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DEFAULTS AND RECOVERIES IN THE GLOBAL CORPORATE BOND MARKETS

Estimating movements over business cycles

Master's Thesis
in Economics

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1   INTRODUCTION

Corporations and financial institutions need to manage their financial risks to succeed. Some firms accept more financial risks than others, but the risks in both cases should be monitored carefully because of their potential for substantial damage. Risk and the willingness to take risk are, however, essential to the growth of our economy, and therefore a significant part of the every-day business (Jorion 2001, 3–8). This chapter gives a brief introduction to credit markets and the risks involved, initiates the reader into related previous research and discusses the research question.

1.1   Motivation

The recent significantly increased focus on credit risk can be traced in part to the concerns of regulatory agencies and investors regarding the risk exposures of financial institutions through their substantial positions in OTC derivatives and to the rapidly developing markets for price- and credit-sensitive instruments that allow institutions and investors to trade these risks. At a conceptual level, market risk – the risk of changes in the market value of a firm's portfolio of positions – includes the risk of default or fluctuation in the credit quality of one's counterparties. Credit risk, on the other hand, could be said to be a source of market risk. An example is the common practice among broker-dealers in corporate bonds of marking each bond daily so as to reflect changes in credit spreads. More pragmatically, both the pricing and management of credit risk introduces some new considerations that trading and risk management systems of many financial institutions are not currently fully equipped to handle. These are partially the reasons why the demand for professionals in credit risk management has constantly increased (Duffie & Singleton 2003, 1–2).

Assumptions about the conditions that result in default are always present in any discussion involving risky debt. Moreover, in the aftermath of credit crunch but real economy still tumbling, the importance of credit risk management has grown since the number of bonds and loans to default has been increasing continuously. Credit risk, more precisely, affects virtually every financial contract. The measurement, pricing and management of credit risk has received much attention from practitioners with strong interest merely in pricing and managing, financial economists, who have still much to learn how such risk is priced in the market, and bank supervisors, who need to design minimum capital requirements that correctly reflect the credit risk of banks' loan portfolios (Altman, Resti & Sironi 2001, 7).

We know that in recession number of defaulting firms rises but on top of this earlier findings support the view that the average amount recovered on the bonds of defaulting firms tends to decrease. In addition, the market for corporate bonds is growing continuously and issues of lower credit qualities have also risen constantly. As the demand for more comprehensive understanding of credit risk management and pricing is taking place, the importance to understand factors behind them is growing. Thus, the interest in examining credit specific factors has led to discover more these two aforementioned highly important factors – probability of default (PD) and recovery rate (RR).

1.2   Previous research

The aim of this sub-chapter is to initiate the reader into the research of credit risk. More precisely, we go first through the early research of default risk models, move to examine the more subsequent research, from which it is natural to move to discuss the recently published literature of the characteristics of credit, and more accurately, default risk. The emphasis is on the examination of default risk in the viewpoint of corporate bond markets and the relation between default rates and recovery rates. Recent studies in this area, which is used as a proxy for this study, are introduced in the latter part of this sub-chapter.

The first category of credit risk models are the ones based on the framework developed by Merton (1974). Merton used the principles of option pricing models invented by Black and Scholes (1973) in his research. In Merton's framework, the risk of a firm's default is linked to the variability in the firm's asset value. Under the Merton model, including default and recovery at default, the relevant credit risk element is a function of the structural characteristics of the firm: asset volatility and leverage. The Merton model generated a background for the subsequent research of credit risk.

Merton approach has been useful in addressing the qualitatively important aspects of credit risk but less useful in practice. In response to this difficulty, an alternative approach adopts the original Merton framework as far as the default process is concerned but, at the same time, removes one of the unrealistic assumptions of the model i.e. that default   can occur only at maturity of the debt when the firm's assets are no longer sufficient to cover debt obligations. This approach assumes that the default can occur any time between the issuance and maturity of   the   debt. Models include Kim, Ramaswamy and Sundaresan (1993), Hull and White (1995), Longstaff and Schwarz (1995) and others.

The above mentioned second generation models after Merton (1974) are also suffering from significant drawbacks and have thus performed poorly in practice. The attempt to overcome shortcomings of structural-form models gave rise to so called reduced-form models, which do not condition default on the value of the firm like structural-form models. The idea in these models is to assume that an exogenous random variable drives default. These models include contribution from Jarrow and Turnbull (1995), Lando (1998), Duffie and Singleton (1999) and others (Altman, Resti & Sironi 2002, 1–4).

During the recent years, there have been different approaches explicitly modeling and empirically investigating the link between PD and RR. Frye's (2000) evidence indicates a simultaneous increase in default rates and losses given default in 1999–2001. His empirical analysis concludes that in a severe economic downturn, bond recoveries might decline substantially from their normal-year average. Jarrow (2001) presents a methodology for estimating RRs and PDs in both debt and equity prices. In his study, like in Frye's (2000), RRs and PDs are negatively correlated and depend on the state of the economy. Hu and Perraudin (2002) use historical bond market data to examine the dependence between recovery rates and default rates and find evidence of the negative correlation as well.

The latest and presumably most remarkable contribution on the PD-RR relationship is from Altman, Brady, Resti and Sironi (2005). They suggest that since ratings and default rates respond to the cycle, risks increase capital charges and limit credit supply when the economy is slowing (vice versa when the economy is growing at a fast rate). The key findings support statistically the view that default rates and recovery rates are negatively correlated and that the rate of default is a remarkable indicator of the likely average recovery rate amongst corporate bonds. Moreover, Bakshi, Madan and Zhang (2006) suggest that market participants subject to credit risk should not just evaluate the risk of default but also assess recovery rate if default occurs. Their findings are rather technical but comprise some significant comments on specifications and pricing of defaultable securities. Bruche and González-Aguado (2008) use an econometric model to estimate relationship between defaults and recoveries. They found some indicators that default rates and recovery rates are more tightly related to each other than to macroeconomic variables. They also examine the lead-lag relationship between recovery rates and GDP growth in order to study the different phases of the credit and business cycle. These are the findings that I also concentrate on. The aim is thus to utilize global default and recovery data to explain the relationship between these key variables and the business cycle. The model I use also comprises other macroeconomic variables that the earlier research has utilized.

The proxies, rather in the structuring of econometric model, also include the study from Pesaran, Schuermann, Treutler and Weiner (2003). They explicitly link the asset value changes of a credit portfolio to a dynamic global macro econometric model. Their key findings include the view that default probabilities are driven primarily by how firms are tied to business cycle.

This study is mostly influenced by the latest contribution on the relationship between default rates and recovery rates. The basis of these kinds of studies, however, lies behind the structural- and reduced-form models, which are thus important to discuss. The categorization between these models is presented in the following table.

Table 1   Different credit risk models and the treatment of default rate and recovery rate (Altman et al. 2002, 6)

Main Model	Related Empirical Studies	Treatment of Loss Given Default	Relationship Between RR and PD
First generation structural-form models	Merton (1974)	PD and RR are a function of the structural characteristics of the firm. RR is therefore and endogenous variable.	PD and RR are inversely related.
Second generation structural-form models	Kim, Ramaswamy and Sundaresan (1993), Hull and White (1995) and Longstaff and Schwarz (1995)	RR is exogenous and independent fromn 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	Jarrow and Turnbull (1995), Lando (1998) and Duffie and Singleton (1999)	RR is exogenous that is either a constant or a stochastic variable independent from PD.	Separate assumptions on the dynamic of PD and RR, which are modeled independently from the structural features of the firm.
Lates contribution on the PD-RR relationship	Frye (2000), Jarrow (2001), Hu and Perraudin (2002), Altman, Brady, Resti and Sironi (2005), Bakshi, Madan and Zhang (2006) and Bruche and González-Aguado (2008)	Both PD and RR are stochastic variables which depend on a common systematic risk factor such as 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" this derives from the supply and demand of defaulted securities.

Table 1 breaks down the credit risk models to simplify the discussion above. It also summarizes the recent research of default rates and recovery rates that I use as a proxy in this paper.

In addition, the paper is somewhat influenced by the dynamic factor analysis. Cipollini and Missaglia (2007) present a dynamic factor model to analyze a dataset of default rates and macro-variables for Italy. They implement the econometric model and use VAR (vector auto regression) model to analyze the factors affecting on defaults.

1.3   Aim of the study

Recently, the studies of credit risk and more specifically the studies of defaults and recoveries have risen partly due to the increased number of issues in lower credit ratings, which in turn has increased the focus on credit risk management. On the other hand, stricter capital regulations due to Basel II and presumably upcoming Basel III have led in deeper discussions on credit risk management as well. Latest contributions on credit risk models have explored more deeply the relations between default rates and recovery rates, and their joint time-variation over the business cycle in order to better outline the relation between the business and the credit cycle. This thesis reproduces the recent research on this phenomenon and updates the results by using global data from corporate bond markets as the earlier research has merely concentrated on U.S. corporate bond markets.

The goal of this thesis is to go through how the global bond market is functioning and to examine the characteristics of credit risk in this market. I construct a model to estimate the movements of significant factors behind the credit risk (defaults and recoveries mainly) of corporate bonds by using macroeconomic variables. The examination of default rates and recovery rates over business cycles is put into practice by using univariate and multivariate econometric models. I emphasize on examining the lead-lag properties of credit variables, their relationship to each other as well as to macroeconomic variables concentrating particularly on relationship between credit variables and the business cycle (GDP). This study concentrates on examining the expected inverse relationship between default rates and recovery rates over business cycles.

1.4   Structure of the thesis

The rest of this thesis is structured as follows. Chapter 2 discusses the global bond market in general concentrating on corporate bonds. Classification of types of issues and the main risks that are present are covered. These things, although essential in order to further understand how corporate bond market is functioning, are presented relatively briefly. A brief discussion of defaults and recoveries, and high yield bonds concludes section 2.

Chapter 3 begins with discussion about the role of information asymmetries in credit markets. After this, the common tools and ways to measure credit risk are introduced. Last and the most relevant part of chapter 3 presents the appropriate models in the viewpoint of this study and discusses the basics behind credit risk modeling.

Chapter 4 presents the theoretical framework of default rates and recovery rates, and discusses more deeply about the factors affecting on pricing of credit risk. Some common factors usually incorporated in credit risk models are introduced as well. In this context the concept *defaultable bond* is used to emphasize the characteristics of a risky debt instrument i.e. more likely a corporate bond than any other type of bond. Chapter 5 further introduces the dataset used in this study and presents the methodology and methods utilized in empirical part of the thesis. Chapter 6 is empirical and provides conclusions. Chapter 7 summarizes the thesis.

2   GLOBAL CORPORATE BOND MARKETS

Investors all over the world have become increasingly aware of different countries' interest rate movements and their relationship to each other. In addition, many countries have liberalized their bond markets, making them more liquid and accessible to international investors (Fabozzi 2010, 206–209).

There is, however, no uniform system for classifying the sectors of the global bond market, but one possible is as follows:
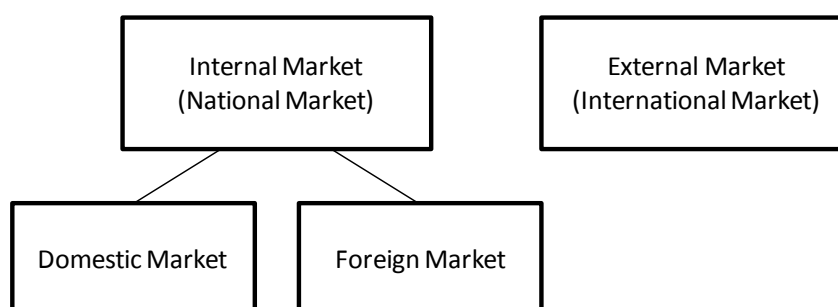
Figure 1   Classification of global bond markets (Fabozzi 2010, 207)

As depicted in figure 1 the global bond market can be classified into two markets: an internal and an external bond market. Furthermore, the internal or national bond market can be decomposed into two parts: a domestic and a foreign bond market. The domestic bond market is where issuers domiciled in the country issue bonds and where those bonds are then traded. The foreign one is where bonds of issuers not domiciled in the country are issued and traded. The external bond market, which is also called international, offshore or Eurobond market, includes bonds that are typically underwritten by an international syndicate, are offered simultaneously to investors in a number of countries at issuance or that are issued outside the jurisdiction of any single country. Another way to classify the global bond market is in terms of trading blocs. The blocs include dollar bloc (United States, Canada, Australia, and New Zealand), European bloc (euro and non-euro zone markets separately), Japan and emerging markets (Fabozzi 2010, 206–209).

Corporate bond market is not as popular among global investors as government bond market because of higher credit risk and lower liquidity. The size of corporate bond market is, however, growing constantly and the increased interest in more efficient credit risk management has lowered barriers for investors to enter the market (Fabozzi 2010, 206–209).

I have discussed above the form of global bond markets. In order to understand the corporate bonds as investment instruments, we have to know about their basic features from issuance to trading in the secondary markets. This chapter covers the most important topics, and gives an introduction to further understand the features of risk specific factors behind the corporate bonds.

2.1   Features of corporate bonds

2.1.1   *Aspects of the issue and primary market*

Corporate debt instruments are financial obligations of a corporation that have priority over its common stock and preferred stock if bankruptcy occurs. Corporate bond is a typical form of corporate debt instrument (Fabozzi 2010, 147). I concentrate here solely on corporate bonds as the nature of this thesis leads to.

Corporate bonds are classified by the issuer's type. The four general classifications according to Fabozzi (2010, 147) are (1) public utilities, (2) transportation, (3) banks/finance, and (4) industrials, although finer breakdowns also exist to make more homogeneous groupings. For instance, public utilities are subdivided into electric power companies, gas distribution companies, water companies, and communication companies. Transportations are divided further into airlines, railroads, and trucking corporations. Banks/finance include both money center banks and regional banks, savings and loans institutions, brokerages, insurance companies, and finance companies. Industrials are the most heterogeneous of the groupings and often include manufacturers, mining companies, merchandising, retailers, energy companies, and service-related industries.

As an instrument, corporate bond is relatively simple. The corporate issuer promises to pay an agreed percentage of par value (coupon payments) on designated dates and to repay par or principal value of the bond at maturity. Failure to pay either the principal or interest on due date constitutes legal default, and investors can go to court to enforce the contract. Bondholders have prior legal claim over common and preferred stockholders (Fabozzi 2010, 147).

The promises of corporate bond issuers and the rights of investors who buy the bonds are detailed in contracts called *bond indentures*. However, these indentures are often specified in such a great detail that the bondholders (investors) would have great difficulty to follow up that the corporate issuer were keeping all the promises from time to

time. That is why the third party, the corporate trustee, exists in the contract. The indenture is made out to the corporate trustee as a representative of bondholder's interest i.e. a trustee acts in a fiduciary counterparty for investors who own the bond issue (Fabozzi 2010, 148).

