3,36	0,89	0	0,25	0,01
2000	0,25	-1,38	0,06	-2,84	0,00	0,42	0,02	4,24	0,89	0	-0,13	-0,38
2001	0,22	-1,53	0,16	-1,85	0,10	0,50	0,08	1,72	-2,52	1	-0,17	-0,04
2002	0,30	-1,21	0,22	-1,49	0,07	0,47	0,10	2,06	0,34	1	-0,20	-0,03
2003	0,40	-0,91	0,06	-2,87	-0,17	0,62	0,04	2,80	0,74	1	0,34	0,53
2004	0,59	-0,54	0,02	-3,97	-0,04	0,63	0,01	4,17	1,37	0	0,15	-0,19
2005	0,57	-0,57	0,04	-3,27	0,02	0,71	0,03	3,61	-0,56	0	0,10	-0,05
2006	0,55	-0,60	0,01	-4,56	-0,03	0,74	0,01	4,08	0,47	0	0,21	0,11
2007	0,55	-0,60	0,01	-5,11	-0,00	0,79	0,00	3,96	-0,12	0	0,10	-0,11
2008	0,34	-1,08	0,06	-2,85	0,05	0,95	0,06	1,44	-2,52	1	-0,40	-0,50
2009	0,34	-1,08	0,17	-1,76	0,11	0,85	0,15	-2,11	-3,55	1	0,31	0,71
2010	0,52	-0,66	0,02	-4,08	-0,15	1,21	0,02	4,01	6,12	0	0,12	-0,18
2011	0,45	-0,79	0,02	-4,04	0,00	1,66	0,03	2,83	-1,18	1	-0,05	-0,17
2012	0,45	-0,81	0,02	-4,08	-0,00	1,81	0,03	2,34	-0,49	1	0,17	0,22

Sources:	BRR:	Moody's	BOA:	bn $
	BDR:	Moody's	BDA:	bn $
	GDP:	The World Bank		
	MSCIW:	MSCI		

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