Corporate bonds may be either secured or unsecured. In the case of bond issue, a typical way to provide security beyond the issuer's general credit standing is to offer either pledged real property or personal property. Real property refers to the case where bondholders are secured with a legal right to sell the mortgage property to satisfy unpaid obligations to them. These bonds are often called *mortgage bonds*. However, some companies do not own fixed assets or other real property and so have nothing on which they can give a mortgage lien to secure bondholders. Instead, they will pledge stocks, notes, other bonds or whatever kind of obligations to satisfy the desire of bondholders for security. These assets are termed collateral and thus the bonds secured this way are called *collateral trust bonds*. Debt securities that are not secured by a specific pledge of property are called *debenture bonds*. Debenture bondholders have the claim of general creditors on the assets that issuer not pledged specifically to secure other debt. They, however, have a claim on pledged assets that have more value than necessary to satisfy secured creditors. Debenture bonds rank thus after secured debt but subordinated debenture bonds only after some general creditors. The superior legal status of any debt security will not prevent bondholders from suffering financial loss when the issuer's ability to pay its obligations is seriously eroded, as will be noticed later on. (Fabozzi 2010, 148–149).

2.1.2   *Private placement market*

Securities privately placed are issued in transactions that do not involve a public offering. The nature of this market varies slightly between U.S. and Europe although fundamentals are the same. The private-placement market in the U.S. has undergone a vast change since the adoption of SEC Rule 144A in 1990, which allows the trading of privately placed securities among qualified institutional buyers. However, not all the privately placed corporate bonds are under the Rule 144A. Hence, the private placement market can be divided into two sectors. The first one is the traditional private-placement market and the second one is for 144A securities. The features in the issues under the Rule 144A are similar to those of publicly issued bonds as the restrictions imposed on the borrower are less onerous than for traditional private-placement issues. The size of the offering is also comparable to that of publicly offered bonds. This special feature in

the U.S. corporate bond market makes the private-placement market more liquid than it is for instance in the Europe. Although the liquidity in the U.S. corporate bond markets for privately placed securities has increased since the Rule 144A became effective, it is still not comparable to that of publically offered issues. Yields on privately placed debt issues are still higher than those in the public market (Fabozzi 2010, 166).

Unlike publicly issued bonds, the issuers of privately placed bonds tend to be less well known. The private-placement market thus shares a common characteristic with the bank loan market. In addition, borrowers in the publicly issued bond market are typically large corporations whereas in the privately issued bond market they tend to be medium-sized corporations. Furthermore, corporations that borrow just from banks tend to be more usually small corporations (Fabozzi 2010, 166). In this study I concentrate on publicly issued corporate bonds and therefore the default rate data consist of the defaults of large companies. The same applies, naturally, to the recovery rate data.

2.1.3   Secondary market

The secondary market is the market where securities that have been issued earlier are traded. Secondary trading of stocks occurs at several trading locations as centralized exchanges and the over-the-counter (OTC) market. Centralized include the major national stock exchanges as New York Stock Exchange (NYSE) and Frankfurt Stock Exchange (part of the Deutsche Borse Group). The OTC market is a geographically diversified group of market makers linked to one another via telecommunication systems. The secondary market for bonds throughout the world is quite different from those for stocks. The secondary bond markets are not operating in centralized exchanges but they are mainly operating in the OTC market. It is a network of non-centralized or fragmented market makers, each of which provides bids and offers for each of the issues in which they participate. Hence, investor's buy or sell is conducted with an individual market maker at his quoted price, which does not emanate from any centralized organization such as an exchange (Fabozzi 2010, 10–11).

As with all other bonds as well, the principal secondary market for corporate bonds is the OTC market. As the major concern in the OTC is the market transparency, the credit risk is well presented.

Traditionally, corporate bond trading in the OTC market has been conducted via telephone and based on broker-dealer trading desks. However, there has been a transition away from this traditional form of bond trading towards the electronic trading. Electronic trading has brought many advantages to this traditional market such as (1)

improved liquidity to the markets, (2) price discovery (particularly for less liquid markets), (3) use of new technologies, and (4) trading and portfolio management efficiencies (Fabozzi 2010, 164–165).

The data used in empirical analysis comprise only bonds traded in the secondary market. Recovery rates thus reflect the market price for a bond after the default.

2.2   Introduction to risk of default

2.2.1   Main risks in the corporate bond markets

When discussing the corporate bonds it is important to break down the risks faced by financial institutions and companies to own categories:

1. Market risk – the risk of unexpected changes in prices or rates.
2. Credit risk – the risk of changes in value associated with unexpected changes in credit quality.
3. Liquidity risk – the risk that the costs of adjusting financial positions will increase substantially or that a company will lose access to financing.
4. Operational risk – the risk of fraud, systems failures, trading errors and many other internal organizational risks.
5. Systemic risk – the risk of breakdowns in market wide liquidity or chain reaction default.

More accurately, credit risk is the risk of default or of reductions in market value caused by changes in the credit quality of issuers or counterparties. The nature of this thesis leads us to concentrate mostly on credit risk since it is a dominant factor in the corporate bond market (Duffie & Singleton 2003, 2–4).

The reasons to track credit risk lie behind the systems in credit markets. Two important market imperfections, *adverse selection* and *moral hazard*, imply that there are additional benefits from controlling counterparty credit risk and limiting concentrations of credit risk by industry, geographic region etc. For example, a proposed increase in the exposure to a given counterparty is either declined or approved. The decision made by the seller or a buyer of a single contract in this context is ultimately dependent on the information and view of how creditworthy the object of a contract in each separate case

is estimated to be. More precisely, the information asymmetries underlying bilateral financial contracts elevate quality pricing to the front line of defense against unfavorable accumulation of credit exposures. If the credit risks in a contract are not appropriately priced into a deal, then a trading desk (the seller or a buyer of a contract in this case) will either be losing potentially or accumulating credit exposures without full compensation for them. The case is similar in a simple lender-borrower example in the corporate credit market where borrowers with varying default risks simultaneously seek credit, often without meaningful distinguishing signals. Hence, there is a risk that lenders may be incapable of sorting borrowers out. In the imperfect credit markets the problem of *asymmetric information* plays an important role and thus the price of a single contract is heavily dependent on the creditworthiness of a borrower (Duffie & Singleton 2003, 2–4; Besanko & Thakor 1986).

The information systems necessary to quantify most forms of credit risk differ notably from those appropriate for more traditional forms of market risk, such as changes in the market prices or rates. Among broker-dealers market values of open positions should be re-marked each day, and the underlying price risk can be offset over relatively short time periods, measured in days or weeks. For credit risk, however, offsets are not often as easy. The credit risk on a given position frequently accumulates over longer time horizons. In addition to this distinction, there are important methodological differences between credit risk and market price risk. The ultimately necessary information to estimate credit risk, such as the likelihood of default of counterparty, and the extent of loss given default (LGD), is typically very different and obtained from different sources, than the information underlying market risk, such as price volatility. The only exception in this case is a highly liquid corporate bond. The risk of changes in the spreads is very dependent on credit risk, which is also more directly captured through yield-spread volatility measures (Duffie & Singleton 2003, 2–4; Besanko & Thakor 1986).

Going a little bit deeper in the specifications of credit risk, we recognize three main variables affecting the credit risk: (1) the probability of default, (2) the loss given default, which equals one minus the recovery rate in the event of default, and (3) the exposure at default. Significant attention has been devoted by the credit risk literature to the estimation of the first component (PD), which is a function of default rate (DR) (Altman et al. 2001, 7). As much less attention has been paid to the estimation of RR and to the relationship between DR and RR, it is natural for us to take this relationship under examination.

To understand the factors behind the probability of default and recovery rate, the concept default rate has to be examined. Default rate is calculated from annual default counts.
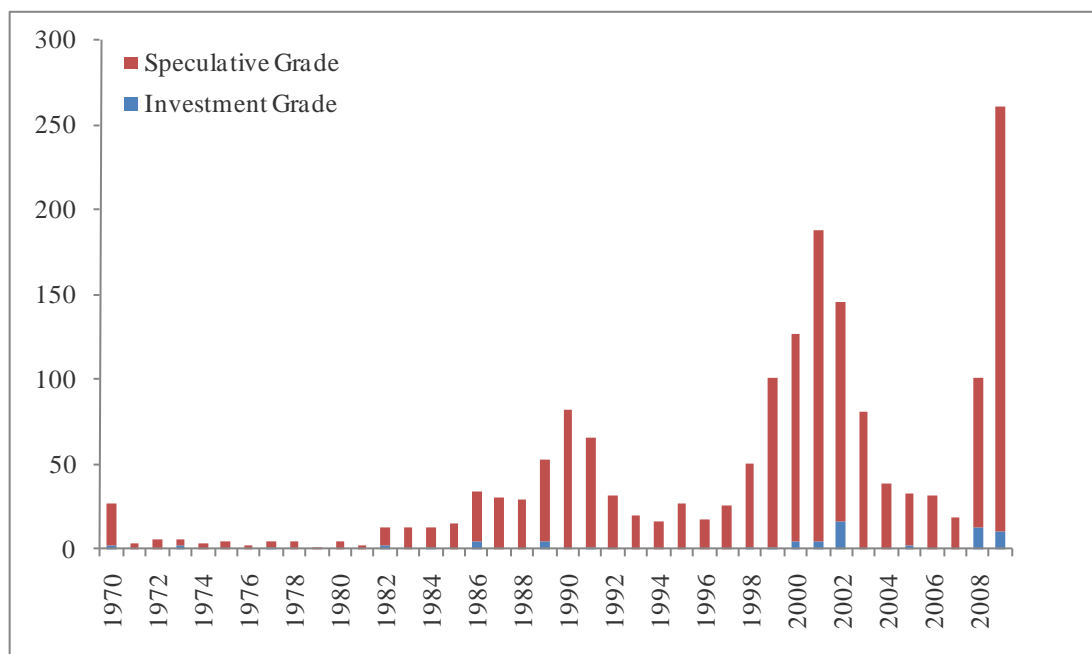
Figure 2   Annual global corporate issuer default counts during 1970–2009

Figure 2 plots the annual default counts of corporate issuers between 1970 and 2009. Issuers are broken down by their credit quality i.e. they are classified in investment-grade category and high yield (speculative-grade) category. All the bonds issued by companies below a certain credit rating belong to the speculative-grade category. The breakdown between rating categories and the probabilities of default regarding are, however, explained more detailed later on. Data are retrieved from Moody's database. In the figure we clearly see periods with higher default counts from time to time. This is due to recession eras in the 1970s, during the savings-and-loan crisis initiated by the Black Monday in late 1980s and early 1990s, and in the aftermath of so called IT bubble in early 2000. Relatively high default counts can be observed after the Asian financial crisis of 1997 as well. Recent peaks in defaults are caused by the credit crunch, whose most deteriorating effects to default counts were seen in 2009.

Default rates are, naturally, calculated from default counts and are thus a significant factor in credit risk modeling. In this thesis, the data of default rates are utilized in the empirical part and are a vital factor in my model structuring.

2.2.2 High-yield sector

When discussing the aspects of default risk, high-yield bonds are more commonly taken into account than investment-grade bonds. The reason is that the probability of default for high-yield bonds is more than for investment-grade bonds. The aspects related to this riskier sector are discussed in this sub-chapter.

As will be analyzed more specifically in subsequent parts of the study, high-yield bonds or more commonly called junk bonds are issues with credit ratings below BBB- or Baa3, depending on the credit rating agency. Issues in this sector may have been rated investment grade (BBB- or Baa3 and above) at the time of issuance and have been downgraded subsequently to non-investment grade. Alternatively, they may have been rated non-investment grade at the time of issuance when they are called *original-issue high-yield bonds.* Bonds that have been downgraded to non-investment grade fall into two groups: (1) issues that have been downgraded as the issuer voluntarily significantly increased their debt as a result of a leveraged buyout (LBO) or a recapitalization, and (2) issues that have been downgraded for other reasons. Latter ones are usually called *fallen angels* (Fabozzi 2010, 159).

In the early years of the junk bond market, all the issues had a conventional structure i.e. the issues paid a fixed coupon rate and were term bonds. Today the structures are more complex, particularly for bonds issued for LBO-financing and recapitalizations producing higher debt. This stems from the heavy payment burden that the corporation assumes from high risk premiums and the ways they try to reduce this burden (Fabozzi 2010, 159–160).

Historically, the promised yields offered on high-yield bonds have been significant as can be seen in the following graph.
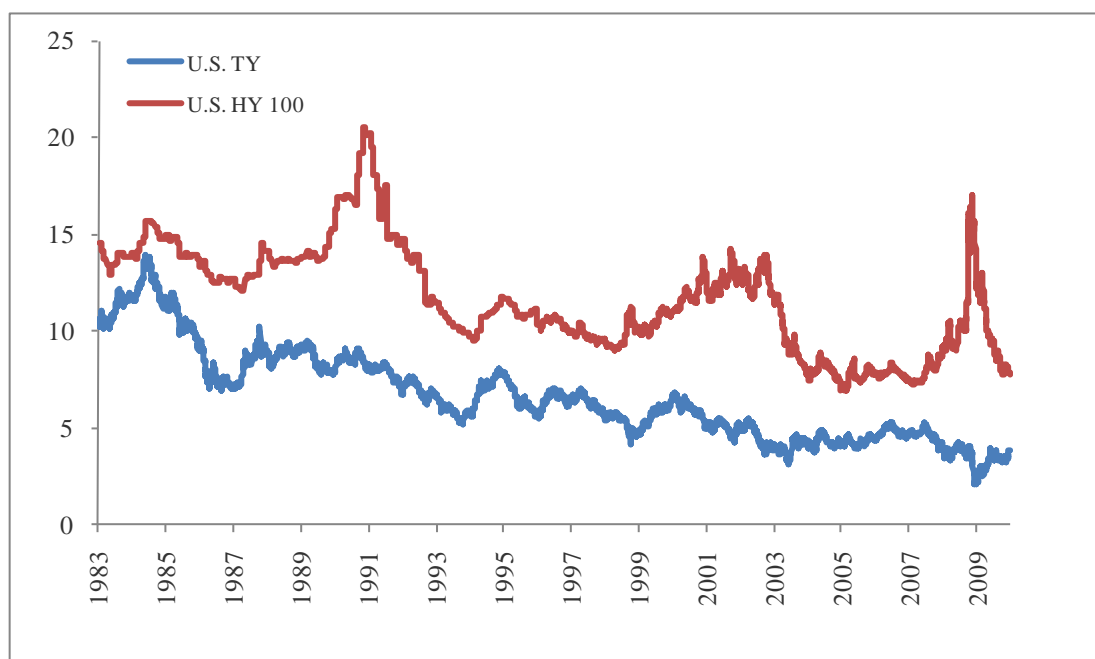
Figure 3   Yields on U.S. high-yield bonds compared to yields on U.S. treasury
                bonds during 1983–2009

Figure 3 depicts the promised yield spread of U.S. high-yield bonds over 10-year Treasury securities[1]. The data for high-yield bonds consist of 100 largest companies in the U.S. high-yield sector. Both time series are retrieved from Datastream. As can be seen, the promised yield spread has been varying significantly during the period. The yield spread reached the top in 1990 and 1991 when it was well over 1 200 basis points. Another period with vast spreads was during the IT-bubble when the promised yield spread reached nearly 1 000 basis points. However, the period with great uncertainty and even more significant yield spreads was yet to come, as the fatal consequences of subprime crisis began to take over. During the post-Lehman era[2] the yield spreads were over 1 000 basis points regularly and the top, nearly 1 380 basis points, was reached in late 2008. The annual average of the Treasury bonds was more than 674 basis points during the period as for high-yield bonds it was more than 1 174 basis points.

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[1] The yield to maturity is a measure of the promised yield because it assumes that the security is held to maturity, coupon payments can be reinvested at the computed yield to maturity, and the issue does not default. Thus, the difference between two promised yields is a promised yield spread.

[2] One of the traditional U.S. investment banks, Lehman Brothers Holdings Inc., went into bankruptcy 15 September 2008 and is still the largest bankrupted company ever. The term post-Lehman era has been implemented to describe the financial markets after the incident.

But are the promised yield spreads similar to the above presented justified by the higher potential default rate for high-yield corporate bonds? This question has been investigated extensively. Most of the research on the junk bond sector concentrates on default rates. From an investment perspective, default rates by themselves are not of paramount significance as it is perfectly possible for a portfolio of high-yield bonds to suffer defaults and to outperform Treasuries at the same time, provided that the yield spread of the portfolio is sufficiently high to offset the losses caused by defaults. Furthermore, as holders of defaulted bonds typically recover a portion of the par value, the default loss rate is lower than the default rate (Fabozzi 2010, 162–163).

3   ECONOMICS OF CREDIT RISK

This chapter gives an introductory presentation to the nature of credit risk and the aspects that need to be known in order to further understand how dominant factor credit risk really is in corporate bond markets. First I go through the essential phenomenon in the credit markets in general. That is the information asymmetry. After that I turn to discuss how the credit risk is measured. The last part of this chapter presents the basics of credit risk models, demonstrates the relevant models in the viewpoint of this study, and discusses the challenges in credit risk modeling.

3.1   The role of information asymmetries

3.1.1   *Adverse selection in credit markets*

Getting first back to the simple lender-borrower example introduced in the first chapter, and making an assumption that the borrower is in most cases more aware of its credit risk than the lender (say a bank), it may be profitable for lender to limit borrower's access to the bank's credit. There would be no point allowing borrower to select the size of its loan without restrictions (Duffie & Singleton 2003, 26).

    Another option would be to increase borrower's interest rate or to schedule the interest rates so that they would increase with the size of the loan. This would, however, have unintended consequences. A disproportionate fraction of borrowers willing to pay higher interest rate on a loan are privately aware that their own poor credit quality makes even the high interest rate attractive. An interest rate high enough to compensate for this adverse selection could mean that almost no borrower finds a loan attractive and that the bank would eventually do little or no business at all. Depending on the variation in credit risk over the borrowers, it usually would be more effective to limit the access to credit. This dilemma is considered as *market for lemons* and even though adverse selection can still occur to some extent, the bank can earn profits on average, depending on the distribution of default risk and private information of borrowers. Thus we expect that credit limits for companies should be based on information available on credit quality. For example, better-rated counterparties should have higher limits than worse-rated ones (Duffie & Singleton 2003, 26–27).

An analogous asymmetry of credit information exists in the over-the-counter (OTC) market, where for example counterparty A is typically better informed about its own credit quality than about the credit quality of counterparty B. Likewise, naturally, B usually knows more about its own default risk than about the default risk of A. By the same reasoning described above for loans, A may wish to limit the extent of its possible exposure to default by B. The case is similar with B towards A (Duffie & Singleton 2003, 26).

3.1.2   Moral hazard

> *Within banking circles, there is a well-known saying: "If you owe your bank $ 100 000 that you don't have, you are in big trouble. If you owe your bank $ 100 million that you don't have, your bank is in big trouble"*(Duffie & Singleton 2003, 28).

This common phrase reflects well the usual situation in the credit markets. One of the reasons that large loans are riskier than small ones is that they provide incentives for borrowers to undertake riskier behavior, other things being equal of course. A typical example is the U.S. savings-and-loan crisis of the 1980s. The crisis was namely a consequence of giving savings-and-loan institutions access to extensive credit through federal deposit insurance, while at the same time not enforcing sufficient limits on the riskiness of savings-and-loan investments. That resulted to the situation, where some savings-and-loan owners took on highly levered and risky portfolios of long-term loans, mortgage-backed securities and other risky assets. If these "investments" turned out badly, as in many cases the situation was, and if savings-and-loan institutions failed as a result, its owners walked away (Duffie & Singleton 2003, 28).

Limiting the access to credit is identically a defense against moral hazard induced by large loan offerings to risky borrowers. Large borrowers are often in a better bargaining position and can therefore extract more favorable terms for bankruptcy or restructuring than small borrowers, when the default occurs. This could reduce the profitability of larger loans, putting aside fixed costs for setting up loan arrangements. As in this case of borrower-lender, a derivatives broker-dealer may wish to limit the extent of credit exposure for certain counterparties (Duffie & Singleton 2003, 29; Hoff & Stiglitz 1990, 235–250).

3.2 Measuring credit risk

Credit risk measurement has developed dramatically over the recent decades in response to a number of important reasons that have made its measurement more important than ever before. Among these reasons have been (1) a worldwide structural increase the number of defaults and bankruptcies, (2) a trend towards disintermediation by the highest quality and largest borrowers, (3) more competitive margins on loans, (4) a declining value of real assets (and collateral) in many markets and (5) a dramatic growth of off-balance-sheet instruments with inherent credit risk exposures.

In response to this academics and practitioners have responded by (1) developing new and more sophisticated credit scoring systems, (2) moving towards developing measures of credit concentration risk such as the measurement of portfolio risk of fixed income securities (instead of just analyzing individual loans and securities), (3) developing new models to price credit risk and (4) developing models to measure better the credit risk of off-balance-sheet instruments (Altman & Saunders 1997, 1).

3.2.1 Reasons to measure

Referring to the problem of asymmetric information i.e. the problem of adverse selection and moral hazard, there are additional benefits of controlling counterparty credit risk and limiting concentrations of credit risk by industry, geographic region, and so on. Risk managers have explored several measures of credit risk to better understand the nature of their exposures to credit risk. These include: (1) market value of default loss and (2) exposure. The first one refers to reliable estimates of the impact of credit risk on fair market values. This furthermore contributes to the accuracy of pricing and profitability of making markets. This information is also very useful for financial institutions when they determine liquidity buffer for default losses. The latter one refers to the loss that occurs in the event of default. Accordingly, the exposure to a given counterparty equals the amount of money lost if the counterparty in question defaults (Duffie & Singleton 2003, 38).

The use of these specialized measures varies through financial institutions, also depending on the nature of credit-sensitive business. For example, investment banks or institutions in general emphasizing trading set counterparty exposure limits based on estimates of future potential credit exposures of derivatives positions. In contrast, traditional banks focusing primarily on direct lending have tended to view credit risk more from the aspect of current credit granted. These policies and measures, and especially

how different types of financial institutions implement them, have been recently criticized by decision makers and many practitioners, who have been arguing that distinction between investment banks and regular banks has continuously blurred.

3.2.2   Tools to measure

Policies and systems for credit risk management and measurement in financial institutions and companies are developed by senior managers, credit managers and their research staffs. According to Duffie and Singleton (2003, 29) the key ingredients of credit risk pricing and risk measurement systems include: (1) the source of risk (the risk factors) to be examined and their joint probability distribution, and (2) methodologies for measuring changes in credit quality and default over a large set of counterparties. The outline is illustrated in figure 4.
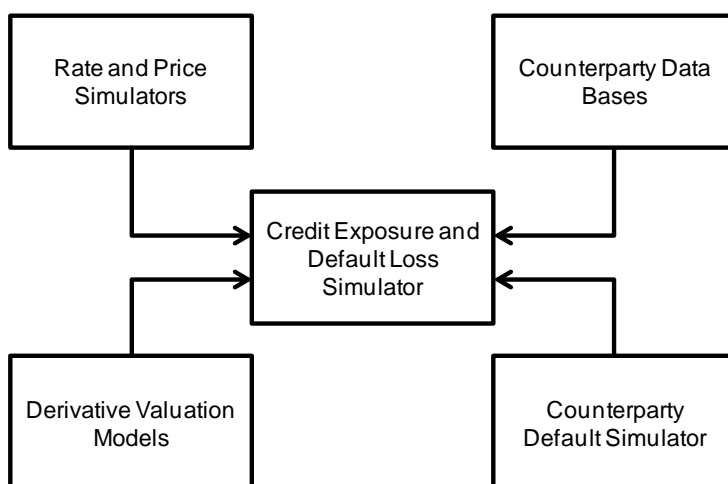
Figure 4   Key elements of pricing and measurement systems for credit risk (Duffie & Singleton 2003, 29)

The box labeled *Counterparty Data Bases* represents a dataset of portfolio positions, including the contractual definitions of each position (derivative, bond etc.) as well as its collateralization and netting arrangements. One needs the contractual definitions of each position in order to mark it to market. Furthermore, the more challenging part of this is to organize information related to credit risk, including details regarding collateral and netting arrangements. The box labeled *Counterparty Default Simulator* states the effect of default and credit-rating transition risk for a single counterparty and the correlation of default and transition risk among multiple counterparties. *Rate and Price*

Simulators states the market-risk-part of the measurement, and *Derivative Valuation Models* includes the efficient estimation of the responses of the market values of derivatives positions to changes in underlying prices and rates and to changes in credit quality, including default (Duffie & Singleton 2003, 29–30).

The exact tools to quantify the credit risk are discussed briefly in the following to get better view of the background models developed, in order to better understand the nature of credit risk measurement. Firstly, CreditMetrics[3] approach is based on credit migration analysis, i.e. probability of moving from one credit quality to another, including default, within a given time horizon, which is often taken as one year. CreditMetrics models the entire forward distribution of the values of any bond or loan portfolio. For example, in a one-year forward framework, where the changes in values are related to credit migration only and interest rates are assumed to evolve in a deterministic fashion. Credit-Value-at-risk of a portfolio is then derived in a similar fashion as for market risk as it is simply the percentile of the distribution corresponding to the desired confidence level. Secondly, there is a credit risk methodology called KMV's methodology[4], which differs somewhat from CreditMetrics as it relies upon the "Expected Default Frequency", or EDF, for each issuer, rather than upon the average historical transition frequencies produced by the rating agencies, for each credit category. Thirdly, methodology called CreditRisk+[5] focuses only on default and assumes that default for individual bonds or loans follows a Poisson process. Credit migration risk is not explicitly modeled but this methodology allows for stochastic default rates which partially account for migration risk. Finally, the methodology called CreditPortfolioView[6] measures only the default risk as well. It is a discrete time multi-period model where default probabilities are a function of certain macro-variables such as interest rates, growth rate in the economy and so on (Crouhy et al. 2000, 61).

Currently it seems that any of these aforementioned models can be considered as a reasonable internal model to assess credit risk for straight bonds and loans without op-

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[3] A methodology based on the estimation of the forward distribution of the changes in value of a portfolio of loan and bond type products at a given time horizon (usually a year).

[4] KMV is a trademark of KMV Corporation founded by Stephen Kealhofer, John McQuown and Oldrich Vasicek. KMV methodology is a tool for quantitative credit risk analysis and nowadays part of Moody's.

[5] Developed by Credit Suisse and launched in 1997, CreditRisk+ is a methodology for calculating the distribution of possible credit losses from a portfolio.

[6] A multi-factor model which is used to simulate the joint conditional distribution of default and migration probabilities for various rating groups in different industries, for each country, conditional on the value of macroeconomic factors like the unemployment rate, the rate of growth in GDP, the level of long-term interest rates, foreign exchange rates, government expenditures and the aggregate savings rate.

tion features. Hence, these models are inappropriate to measure credit risk for swaps and other derivative products. In order to measure the credit risk of derivatives, the model has to allow at least for stochastic interest rates, and possibly default and migration probabilities which depend on the state of the economy, e.g. the level of interest rates and the stock market (Crouhy, Galai & Mark 2000, 61–62).

These elements partially lead thinking that credit risk should be treated as part of the market risk. The measurement of credit risk, however, further sets its own challenges. Many credit-sensitive instruments are relatively illiquid, remain on a firm's books for a long time, and cannot be reliably marked to market as already stated in the first chapter.

3.3   Credit risk modeling

Credit risk models are mainly used to measure, monitor and control a portfolio's credit risk but also in fixed-income analysis in the pricing of credit risky debt instruments. Models are classified, as I have earlier shown, into structural models or reduced-form models. The debate as to which type of model is the best to employ has been considerable during recent years and actually these two main models have laid the background for the more specific research on relationship between recovery rates and default rates (Fabozzi 2010, 497).

3.3.1   Overview of credit risk modeling

Credit risk modeling is used empirically for (1) estimating the default probability, (2) pricing individual corporate bonds, or (3) measuring a portfolio's credit risk. The probability of default is the likelihood that a borrower will default sometime over the life of the debt obligation. Default means that the borrower fails to honor the terms of agreement, such as the failure to pay a principal or a coupon payment required under the agreement. The violation of a covenant also usually leads to default. In practice it is common to look at the default over the next one year. The default probability is sometimes referred to as an *expected default frequency* as well (Fabozzi 2010, 499).

A fair value for the credit spread for an illiquid or mispriced corporate bond with for instance a given credit rating can be estimated with a credit model and observed market prices for corporate bonds and/or credit derivatives. This credit spread is often referred to as the *fair market credit spread*. The fair market credit spread is then used for pricing other credit risky assets with similar characteristics (Fabozzi 2010, 499).

Measuring a certain portfolio's credit risk requires a model for linking the defaults of corporate bonds. Structural models, which were discussed briefly already in the introductory part of the thesis, are often used for assessing the credit risk of an individual company, but in credit risk management the term *default correlation* is used when assessing the credit risk of an entire portfolio (Fabozzi 2010, 506). However, I do not go much further as these techniques are not that relevant in the viewpoint of this study as the focus is more on econometric modeling, considering factors important in fixed income securities' markets. More sophisticated models are relevant in the viewpoint of further studies.

3.3.2   Relevant models

In the viewpoint of this thesis and econometric modeling it is not at utmost importance to discuss just the traditional credit risk models. Therefore, the focus here is on going through some of the econometric based models used earlier in macroeconomic-variable and credit-variable modeling.

As mentioned by Pfaff (2008, 1), multivariate data analysis in the context of vector autoregressive models (VAR) has evolved as a standard instrument in econometrics. As statistical tests are frequently used in determining inter-dependences and dynamic relationships between variables and VAR models explain the endogenous variables solely by their own history apart from deterministic regressors, this methodology has become very popular in econometric modeling with macroeconomic variables. Business cycle modeling has been also used broadly since the early 80's by modeling with standard univariate models such as autoregressive moving average (ARMA) models and autoregressive integrated moving average (ARIMA) models (Hamilton 1989, 357).

Altman et al. (2005) as well as Bruche and González-Aguado (2008) concentrate on econometric credit risk modeling in their papers. I have also used the models applied in these studies as proxies for this study. Both of these studies concentrate on examining the link between default rates and recovery rates by using econometric models.

Specifications by Altman et al. (2005) include both the univariate model and multivariate model. The univariate regression analysis consists, however, of the analysis of bivariate regressions between recovery rates and default rates and the aim is to explain recoveries with different explanatory variables separately. Authors do not concentrate on examining lead-lag properties as the methodology used is just a normal regression analysis. Authors do not ask whether the recoveries could explain default rates, either. The multivariate analysis also consists of normal regression analysis and the focus is on

explaining recoveries with several macroeconomic variables. This standard approach is rather straightforward when incorporating several variables in the same model. In this thesis, in turn, the focus is on VAR models in the multivariate analysis and thus, in order to keep the approach rather simple, models with four or more variables have not been implemented.

Bruche and González-Aguado (2008), in turn, use somewhat more complicated econometric models. They do not use just VAR model to examine causal relationships between variables, but incorporate a two-state Markov chain in order to determine the state of the credit cycle. This approach is rather interesting and a possible way to extend the model specification in further study. The Markov model of trend is a probit model, where the economy can either be in either state 1 or state 0. If the economy is in state 1 it will remain in this state with a probability of p and further move into state 0 in the next period with probability $1 - p$. If it is in state 0, it will remain in this state with probability q and move into state 1 with probability $1 - q$. Given the state of the credit cycle, the number of defaulting firms is then drawn using a state-dependent default probability. This methodology captures trends more efficiently than plain autoregressive models would do and thus it is sometimes used in credit risk modeling as well as in business cycle modeling[7].

Pfaff (2008) shows in his study, how VAR, structural vector autoregressive (SVAR) and structural vector error correction (SVEC) models can be utilized with macroeconomic time series in order to find causality between variables. He also implements impulse response functions in order to examine responses of different variables to economic shocks. VAR models and impulse response analysis are also utilized in this study. On the other hand, SVAR and SVEC could be relevant models to utilize in further studies.

3.3.3 Challenges in credit risk modeling

To quantify the interest rate risk exposure for a specific bond portfolio is less complicated than modeling credit risk exposure. The following reasons tell us why (Fabozzi 2010, 498):

1. Credit default risk is a rather rare event and the historical data needed to compute the inputs into credit risk model (e.g. default and recovery rates) are considerably

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[7] See for example Hamilton (1989).

less in comparison to the data available for the modeling of interest rate risk. For instance, historical U.S. Treasury bill prices are available on a daily basis but recovery rates might be on a yearly basis. This is exactly the case with my and earlier researchers' datasets as well.

2. Even with the default data that are available, it is difficult to draw meaningful and predictive conclusions about the probability of default because of the diversity of the corporations involved and the lack of complete information regarding corporate practices.

3. There are various causes of default by a corporate borrower ranging from microeconomic factors such as poor management to macroeconomic factors such as recession. This makes defaults difficult to predict and therefore research has divided into microeconomic and macroeconomic perspective.

Moreover, default is not a universal concept which brings more challenges to my research methodology as well. Every country has its own bankruptcy code to deal with defaults so analyzing the global data on a micro-level would be complicated. This would mean the analysis of, for example, both a specific U.S. entity and a specific European entity and the factors affecting on their probability of default. These matters bring some constraints to my econometric model structuring as well but are not as distinct when modeling on macroeconomic level.

4   THEORY OF DEFAULTABLE BONDS

This chapter gives a theoretical background for default risk in the corporate bond markets. I discuss the factors that affect on the pricing of corporate bonds, and those that are usually incorporated in the default risk models. The concept of default rate and recovery rate are discussed. After that I turn to discuss the probability of default. The last sub-chapter discusses the rationale behind credit ratings and briefly the cyclical nature of credit ratings and default rates. The aim is to examine the link between default rates and recovery rates from the viewpoint of corporate bond portfolio and thus the joint time-variation of these variables is under review. The focus is on defaults and recoveries, not that much on expected loss or the worst possible outcome. This is the reason why I do not necessarily have to discuss the credit VaR (value-at-risk) or why I do not concentrate only on default rates.

4.1   Default rates

In the event of default, a company cannot meet its liabilities. Default is not necessarily the same thing as bankruptcy, although usually a company that defaults is likely to fall. Default rate further stands for a rate at which debt holders default on the amount of money that they owe. It typically refers to the rate at which corporations default on their loans. For example if there are 100 corporations in the markets that each have issued a corporate bond, and 10 out of those default during a year, the default rate ends up to be 10%. I earlier depicted in chapter 2 the annual default counts of global corporate bonds. The following graph illustrates the annual default rates in the same market.
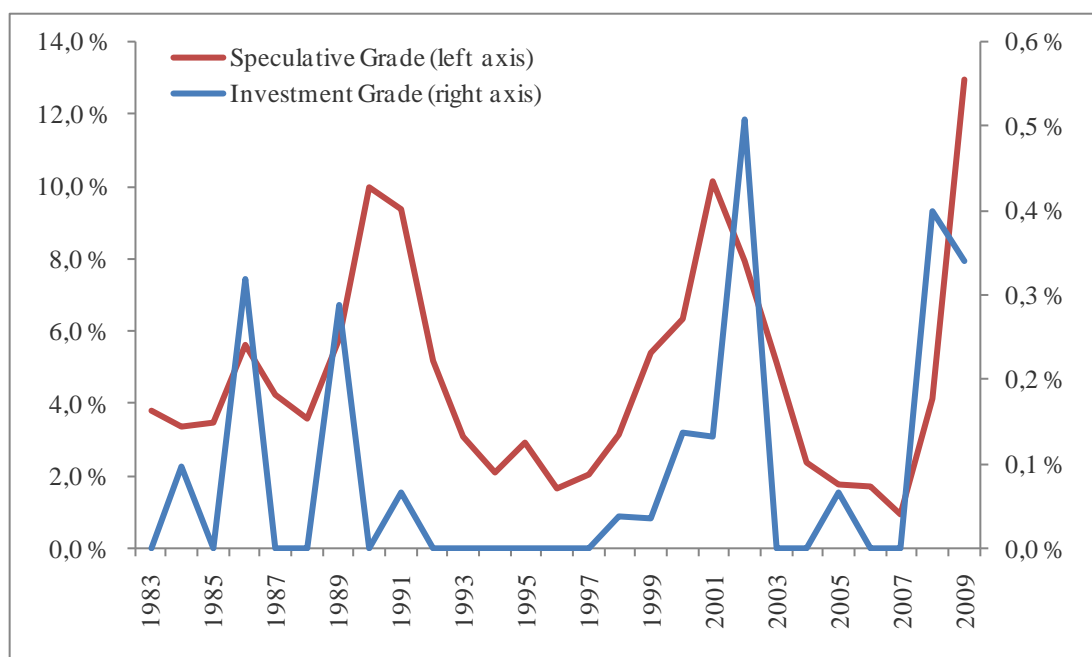
Figure 5   Annual global corporate issuer default rates during 1983–2009

Figure 5 depicts the annual defaulted issues each year from 1983 to 2009 for all corporate bonds broken down by their original rating for investment-grade (right axis) and speculative-grade bonds (left axis). Data are retrieved from Moody's database. As expected, a higher percentage of defaults are for speculative grade rated bonds. We also clearly see again that default rates have cyclical effects as relatively high default rates can be obtained both during 1989–1991 and 2000–2002. Historically highest default rates so far were seen in 2009 when the world economy experienced its deepest recession since 1930's. Theoretically, it is assumed that amount of defaults rise (decline) when economy shrinks (booms). High yield bond market is also usually the market where the most defaults occur. To examine the default rates in more specific breakdowns I have categorized the cumulative default rates by investment-grade and speculative-grade rated bonds. Cumulative default rate comparison is for up to 10 years. The data are retrieved from Moody's database.

Table 2   Average cumulative default rate by rating category during 1983–2009

Category	Horizon (years)									
	1	2	3	4	5	6	7	8	9	10
Investment Grade	0.07	0.23	0.44	0.67	0.92	1.15	1.38	1.60	1.80	2.01
Speculative Grade	4.35	8.92	13.37	17.32	20.69	23.70	26.39	28.69	30.71	32.52

Table 2 shows the estimated cumulative default rates after a given number of years following the origination of a corporate bond. The data are computed from the period of

1983–2009. The cumulative default rates are from one to 10 years. For example, an average proportion of speculative-grade rated bonds that defaulted 10 years after origination was 32.52% during 1983–2008.

To evaluate the performance of the corporate bond sector, more than just default rates have to be taken into account. The reason is that just default rates are not of paramount significance. It is possible for a portfolio of corporate bonds to suffer defaults and to outperform risk-free interest rate at the same time, provided the yield spread of the portfolio is sufficiently high to offset the losses from default. Furthermore, holders of defaulted bonds typically recover a percentage of the face value of investment. It is called the recovery rate as pointed out earlier in chapter 2. Therefore it is important to study the relation between default rates and recovery rates and an important measure in examining the performance of the corporate bond sector, the *default loss rate*, is important to take into account as well. It is defined as follows:

$$\text{Default loss rate } (DLR) = \text{Default rate} \times \left[100\% - \text{Recovery rate} \right] \qquad (4.1)$$

For example, a default rate of 2% and a recovery rate of 40% produce a default loss rate of only 1.2%. Thus focusing only on default rates merely highlights the worst possible outcome that a diversified portfolio of corporate bonds would suffer, assuming no recovery for defaulted bonds (Fabozzi 2010, 155–158).

4.2   Recovery rates

As a background for the specification of recovery rate we assume that a random company goes bankrupt. When the bankruptcy occurs, those that are owed money by the company file claims against the assets of the company. There may be a reorganization in which these creditors agree to a partial payment of their claims. In other cases the assets are sold and the proceeds are used to meet the claims as far as possible. Some claims, in addition, typically have priorities over other claims. The term recovery rate, however, often relates to the event of default as well (Hull 2007, 260).

The recovery rate for a bond is typically defined as the bond's market value immediately after a default as a percent of its face value, which is usually 100%. As stated in the chapter 2 already, recovery rate equals one minus the loss given default. However, a variety of recovery assumptions appears in the bond pricing literature. We need to discuss this theoretical framework of recovery rates in order to understand and question the reasons that cause fluctuations for recoveries over time.

In the simplest form, it is assumed, that the bond has a given expected fractional recovery. However, as mentioned already, assumptions of recoveries vary in the literature and one example introduced by Jarrow and Turnbull (1995) is that the recovery in default is a given fraction of a default-free but otherwise equivalent bond. However, this seems quite vague for my purposes. Another, owing to Duffie and Singleton (1999) is that the recovery in default is a fraction of the market value of the bond just prior to default (or, equivalently, the same fraction of an otherwise similar bond that has yet to default). This type of recovery assumption is more widely used in the studies about default and recovery rate modeling and thus it is better for my purposes. However, measuring recovery on defaulted debt is difficult. As a proxy for traded debt, I use the same as Moody's since the data are retrieved from Moody's database. That is the trading price of the defaulted debt, expressed as a percentage of par and measured approximately 1 month after default. This proxy is likely to be imperfect, but as based on market prices, it is in principle the value that bondholders would receive by selling their positions when default occurs (Duffie and Singleton 2003, 122–123).

Recovery rate varies between type of debt instruments and seniorities a lot. The highest recovery can be typically obtained among bank loans and equipment trusts. Then comes rated publicly issued corporate debt, which is under my examination in this thesis as well. Median recovery rates for bonds naturally decline with seniority. This means that senior secured and senior unsecured bonds typically have highest recovery rates and subordinated bonds lowest. This is because some lenders, typically senior lenders, have priorities against junior ones. But recoveries may also vary within a certain seniority category as well. Duffie and Singleton (2003, 124) suggests that there is a significant idiosyncratic component to the recovery experience for bonds with the same seniority. They find that the dispersion within each seniority classification may be due in part to variation in rating among bonds at the time of default or to different recovery patterns for different industrial classifications. There may also be significant heterogeneity within a seniority category in terms of collateral, the existence of sinking funds, maturity, etc. This is why simply setting the recovery of a bond of a given seniority to the median value for that seniority is likely to lead to inferior pricing compared to recovery assumptions that condition on the characteristics of a bond, including its rating and industrial classification. In the end, however, even after conditioning on all public information available before default, it is natural to presume uncertainty regarding recovery rate. Previous research has mainly concentrated on examining recovery rate with primary focus on seniorities. However, recent studies of the link between defaults and recoveries have argued that credit variables are clearly related, not just to each other, but

also to business cycle. The discussion on recovery rates follows with figure 6 capturing the trend over time.
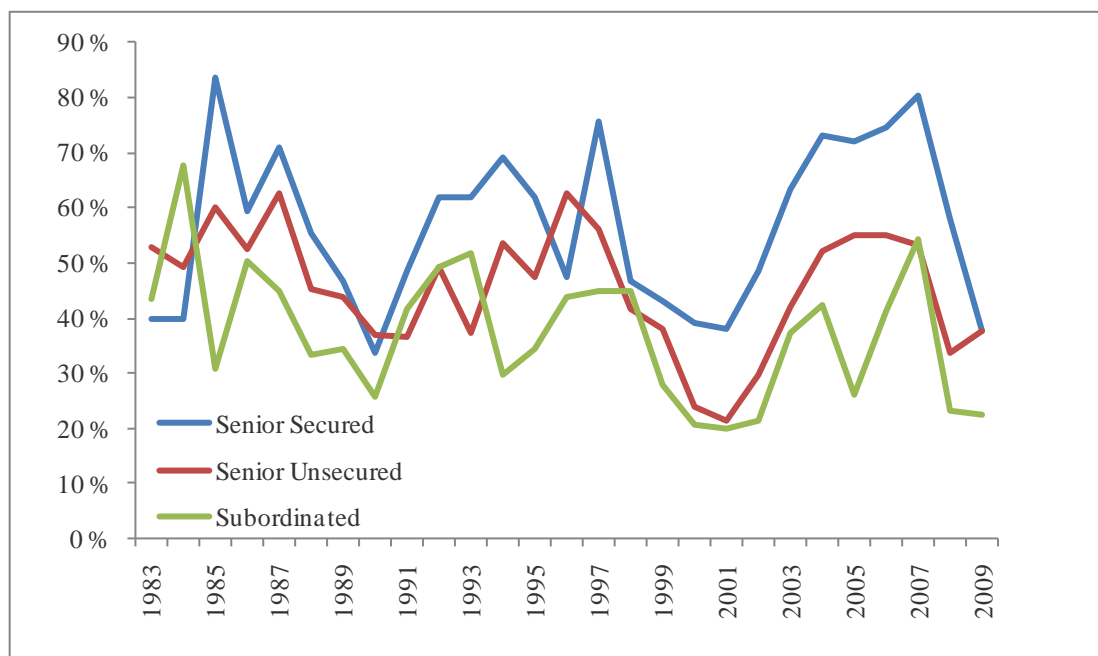

Figure 6   Bond recoveries by seniority during 1983–2009

Figure 6 plots the temporal perspective of annual average recovery rates of defaulted bonds globally. Data are, again, from Moody's database. We clearly see that in most cases recoveries for senior secured debtors are highest and for subordinated debtors they are lowest. We also obtain some variation over cycles. For instance during 1989–1991, when default rates among bonds were very high, recoveries for all categories were relatively low. The same applies for the period of time during 2000–2002. In proportion, during booms recoveries seem to be relatively high.

As the purpose of this thesis is to examine the movements of credit variables over business cycles, henceforth I do not focus that much on examining recovery rates by different seniority levels. More specified examination on the relation between recoveries and cycles will be carried out in the empirical part of this thesis.

4.3   Real-world and risk-neutral default probabilities

A feature of credit markets is the difference between probabilities of default calculated form historical data and probabilities of default implied from bond prices. But why are

the two estimates of the probability of default so different? The answer lies behind the fact that bond traders do not base their prices for bonds only on the actuarial probability of default. Instead, they include an extra return to compensate for the risk they are bearing. The default probabilities calculated from historical data are usually called *real-world* default probabilities. The ones backed out from bond prices are known as *risk-neutral* default probabilities. Real-world default probabilities are usually less than risk-neutral. This means that bond traders earn more than the risk-free rate on average from holding corporate bonds. The difference between the implementation of these two default probabilities is that the risk-neutral default probabilities are used when credit dependent instruments are valued and the real-world ones are used in scenario analysis and in the calculation of bank capital under Basel II (Hull, Predescu & White 2005, 53).

Differences between actual and risk-neutral default probabilities reflect risk premia required by market participants to take on the risks associated with default. In general default-risk premia reflect aversion to both the risk of timing of default and to the risk of severity of loss if the default occurs. Particularly in credit markets the price of a new security could differ according to which risk-neutral probabilities are used. To illustrate the difference between risk-neutral and actual default probabilities, we assume a 1-year par bond that promises its face value and a 6% coupon at maturity. The 1-year risk-free rate is 4%. If the issuer survives, then the investor receives €106 at maturity, and this happens with actual probability of 0.99. On the other hand, if the issuer defaults before maturity, with actual probability of 0.01, the investor is assumed to recover 40% of the par value. The default recovery is known with certainty in this example and therefore no recovery risk premium is assumed. It is natural, especially since default risk is correlated with downturns in the business cycle as I earlier stated, to assume that investors demand a premium beyond expected default losses for bearing default risk. The pricing must thus account for this risk premium. However, discounting at the risk-free rate of 4% the expected payoff computed with actual probabilities, $106 \times 0.99 + 40 \times 0.01$, presumes no default-risk premia as it overstates by approximately 1.3 the actual market price of 100 (Duffie & Singleton 2003, 102–103).

To demonstrate how this goes with risk-neutral probabilities, I show the case in figure 7.

	6 % par 1-year bond pays	Actual probability	Risk-neutral probability
Survival	106	0.99	p^*
Default	40	0.01	$1 - p^*$

Figure 7   Outline of the implied risk-neutral probability (Duffie & Singleton 2003, 103)

We let p^* denote the risk-neutral probability that the issuer will survive through the maturity date of the bond. Then, according to the risk-neutral valuation paradigm, the fact that the bond is priced at par (100) implies that its price is the present value of the risk neutral expected payoff, so that

$$100 = \frac{1}{1.04}\left[p^* \times 106 + (1 - p^*) \times 40\right] \tag{4.2}$$

Solving the equation yields the market-implied risk-neutral survival probability of $p^* = 0.97$. We note that p^* is now less than the actual survival probability of 0.99. Equivalently, investor assumes a default probability of 0.03, which is larger than the actual default probability of 0.01. This makes sense if investors are averse to default-timing risk and thus the difference between $\lambda = 0.01$ and $\lambda^* = 0.03$ reflects the premium for default-timing risk. (Duffie & Singleton 2003, 103–104).

Why do we see then such big differences between real-world and risk-neutral default probabilities? As stated above, this is the same question as why corporate bond traders earn more than risk-free rate on average. Potential reasons could be (Hull 2007, 267–269):

1. Corporate bonds are relatively illiquid and bond traders thus demand an extra return as compensation.
2. The subjective default probabilities of bond traders may be much higher from time to time and traders may be allowing for depression scenarios much worse than anything seen before.
3. Bonds do not default independently of each other as there are periods of time when default rates are very low or high (evidence can be obtained by looking at the default rates in figure 2 on page 12). This gives rise to systematic risk (i.e. risk that cannot be diversified away) which is a vital factor when discussing the corporate bonds. Thus, bond traders should require an expected excess return for bearing that risk as well. The variation in default rates from year to year may be because of overall economic conditions or because a default by one company has a domino effect resulting in defaults by other ones. The latter is referred to as *credit contagion*.
4. Bond traders may require an extra return for bearing unsystematic risk as well as for bearing the systematic risk. This is because risks in a bond portfolio are much more difficult to diversify than for instance in an equity portfolio as bond returns are highly skewed with limited upside.

In the analysis of credit risk, real-world default probabilities are often used when carrying out scenario analyses to calculate potential future losses from defaults. Risk-neutral default probabilities are used when valuing credit derivatives or estimating the impact of default risk on the pricing of instruments (Hull 2007, 269).

The basic understanding of differences between real-world and risk-neutral default probabilities is important in this thesis as my purpose is to model default and recovery rates with data series their movements might be sensitive to. The dataset I use includes time series of credit spread data. Time series of credit spreads represent the risk-neutral default probabilities in my model. In more theoretical context and mentioned e.g. by Duffie and Singleton (2003, 105), the credit spread is sometimes regarded as *actuarial credit spread*, which is implied by assuming that investors are neutral to risk and use historical frequencies of default and average recovery rates to estimate default probabilities and expected recoveries, respectively. However, the purpose is to analyze and discover the effect of macro-variables to defaults and recoveries and thus, the credit spread is reasonable to incorporate into the econometric model.

4.4   Default probabilities and equity prices

Corporate defaults remain a major source of potential large losses to equity investors as stock shares are the most junior claims on the assets of a defaulted firm. But should equity investors be compensated for being exposed to default risk? Explained by Sharpe (1964), Lintner (1965) and Mossin (1966), investors should be compensated only for bearing systematic or unavoidable risk and not for bearing firm-specific default risk (Chan-Lau 2006, 4).

I stated earlier that default risk, measured by default rates, is highly dependent on the stage of the business cycle. The casual analysis discussed by Chan-Lau (2006) suggests that there is an important systematic component of default risk in the corporate sector that must be priced in equity returns as well. This also supports the relevance to incorporate equity returns in the model to estimate the default risk.

The analysis of business risk, corporate governance risk, and financial risk are commonly included in fixed income analysis, but these elements are the type that a common stock analyst would undertake as well. Many fixed income portfolio managers thus strongly believe that bond analysis, particularly high-yield bond analysis, should be viewed from an equity analyst's perspective. If analysts think about whether they would want to buy a particular high-yield company's stock and what will happen to the future

equity value of that company, they have a good approach because, as equity values go up, so does the equity cushion beneath the company's debt. All else being equal, the bonds then become better credits and should go up in value relative to competing bonds (Fabozzi 2010, 494).

In addition, when utilizing statistics such as presented in table 4 to estimate a company's real world probability of default, we are relying on the company's credit ratings. Credit ratings are, however, revised relatively infrequently, which has led to some analysts to argue that equity prices can provide more up-to-date information for estimating default probabilities. I have discussed briefly about equity based models such as Merton's model. Merton's model laid the background for equity based modeling for default probabilities. Equity prices have proved to be good indicators in estimating default probabilities and thus many researchers and practitioners use equity prices in default modeling. The model I use also comprises an equity price index typically used in macroeconomic models. Merton's model was initially proposed for estimating default probabilities for single companies rather than for default rates on macroeconomic level. Research on macroeconomic level have recently utilized equity price indices presumably to find out whether equity prices tell us something about credit markets and vice versa.

4.5   Credit ratings and the business cycle

4.5.1   Credit ratings

Financial institutions and their money managers need to analyze information on companies and bond issues in order to estimate the ability of the issuer to meet its liabilities. This is called credit analysis and some large institutional investors as well as many investment banking firms have their own credit analysis departments. Many individual investors and institutional bond investors, however, rely primarily on nationally recognized rating companies that perform credit analysis and give credit opinions. The three main commercial rating companies are (1) Moody's Investor Service, (2) Standard & Poor's Corporation, and (3) Fitch Ratings. All of them use similar symbols in their rating systems, although the specification differs slightly (Fabozzi 2010, 153).

Table 3   Summary of corporate bond ratings systems and symbols (Fabozzi 2010, 154)

Moody's	S & P	Fitch	Definition
Investment Grade: High Credit Worthiness			
Aaa	AAA	AAA	Gilt edge, prime, maximum safety
Aa1	AA+	AA+	
Aa2	AA	AA	Very high grade, high quality
Aa3	AA-	AA-	
A1	A+	A+	
A2	A	A	Upper medium grade
A3	A-	A-	
Baa1	BBB+	BBB+	
Baa2	BBB	BBB	Lower medium grade
Baa3	BBB-	BBB-	
Distinctly Speculative: Low Credit Worthiness			
Ba1	BB+	BB+	
Ba2	BB	BB	Low grade, speculative
Ba3	BB-	BB-	
B1	B+	B+	
B2	B	B	Highly speculative
B3	B-	B-	
Predominantly Speculative: Substantial Risk or in Default			
	CCC+		
Caa	CCC	CCC	Substantial risk, in poor standing
	CCC-		
Ca	CC	CC	May be in default
C	C	C	Extremely speculative
	CI		Income bonds; no interest paid
		DDD	Default
		DD	
	D	D	

In the system of all three rating agencies, the term high grade stands for low credit risk i.e. high probability of future payments. Investment-grade bonds fall into categories between high grade and lower medium grade. Lower rated bonds are called speculative-grade, noninvestment-grade, high yield or junk bonds. They are said to have speculative elements or to be distinctly speculative. According to abovementioned, the corporate bond market can be divided into two categories: the investment-grade and speculative-grade markets (Fabozzi 2010, 153).

Rating agencies monitor the bonds and issuers that they have rated. A rating agency may announce that it may state that the outcome of the review may lead to a downgrade

or upgrade. This means that it may assign a lower or a higher credit rating for the issuer. Issuer is said to be under credit watch when this kind of announcement takes place.

Rating agencies typically accumulate statistics on how ratings change over various periods of time. Common way to display this on table is to construct a transition matrix.

Table 4   Hypothetical one-year rating transition matrix (Fabozzi 2010, 155)

Initial Rating	Rating at End of Year							
	Aaa	Aa	A	Baa	Ba	B	C or D	Total
Aaa	91.00	8.30	0.70	0.00	0.00	0.00	0.00	100.00
Aa	1.50	91.40	6.60	0.30	0.20	0.00	0.00	100.00
A	0.10	3.00	91.20	5.10	0.40	0.20	0.00	100.00
Baa	0.00	0.20	5.80	88.00	5.00	0.90	0.10	100.00
Ba	0.00	0.05	0.50	5.50	82.00	8.00	3.95	100.00
B	0.00	0.05	0.20	0.50	6.40	82.00	10.85	100.00
C or D	0.00	0.00	0.00	0.20	3.00	6.00	90.80	100.00

In table 4 the rows indicate the initial rating at the beginning of a year, whereas the columns show the rating at year end. For example, the second row shows the transition for Aa rated bonds. Hence, on average 91.40% of Aa rated bonds remained Aa rated till the end of the year. Only 1.50% of Aa rated bonds were upgraded to Aaa and 6.60% were downgraded to A. The probability for downgrade is thereby much higher than for upgrade.

4.5.2   Ratings risk in the business cycle

In order to understand the relationship between credit ratings and the real economy, I examined the link between rating transition and the business cycle. This experiment points us out how the rationale behind rating transitions works through the time and during the cycles. It is natural to examine this correlation after reviewing the fundamentals of ratings and the transition matrix. This also better describes the purpose of credit ratings. This relationship is important and has been investigated broadly in earlier research. Mutually, it is clear that in downturns and booms credit ratings are revised more often than in normal conditions.

I retrieved the data for credit rating upgrades and downgrades from Moody's database. It leaves us with the total number of Moody's ratings upgrades to the total number of downgrades (Up/Down or U/D ratio). Unlike Duffie and Singleton (2003, 88–89) I use the total U/D ratio for both the investment-grade and speculative-grade bonds and

compare it to the annual GDP growth of the whole world. The latter time series is retrieved from International Monetary Fund's database. For sample period I chose 1983–2009 in this study as Moody's introduced a finer alpha-numeric ratings system in April 1982 and reclassified a large number of firms into different letter ratings back then. Kliger and Sarig (1997, 19–20) suggest that the information release in the new classification system was economically important, in that there was a significant reaction of corporate bond yield spreads to the ratings refinements. The starting year is the same as Duffie and Singletion (2003, 89) implemented in their study and I also take similarly into account the rating refinements by Moody's.
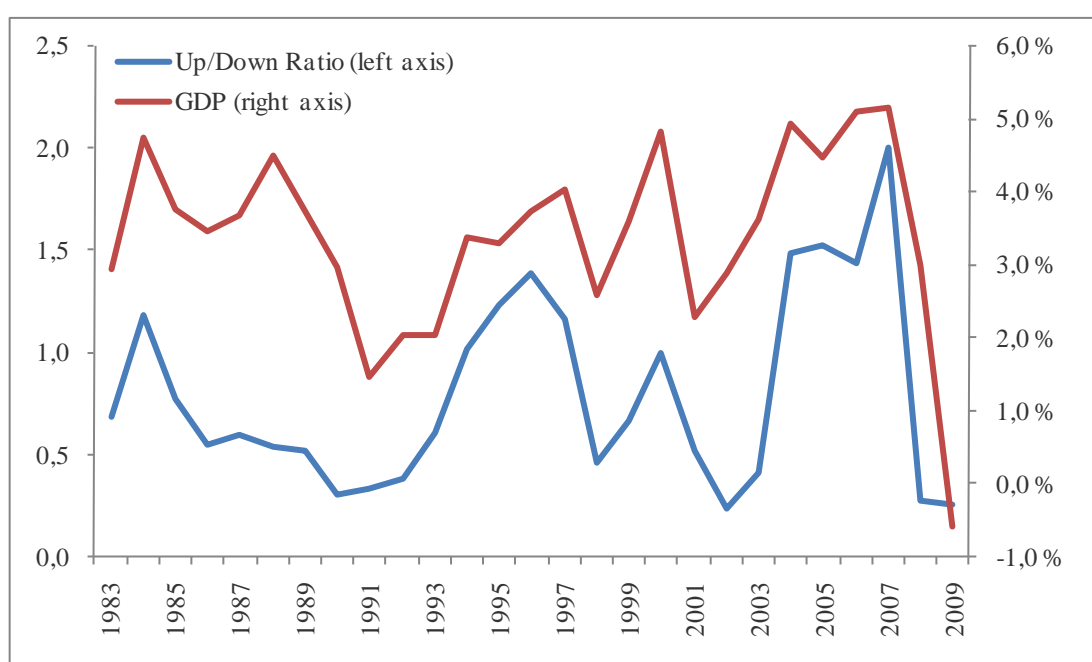
Figure 8   Upgrade/downgrade ratios and GDP for 1983–2009

To illustrate the link between rating transitions and business cycle I compared the world GDP growth (from IMF database) to Moody's upgrade/downgrade ratio of credit ratings. In figure 8 we see that U/D ratios are usually above (below) 1.0 during periods with relatively fast (slow) GDP growth. To clarify this, ratios above 1.0 indicate more rating upgrades than downgrades while ratios below 1.0 indicate more downgrades. Bonds' rating transitions are considered highly sensitive to the state of economy, and both the upgrades and downgrades seem to occur mostly during booms and recessions respectively.

To further analyze the relationship between default risk and the stage of the economy, I examined the link between default rates and the business cycle. Theoretically, default rates should be low during the booms and relatively high during the

recessions. This relationship has been examined broadly and the aim is to study this relationship similarly. In this part of the study, I just briefly discuss this phenomenon as the idea is to examine it more properly in the empirical part. This is just to present the theoretical framework.

In order to illustrate this link between default risk and the business cycle in more exact manner, we have to examine the default rates over the business cycle by comparing the same world GDP growth rate to default rates retrieved from Moody's as the case was also with rating transitions.
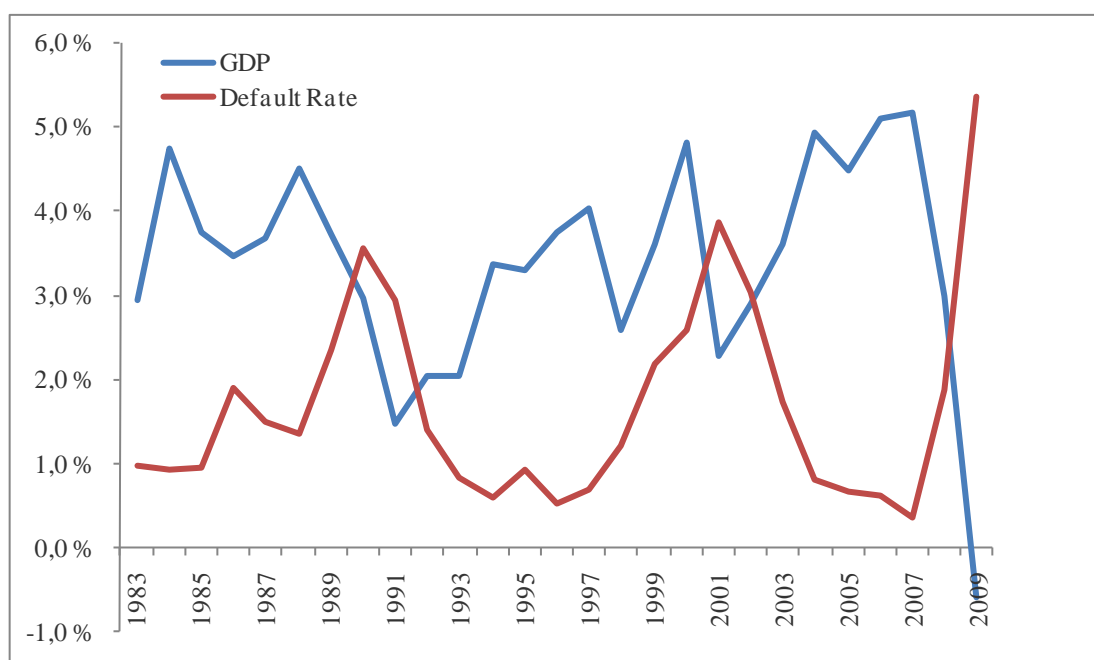
Figure 9   Default rates and the business cycle during 1983–2009

In figure 9 we see that the overall default rate in the global corporate bond market have peaked during large GDP growth drops i.e. during recessions. Default rates have accelerated rapidly during recessions experienced around 1989–1991, 2000–2002 and after 2008. An interesting fact here is that the world GDP growth showed negative figures in 2009, the first time in the history. At the same time, the default rate peaked at record high. Deeper analysis and discussion will follow in the empirical part of the study.

4.5.3   Credit ratings and credit risk models

As we have learned, the long-term credit rating is a prediction of the likelihood that an issuer will default. This raises a question that why would not we simply rely on credit ratings as a forecaster of default. Fabozzi (2010, 500) provides the following reasons for that. First, ratings are discrete with a limited number of rating grades, which were described on page 20. However, default probabilities are continuous and range between [0, 1]. Second, while ratings are updated infrequently, default probabilities can be estimated on a real-time basis. Finally, there is no distinct maturity for a credit rating. While there is a separate short- and long-term credit rating, credit risk models can provide a default probability by maturity. This, in turn, provides insight into the default probabilities for different phases of the business cycle.

5 DATA AND METHODOLOGY

In this part of the thesis I specify the data used in the empirical part. After that I characterize the methodological approach implemented. This thesis is empirical by nature as conclusions are deducted from empirical results and thus the data retrieved from different sources play essential role. The purpose in earlier parts have therefore been in describing the research question as pragmatically as possible in order to smoothly move to examine empirically the joint-time variation between defaults and recoveries in the business cycle. The ultimate goal is to examine the relationship between credit variables and the business cycle, and the predictability between credit and macro variables.

5.1 Description of the data

This thesis applies the similar approach to examine default and recovery rates as Altman et al. (2005), and Bruche and González-Aguado (2008). Some differences, however, are present in the dataset and econometric modeling. For example, the data of default rates and recovery rates are from global corporate bond markets, while the benchmark studies and earlier research in general has mainly concentrated on U.S. corporate bond markets. The reason to capitalize the global data is that bond markets in other continents are growing constantly and the proportion of other countries in the whole market is growing simultaneously. If the U.S. has been dominating global corporate bond markets so far, the case will be different in the future. As previous research has mainly utilized only the U.S. market, this study gives some broader view of corporate bond markets by incorporating the global viewpoint. In addition, in further inspections it is an interesting question to study how the macro variables in different continents react with global defaults and recoveries.

To examine the joint-variation between credit variables and the predictability of their movements I have discovered annual default rate and recovery rate data during 1983–2009. This updates somewhat the previous research. The data are from global bond markets, and circa 85% of defaults have occurred in the U.S. bond market during the time. Europe accounts for roughly 10% of the defaulted bonds, while the rest is decomposed between Asian, Latin American and African issuers. However, the proportion of non-U.S. defaults out of the total count rises steadily over the time period indicating that the corporate bond market outside the U.S. has been growing during the period. Annual

recoveries are deducted from defaults in question. The whole dataset used in this study is structured of the following time series[8]:

- Global default rates (DR[9])
- Global recovery rates (RR)
- The world real GDP growth rate (GDP)
- Global upgrade to downgrade ratio (UD)
- S&P 500 equity index (Equity)
- Credit spread of U.S. high-yield bonds over the 10-year Treasury bill (Spread)

As the data for default and the recovery rate are annual, the rest of the time series used are also annualized. The only limitation, in other words, concerns the frequency as quarterly data of defaults and recoveries were not available. Earlier research has, however, somewhat used annual data as well. For instance, Altman et al (2005) concentrate on examining relationship between defaults and recoveries on annual basis. In this thesis, time period for all the time series is 1983–2009. All the time series used in this thesis have been well represented in previous research of default rates and recovery rates, although datasets have somewhat varied. For instance, Hu and Perraudin (2002) use Moody's historical bond market data to examine the dependence between defaults and recoveries. Altman et al. (2005) examine the interrelationships of S&P 500 price index and U.S. GDP growth to both recoveries and defaults. Bruche and González-Aguado (2008), in turn, use not just S&P 500 price index and U.S. GDP growth but they also model defaults and recoveries with slope of the term structure (10-year yield minus 2-year yield). I have used default spread instead, as it includes information of risk-neutral default probabilities as well.

The world GDP growth represents the key macro variable and, naturally, the business cycle. It is an annual percent change of the world real GDP. As the dataset consists of global and U.S. data, the real GDP growth is more appropriate than nominal, and therefore the pricing effects have been excluded. Global upgrade to downgrade ratio, in turn, has been included into empirical analysis to illustrate the predictive ability of rating agencies. Particularly during recessions up to down ratio seems to be low, indi-

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[8] Default rates, recovery rates and upgrade to downgrade ratios are retrieved from the Moody's database. The world real GDP growth is retrieved from IMF database and the rest of the time series are from Datastream.

[9] Abbreviations in brackets represent the notations in econometric models in empirical part of the thesis.

cating more rating downgrades than upgrades, this being vice versa during booms. The idea is to seek econometric evidence for this by comparing it to default and recovery rates in multivariate analysis. S&P 500 represents the equity index in this study as it is pivotal equity index in the global financial markets in general. Annual averages for S&P 500 are calculated from daily closing prices. S&P 500 price index had to be deflated with annual U.S. CPI to get the annualized real values so that the pricing effects could have been separated and thus the real values are used in econometric analysis. The indicator from credit markets is the U.S. high-yield 100 index over 10-year Treasury bill in this study. This represents the default spread. Annual averages are also calculated from daily closing yields.

Differentiations are carried out for certain time series so that their statistical properties could be examined more comprehensively. This is done in section 6.1. The more specific breakdown of econometric methods used in this thesis follows in the next section.

The total composition of the abovementioned time series is not exactly similar to ones used in previous related research but as many related research papers has utilized these variables it is justified to incorporate them in the model.

5.2   Econometric background

5.2.1   Distributional properties

In the empirical part of this study the descriptive statistics are first represented. To understand how the time series data behave across the different classes and over time we have to first study their distributional properties expressed as four moments of random variables (Tsay 2005, 7–9).

Moments of random variables are discussed in this section relatively briefly, but it gives a background of theoretical properties of the dataset. The first moment is called *mean* and it measures the central location of the distribution. The denotation for the mean of a random variable, say, x is μ_x. The second central moment is called *variance* and measures the variability of a random variable. The denotation for it is σ_x^2. These first two moments of a random variable uniquely determine a normal distribution. For other distributions we need to examine higher order moments as well (Tsay 2005, 8–9).

The third central moment is called *skewness* and it measures the symmetry of x with respect to its mean. The fourth central moment is *kurtosis* and it measures the tail behavior of x. These moments (third and fourth) are often used to summarize the extent of asymmetry and tail thickness. They are defined as:

$$S(x) = E\left[\frac{(x - \mu_x)^3}{\sigma_x^3}\right] \tag{5.1}$$

$$K(x) = E\left[\frac{(x - \mu_x)^4}{\sigma_x^4}\right] \tag{5.2}$$

Skewness tells to which direction the tail is taller. The distribution is skewed to either left (negative skewness) or right (positive skewness). For example, positive (negative) skewness means that more observations are over (under) the mean (Tsay 2005, 8–9).

Quantity $K(x) - 3$ is called the *excess kurtosis* because $K(x) = 3$ for a normal distribution. The excess kurtosis of a normal random variable is thus zero. A distribution with positive excess kurtosis is said to have heavy tails, indicating that the distribution puts more mass on the tails of its support than a normal distribution does. This means in practice that a random sample from such a distribution tends to contain more extreme values and thus such a distribution is said to be *leptokurtic*. On the other hand, a distribution with negative excess kurtosis has short tails and is said to be *platykurtic* (Tsay 2005, 9).

Jarque and Bera (1987) combine the tests for skewness and kurtosis by using test statistic, which is asymptotically distributed as a chi-squered (χ^2) random variable with two degrees of freedom, to test normality. Hypothesis for normality will be rejected if the p-value of the JB statistic is less than the significance level (Tsay 2005, 9–10). Descriptive statistics i.e. the distributional properties of the data are presented in the subsection 6.1.

5.2.2   Stationarity

Very important thing that need to be done before deeper econometric analysis is to find out whether the time series are stationary or not. Two forms of stationarity exist, *strict stationarity* and *weak stationarity*. As stricter version of stationarity is hard to verify empirically, the weaker form of stationarity is often assumed. Thus, it is used in this study as well (Tsay 2005, 25).

A time series is said to be weakly stationary if both the mean of x_t and the covariance between x_t and x_{t-l} are time-invariant, where l is an arbitrary integer. Conditions for weaker form stationarity are as follows:

$$E(x_t) = \mu \tag{5.3}$$

$$Cov(x_t, x_{t-l}) = \gamma_l \tag{5.4}$$

Above-presented equations mean that in the condition of weak stationarity the first two moments of x_t are finite. Weak stationarity enables one to make deductions about future and therefore it is an important source of forecasting power (Tsay 2005, 25).

To test whether the time series is non-stationary a practical way is to find out whether the unit root exists or not. The time series is non-stationary if the unit root exists. Dickey and Fuller (1979) consider three different equations that can be tested for the presence of unit root:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{5.5}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \varepsilon_t \tag{5.6}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \varepsilon_t \tag{5.7}$$

Testing the hypothesis $\gamma = 0$ is here the most important thing in all the regression equations as if the case is such, the unit root exists (Enders 2003, 181). However, as all the time series cannot be well explained by the basic first-order autoregressive model, the augmented Dickey-Fuller test (ADF test) is often applied. Equations for the ADF test are:

$$\Delta y_t = \gamma\, y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta_{t-i+1} + \varepsilon_t \tag{5.8}$$

$$\Delta y_t = a_0 + \gamma\, y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta_{t-i+1} + \varepsilon_t \tag{5.9}$$

$$\Delta y_t = a_0 + \gamma\, y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta_{t-i+1} + \varepsilon_t \tag{5.10}$$

Testing the hypothesis $\gamma = 0$ is here the most important thing as well. The main problem with ADF test concerns the appropriate lag length as too few lags means that

the regression residuals do not behave like white-noise process. In proportion, including too many lags reduces the power of the test to reject the null of a unit root since the increased number of lags needs the estimation of additional parameters and loss of degrees of freedom (One observation is lost for each additional lag included in the autoregression). ADF test may indicate a unit root for some lag lengths but not for others (Enders 2003 189–192). Testing the unit root is carried out by using augmented Dickey-Fuller test in R. The lag length is selected automatically and test resulting the p-value greater (smaller) than chosen significance level (0.05) means that the time series includes (does not include) unit root. Levels containing the unit root feature are modeled with differences. The univariate section includes the analysis of stationarity among others.

5.2.3   *Autocorrelation*

When the linear dependence between r_t and its past values r_{t-1} is of interest, the concept of autocorrelation is present. Furthermore, considering a weakly stationary time series, the correlation coefficient between r_t and r_{t-1} is called the lag-l autocorrelation and is generally denoted by ρ_l. Autocorrelation can be defined as:

$$\rho_l = \frac{\text{Cov}(r_t, r_{t-l})}{\sqrt{\text{Var}(r_t)\text{Var}(r_{t-l})}} = \frac{\text{Cov}(r_t, r_{t-l})}{\text{Var}(r_t)} = \frac{\gamma_l}{\gamma_0} \tag{5.11}$$

A weakly stationary time series is not serially correlated if and only if $\rho_l = 0$ for all $l > 0$. Furthermore, given that a series is stationary, the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) can be used to identify the data generating process (Tsay 2005, 25–26; Enders 2003, 67).

To test the autocorrelation I use the Q-test implemented by Ljung and Box (1978).

$$Q(m) = T(T+2)\sum_{l=1}^{m}\frac{\hat{\rho}_l^2}{T-l} \tag{5.12}$$

The decision rule here is to reject the null hypothesis if the p-value is less than or equal to the significance level used (Tsay 2005, 27). To examine autocorrelation for each model, correlograms of autocorrelation and partial autocorrelation are also utilized.

5.2.4   *AR, MA and ARMA models*

In this section I go through the theoretical background of models used in univariate-section in empirical analysis. Basic models often utilized include autoregressive (AR) and moving-average (MA) models. In addition, a combination of them is usually used alongside. It is called autoregressive moving-average (ARMA) model. Time series to be examined has to be stationary so that these models can be estimated.

If a time series has a statistically significant lag-1 autocorrelation, it indicates that lagged variable, say r_{t-1}, might be useful in predicting r_t. A model that would make use of such predictive power is:

$$r_t = \phi_0 + \phi_1 r_{t-1} + a_t \tag{5.13}$$

In this equation a_t is assumed to be white noise series with mean zero and variance σ_a^2. This is similar to the simple linear regression model in which r_t is the dependent variable and r_{t-1} is the explanatory variable. In time series literature this is referred to as an AR(1) model. AR models are used to predict present observations with past ones (Tsay 2005, 32–33).

Another class of simple models that are used in time series modeling is called moving-average models. One approach to introduce MA models is to treat the model as an infinite-order AR model with some parameter constraints, which is exactly the case here as well. A simple MA model says that, except for the constant, r_t is a weighted average of shocks a_t and a_{t-1}. This is the reason the model is called MA(1) model in its simplest form. Generally it can be written as:

$$r_t = c_0 + a_t - \theta_1 a_{t-1} \tag{5.14}$$

In this equation c_0 is constant and a_t is a white noise series (Tsay 2005, 50–51).

Sometimes AR or MA models discussed above become troublesome because one may need a high-order model with many parameters to describe the dynamic structure of the data. To overcome this dilemma, the autoregressive moving-average models are introduced. Basically, an ARMA model combines the ideas of AR and MA models. At its simplest, a time series r_t follows an ARMA(1,1) model if it satisfies:

$$r_t - \phi_1 r_{t-1} = \phi_0 + a_t + \theta_1 a_{t-1} \tag{5.15}$$

Again, a_t is a white noise series. On the left-hand side we see the AR component of the model and on the right-hand side we see the MA component. To be meaningful, we need $\varphi_1 \neq \Theta_1$. Otherwise the process reduces to white noise series (Tsay 2005, 56–57).

5.2.5   VAR model and impulse response function

In this section I concentrate on explaining the tools that are vital for multivariate purposes in this thesis. Vector autoregression (VAR) is often utilized if we are not confident that a variable is actually exogenous, as the model treats all variables symmetrically without making reference to the issue of dependence versus independence. In addition, the tools employed by VAR analysis – Granger causality and impulse response analysis – can be helpful in order to understand the interrelationships among economic variables. In this thesis I concentrate on these techniques to find some interconnections between credit variables (DR and RR) and other macroeconomic variables implemented. First, the theoretical background of these techniques and models is examined (Enders 2003, 239).

In the two-variable case, we can let the time path of y_t be affected by current and past values of the z_t sequence and let the time path of the z_t be affected by current and past values of the y_t sequence. This simple bivariate system can be written as:

$$y_t = b_{10} - b_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \varepsilon_{yt} \tag{5.16}$$

$$z_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \varepsilon_{zt} \tag{5.17}$$

Here it is assumed that (1) both y_t and z_t are stationary, (2) ε_{yt} and ε_{zt} are white-noise disturbances with standard deviations of σ_y and σ_z, respectively, and (3) ε_{yt} and ε_{zt} are uncorrelated white-noise disturbances. This is a simple two-variable first-order VAR as the longest lag length is unity (Enders 2003, 264).

One typical test of causality is whether the lags of one variable enter into equation for another variable. This test is called *Granger causality*. It is important to notice here that Granger causality refers only to the effects of past values of, say y_t, on the current value of z_t. Therefore, Granger causality actually measures whether current and past values of y_t help to forecast future values of z_t. For example, in a two-equation model with p lags, y_t does not Granger cause z_t if and only if all the coefficients are equal to zero. Thus, if y_t does not improve the predicting performance of z_t, then y_t does not Granger cause z_t. It is important to notice as well, that if all variables in the VAR are

stationary, the direct way to test Granger causality is to use standard F-test (Enders 2003, 283).

A vector autoregression can be written as a vector moving average (VMA). This is a practical tool to examine the effect of different shocks to the variables. VMA allows us to trace out the time path of the various shocks on the variables contained in the VAR system. The moving average representation can be written in terms of ε_{yt} and ε_{zt} sequences as follows:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{yt-i} \\ \varepsilon_{zt-i} \end{bmatrix} \tag{5.18}$$

Coefficients $\phi_{11}(i)$, $\phi_{12}(i)$, $\phi_{21}(i)$ and $\phi_{22}(i)$ are called the *impulse response functions*. Plotting these functions is a practical way to visually represent the behavior of the y_t and z_t series in response to the various shocks (Enders 2003, 272–274).

6　　　　EMPIRICAL STUDY

Recent studies of default risk and more accurately default and recovery rates propose that default rates and average recovery rates are negatively correlated. For instance, Altman et al. (2005), and Bruche and González-Aguado (2008) found evidence of this phenomenon and my purpose is to deepen into this dilemma as well. According to these studies, both defaults and recoveries also seem to be driven by the same common factor that is persistent   over time and clearly related to business cycle. In recessions or industry downturns, default rates are high and recovery rates are low, this being reverse during booms. Figure 10 depicts this in temporal perspective and gives the basis for the research question as it strongly seems that the credit variables are negatively correlated with each other.
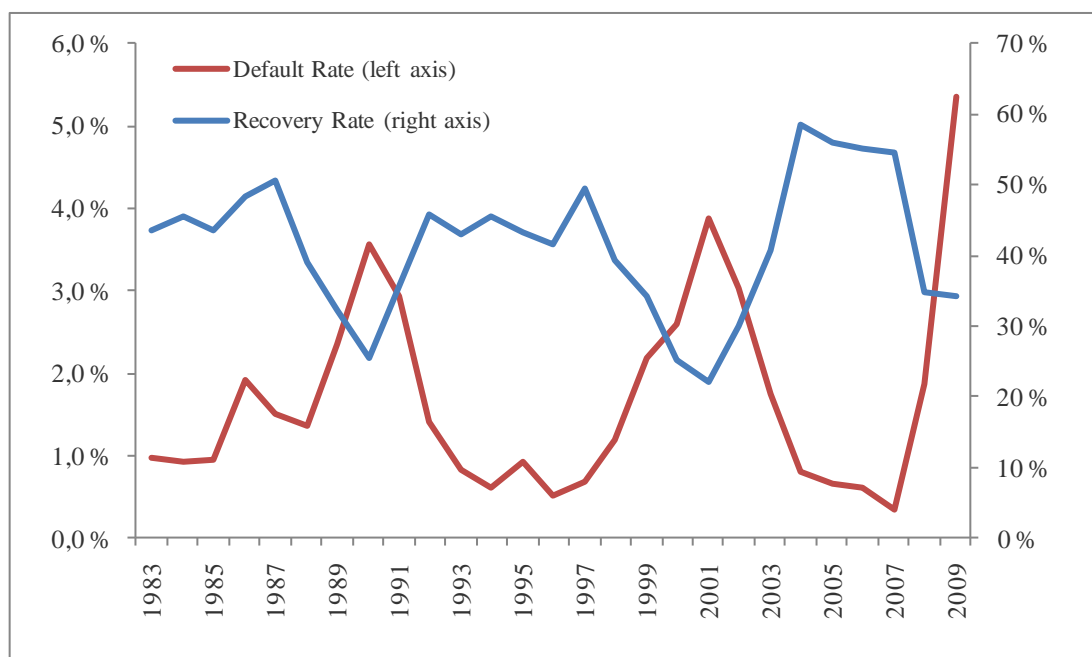
Figure 10　　　　Default and recovery rates during 1983–2009

In this chapter I am going to present the conclusions of empirical results. First, in sub-section 6.1, I go through the distributional properties of time series used in this study. Descriptive statistics encompasses the four moments of random variables to test normality. Tests for stationarity of time series are carried out to deepen the examination of statistical properties of each time series separately. In sub-section 6.2 I concentrate on examining credit variables and their self-predicting properties. Sub-section 6.3, multivariate data analysis, is the primary part of the research results, in which I deepen to examine the joint-time variation of default and recovery rate time series and the

causality between these variables versus other economic variables chosen. The final sub-section, 6.4, summarizes the research results found both in univariate and multivariate analysis. The discussion on the results in previous related research and comparison is also carried out in the final sub-section in chapter 6.

6.1   Descriptive statistics

In this section I go through the distributional properties and stationary features of the time series applied in this thesis. Figures of the selected variables with results of unit root tests are presented in order to illustrate the stationary features of time series. Analysis of distributional properties accomplishes this section.

6.1.1   Stationarity of selected variables

Figures 11, 12 and 13 depict the time series used in this study. Time series of credit variables, default rate and recovery rate, are first presented.
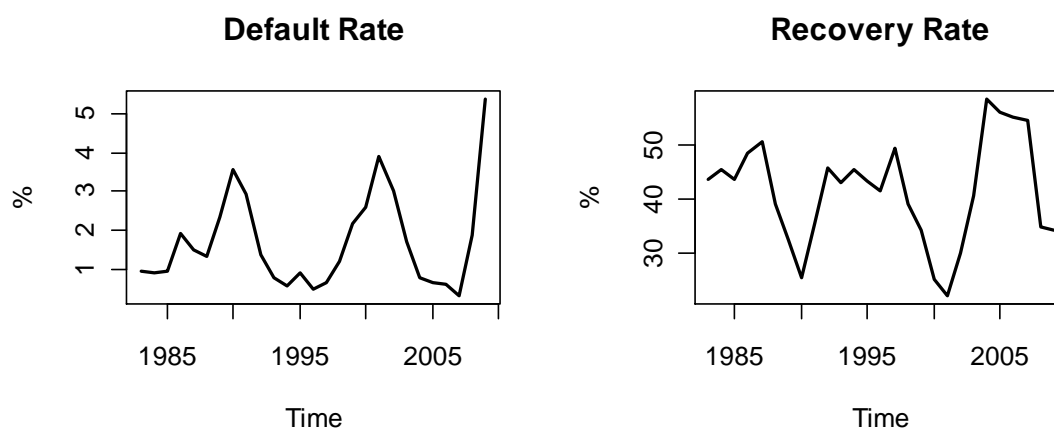
Figure 11   Temporal perspective of default and recovery rates

As analyzed already earlier in this study, default rates peaked in 1990, 2001 and 2009. Recovery rates, in turn, slumped exactly at the same years. Thus, the temporal perspective of these two time series seems to reflect strongly – during downturns default rates seem to soar while recovery rates seem to plummet. As the trend seems to be very

clear, the further econometric analyses need to be carried out to find out some possible reasons for their joint-time variation.

In unit root tests, both the default rate and the recovery rate appeared to be stationary as such, so there is no need to take logarithms or differences of these time series. Level default rate was significant at the 5% level t-test resulting -3.102. Level recovery rate was significant at the 5% level t-test resulting -3.220. The dilemma with relatively long lag lengths would be present concerning annual data time series, which is the reason why lag length has been unity. These results support the view that both the default rate and recovery rate seem to be stationary as the hypotheses for unit root in both cases can be rejected. From figures it is possible to capture as well, as time variation for both the variables do not seem to follow any clear trend.

Altman et al. (2005) also use logarithmic default rates in addition to pure default rates in their empirical part. As default rates seem to be stationary as such, I did not see any reason to also model with logarithmic default rates. Moreover, they not just use ex post default rates i.e. so called actual defaults, but also utilize ex ante estimates of future default rates (i.e. default probabilities). However, as Altman et al concluded in their study, the probabilities of default showed a considerably lower explanatory power than actual default rates. This is the reason why I did not see any reason to model with probabilities of default in addition to actual ones.

Figure 12 captures the temporal perspective of two of the macroeconomic variables used in this study, the world real GDP growth rate and global upgrade to downgrade ratio. These two time series, among others, are considered as macroeconomic variables in this thesis and thus play more important role in the multivariate section.
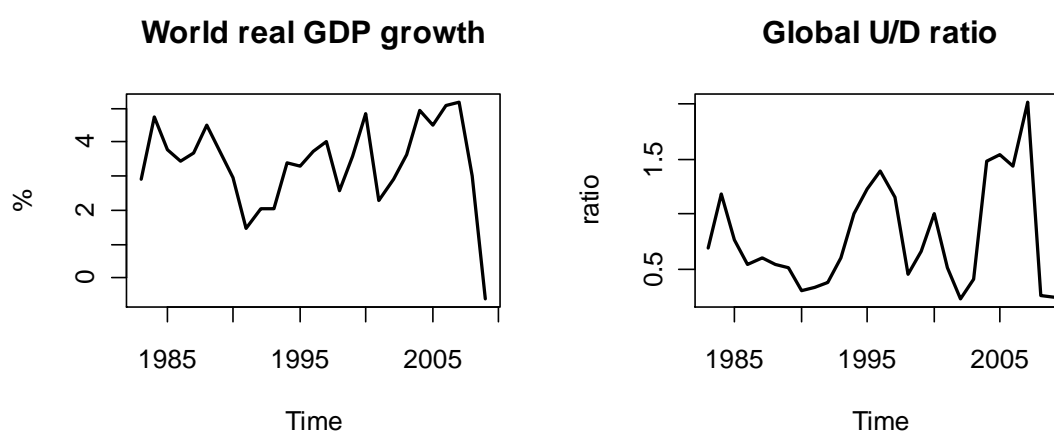
Figure 12   Temporal perspective of world's real GDP growth and global upgrade to downgrade ratio

The world GDP growth rate stands for business cycle in this thesis. As can be seen in the figure 12, the first business cycle during the period examined bottoms around 1990–1991. The second cycle is not as distinct – the boom lasts till 1996–1997, after which the GDP growth rate sharply decreases to rise again during 1998–2000. After that the GDP growth rate decelerates for a while due to the dotcom bubble. A relatively long simultaneous rise can be observed during 2002–2008, after which the most deteriorating downturn in history (or at least at the same magnitude compared to the great depression in 1930's) occurred. We are able to capture three cycles during the period examined, the first one during 1983–1990, the second one during 1991–2001, and the third one during 2002–2009. Time series of the global upgrade to downgrade ratio behaves similarly to default and recovery rate time series as during recessions more rating downgrades than upgrades are present. It can be seen clearly that the ratio is on relatively low levels in 1990, 2000-2002 and after 2008.

Theoretically, GDP growth rate is often considered stationary as such, and according to previous research it would be reasonable to incorporate in the model as such. ADF test was, however, significant only at 10% level, which would indicate unit root nonstationarity with confidence level used in this study. Bruche and González-Aguado (2008) use log U.S. GDP growth rate in their model. Altman et al. (2005) use U.S. GDP growth rate, but also the change in the annual GDP growth rate from the previous year. As the results in ADF tests did not bring any better results when modeling with differences, I make exception and use the world real GDP growth as such. It should be mentioned that dropping out one observation (either in the beginning or in the end of the time series) the GDP growth rate reaches stationarity in unit root tests. This can be explained by rare events i.e. abnormal peaks or slumps in data points. However, there is no reason to remove years from the whole dataset as there would be only minimum influence in the results in regression analysis.

Global up to down ratio was slightly nonstationary with level. When modeling with difference, t-test resulted -3.685 and was significant at 5% level. The differentiated up to down ratio is therefore used in the multivariate sector.

The temporal perspective of last two macroeconomic variables used in this thesis, S&P 500 share price index and the yield spread of U.S. high-yield bonds over 10-year Treasury securities, are depicted in figure 13.

S&P 500
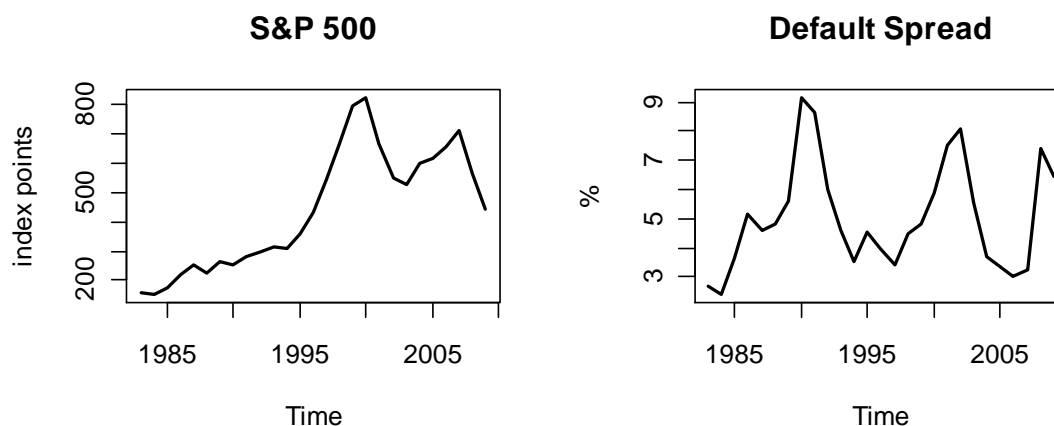
Default Spread

Figure 13   Temporal perspective of S&P 500 equity price index and the yield spread
of U.S. high-yield bonds over 10-year Treasury securities

S&P 500 equity return index is a typical equity time series used in econometric lite-
rature. From the above presented figure can be seen the temporal perspective of real
price index (index is deflated and price effects excluded), so before using it in econo-
metric analysis it has to be converted into return index. This is usually carried out by
taking log difference or difference of equity price index time series. The reason for such
procedure is that in the figure we clearly see the upward trend over time, which is a
clear sign of nonstationarity. ADF tests also lead us to model with differences as the
unit root nonstationary could not be rejected since the level equity price index was
clearly insignificant. Modeling with difference, unit root nonstationarity could be re-
jected at 5% level t-test resulting -3.709. Figure 14 hereafter depicts the time series that
were converted – return of S&P 500 index as well as differences of global upgrade to
downgrade ratio.

The yield spread of U.S. high-yield bonds over 10-year Treasury securities stands for
default spread in this thesis. The spread seems clearly wider during downturns than
during booms. The reason is clear as during downturns the default risk arises as inves-
tors demand higher yield in order to bear their risks. In ADF tests the unit root nonsta-
tionarity could be rejected and level default spread was significant at 5% level t-test re-
sulting -3.727. The result supports the view that default spread can be considered statio-
nary as such.
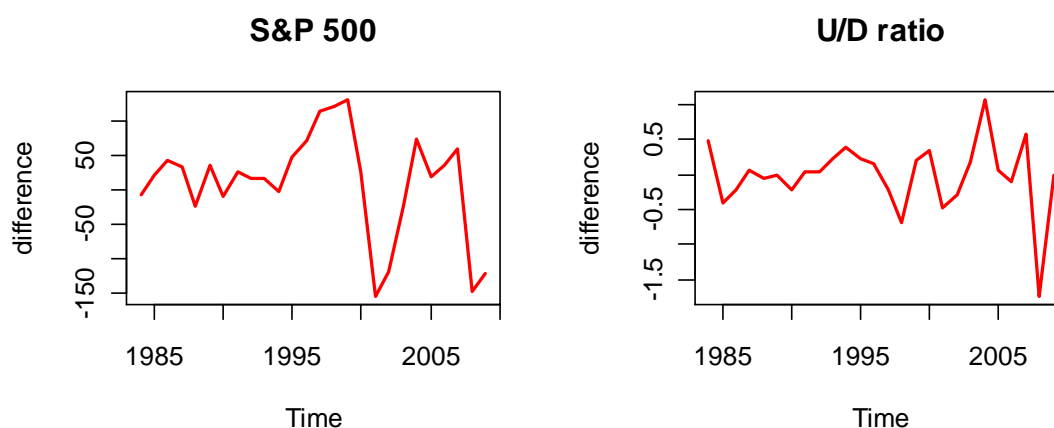
Figure 14   Differentiated S&P 500 price index and differentiated global upgrade to downgrade ratio

Figure 14 captures the temporal perspective of differentiated S&P 500 price index and differentiated upgrade to downgrade ratio. Time series are converted into stationary form accordingly. Distributional properties of these two time series are analyzed in this form as well.

6.1.2   *Distributional properties*

In table 5 I have collected the results of four moments as well as JB statistics of variables used in the empirical analysis.

Table 5   Descriptive statistics of credit and macroeconomic variables

	Mean	Variance	Skewness	Excess kurtosis	JB statistic
DR	1.69	1.48	1.23	0.98	9.51**
RR	41.39	93.08	-0.16	-0.81	0.60
GDP	3.39	1.60	-1.01	1.49	8.99*
UD	-0.02	0.25	-1.15	3.41	23.27**
Equity	10.76	5701.10	-0.73	-0.05	2.66
Spread	5.05	3.42	0.65	-0.67	2.35

** and * designate 1% and 5% significance levels respectively

UD and Equity are in differentiated form

The results in table 5 suggest that three series – default rate, world real GDP growth and up to down ratio – are significantly nonnormal. JB statistics for these time series

indicate significance at 1% level for default rate and up to down ratio, and at 5% level for GDP growth rate. Therefore the hypothesis of normality for these variables can be rejected. The JB statistic suggests normality for the rest of variables examined.

Four moments of random variables – mean, variance, skewness and excess kurtosis – were also analyzed as can be seen. Default rate, GDP growth and difference of up to down ratio seem to be leptokurtic (positive excess kurtosis), which indicates heavier tails and higher peak than for normal distribution. Recovery rate, differentiated equity index and default spread seem to be platykurtic (negative excess kurtosis) indicating short tails. Default rate and default spread seem to be skewed to right (positive skewness). This indicates that default rate has been more often above 1.69% than below it during the period examined. Default spread has also been more often above 5.05% than below it. Furthermore, recovery rate, GDP growth, differentiated up to down ratio, and differentiated equity prices seem to be skewed to left (negative skewness). Recovery rate has obviously been more often below 41.39% than above it. GDP growth rate has been normally slower than 3.39% per annum during the period examined. S&P 500, in turn, has witnessed more often negative returns than positive, more rating downgrades have taken place than upgrades during the period examined. Standard deviation (square root of the second moment) for DR, RR, GDP, difference of UD, difference of Equity, and Spread was 1.22%, 9.65%, 1.27%, 0.5%, 75.5% and 1.85% respectively. Annual volatility for equity returns has been substantial during the period examined.

6.2   Univariate data analysis

In this sub-section the results of univariate data analysis for credit variables – default rate and recovery rate – are presented. The idea here is to explain the movements of these variables with their own lagged values. This predictive performance of both variables separately is examined by using univariate econometric models such as AR, MA and ARMA models. Autocorrelation and partial autocorrelation for default rate and recovery rate time series are checked in the beginning of this section with correlograms and Q-test implemented by Ljung and Box (Ljung-Box Q-statistic). Eventually, the residual statistics for univariate models are examined to help choosing the best fitting model.

As a deeper background for univariate data analysis, the focus in this thesis is on examining the movements and predictability of credit variables over time and thus the univariate analysis is carried out only for default rates and recovery rates. The focus is thus on examining the predictive performance of the lagged values of each variable

separately to find out whether the historical movements can be used to explain their development in subsequent years. To choose the best fitting model (model selection criteria) the Akaike Information Criterion (AIC) is used. The reason to choose this instead of Schwartz Bayesian Criterion (SBC) is clear – in small samples, the AIC often works better than the SBC (Enders 2003, 69–70). Correlograms of residual autocorrelation and residual partial autocorrelation are also used to identify the best fitting model. As a significance level the 5% level is used in each test.

As the sample used in this thesis is relatively small, there is no reason to model with higher-order models. Therefore the models examined are relatively simple, such as AR(1), AR(2), MA(1) and ARMA(1,1). Parameter estimates of each model are presented and the results are concluded. Eventually, the best fitting model or models are chosen.

6.2.1   *Analysis of autocorrelation*

Both the credit variable time series contained autocorrelation when testing with Ljung and Box Q-statistics as well as examining the autocorrelation and partial autocorrelation through the correlograms presented in appendix 1. This indicates that movements of both these time series are clearly predictable. The Ljung and Box Q-statistics are presented in table 6.

Table 6   Ljung and Box Q-statistics of credit variable time series

	DR	RR
Q(1)	6.270*	12.529**
Q(2)	6.270*	13.190**
Q(4)	12.818*	26.281**

*** and * designate 1% and 5% significance levels respectively*

Ljung and Box Q-statistics are tested with lags 1, 2 and 4 respectively

The results indicate that default rates are autocorrelated at 5% significance level with lags 1, 2 and 4. This supports the view that the movements of these time series might be predictable even behind years. The same applies with recover rates. They are autocorrelated at 1% significance level with lags 1, 2 and 4 indicating stronger evidence of autocorrelation than with default rates.

6.2.2   Univariate regressions

Univariate regressions with each model used – AR(1), AR(2), MA(1) and ARMA(1,1) – seemed to be quite adequate, although some clearly outperformed others. Results were acceptable, but still the best fitting models were relatively comfortable to choose. Correlograms of residual autocorrelation and residual partial autocorrelation were mainly decent. They are presented in appendix 2. Results of univariate regressions are presented in table 6. To better describe the phases of data-generating process and the results, I have gathered the results of all the models, and chosen the best fitting model or models after that.

Table 7   Parameter estimates of default rate and recovery rate univariate analysis

	AR(1)	AR(2)	MA(1)	ARMA(1,1)
DR				
Intercept	0.602	1.039**	1.790**	0.858
a_1	0.721**	1.307**		0.598*
a_2		-0.874**		
b_1			0.770**	0.622**
AIC	80.84	69.89	77.39	74.63
Q-statistic	3.199	0.084	0.116	0.578
RR				
Intercept	13.82*	21.048**	41.369**	32.545
a_1	0.66**	0.959**		0.217
a_2		-0.472**		
b_1			0.889**	0.823**
AIC	189.01	185.27	184.63	185.72
Q-statistic	3.021	0.336	1.129	0.006

** and * designate 1% and 5% significance levels respectively

Ljung and Box Q-statistics are presented as Q(1) indicating that

lag length is unity

Even a quick glance at the table 6 strengthens the view that both the lagged default rate explains default rate and the lagged recovery rate explains recovery rate very well. However, when screening the best fitting model to examine the predictive performance of lagged default rates, two models – AR(2) and MA(1) – came up out of these four. Correlograms of autocorrelation and partial autocorrelation, however, support the view

that the data-generating process is nearest to AR(2). As can be seen, the intercept in AR(1) was insignificant and although the lagged default rate (coefficient a_1) was significant at 1% level, AIC was relatively high. In addition, the Ljung Box statistic rejects the hypothesis of residual autocorrelation quite arguably, as the p-value was 0.074 suggesting over 7% probability for autocorrelation. In the other end, AR(2) was relatively easy to choose as the intercept, first lag of default rate and the second lag of default rate were all significant at 1% level. As Ljung Box statistic rejects the hypothesis of residual autocorrelation and AIC was lowest of all these four models, it is justified to choose AR(2) as the best fitting model. In fact, this model does capture the actual data-generating process quite well. Furthermore, results of the last two models – MA(1) and ARMA(1,1) – were quite interesting. MA(1) was almost as informative as AR(2), but according to AIC, this model does not capture the data-generating process that well. ARMA(1,1), in turn, stood out when looking the AIC, but as the intercept was insignificant and AR(1)-component was significant "only" at 5% level, it is not reasonable to assume that ARMA(1,1) would outperform AR(2).

When examining the correlograms of autocorrelation and partial autocorrelation for the residuals of default rate, it can be noticed that residuals for AR(1), AR(2) and ARMA(1,1) were behaving very similarly. Residual autocorrelations and partial autocorrelations for MA(1), in turn, seemed to be implausible as the hypothesis for autocorrelation at lag 5 in both cases cannot be rejected. This strengthens the view that AR(2) is the best fitting model for forecasting default rates with own lagged values in this thesis. The equation for AR(2) default rate model can be written as:

$$DR_t = 1.039 + 1.307 DR_{t-1} - 0.874 DR_{t-2} \qquad\qquad (6.1)$$

Screening the best fitting model to examine the predictive performance of lagged recovery rates was not as unambiguous. Although AR(1) and ARMA(1,1) could be refused in the beginning, AR(2) and MA(1) seem to explain the data-generating process for recovery rates equivalently. Correlograms of autocorrelation and partial autocorrelation seemed similar to the ones regarding default rates, but this does not directly confirm that the process would be AR(2). Other aspects, such as information criteria and regressive results, have to be taken into account as well.

Regarding the AR(1), intercept was significant at 5% level and first lag of recovery rate was significant at 1% level. AIC was highest of all these four models and a problem arises when looking the Ljung Box statistic of residual autocorrelations – hypothesis of residual autocorrelation can be rejected only arguably here as well, as the p-value was 0.082 suggesting over 8% probability for autocorrelation. Both the AIC and Ljung Box

statistic seem very similar for ARMA(1,1) and AR(2), but as both the intercept and AR(1)-component in ARMA(1,1) were insignificant, it is justified to refuse this model. An interesting detail can be noticed when examining the data-generating process for AR(2) and MA(1)-models − both models seem to explain the data-generating process similarly. Intercept and coefficients seem to be significant at 1% level in both cases and Ljung Box statistic does not capture signs of autocorrelation. Even the AIC is nearly the same. In this case, I have chosen both AR(2) and MA(1) models. AR(2) and MA(1) recovery rate models can be written as:

$$RR_t = 21.048 + 0.959 RR_{t-1} - 0.472 RR_{t-2} \tag{6.2}$$

$$RR_t = 41.368 + 0.889 RR \varepsilon_{t-1} \tag{6.3}$$

Unfortunately, previous research has mainly concentrated on examining the joint-time variation of credit variables and credit and macroeconomic variables over time. Therefore it is difficult to make comparisons between univariate data analysis presented in this thesis and conclusions of previous research. However, this analysis strengthened the view that both default rate and recovery rate have clearly cyclical effects. Predictability for both default rates and recovery rates can be obtained behind two years. On average, it seems that both default rates and recovery rates seem to rise more rapidly than they decline. It also seems that a declining year in defaults or recoveries two years ago and a rising year one year ago indicate rise in defaults or recoveries, respectively.

Descriptive statistics, and particularly skewness for default rates, support the view that default rates have been more often above the average level during the period examined. This is in line with conclusion of on average more often rising than declining defaults. Although recoveries have been more often below than above their average level, the conclusion of more often rising than declining recoveries during the period seems rational. The reason is that the volatility in recoveries over time has been substantial. Platykurtic properties of recoveries support that as well. The median for recoveries (43.08%) is also greater than mean indicating that, on average, recoveries seem to have been rising more often than declining during the period.

6.3   Multivariate data analysis

The results of multivariate data analysis are presented in this sub-section. The analysis is divided into three phases to discover the joint-time variation and causality of credit

variables and macroeconomic variables. First, the correlation matrix is examined to get a preliminary view how different variables used in this section are tied up to each other. Deeper discussion follows with multivariate regressions. Interrelations are examined by using VAR model to discover the bivariate and multivariate relationships between credit variables, lagged credit and lagged macroeconomic variables respectively. This also includes causality checks by using Granger causality tests. The idea is to examine whether one variable predicts another and the emphasis is on explaining how movements in credit or macroeconomic variables predict movements in credit variables. Ultimately, the analysis deepens to examine the relationships between GDP growth rate and credit variables with impulse response tests. The idea is to examine separately the shocks in GDP growth rate as impulse, in order to see the response in default rates and recovery rates, respectively.

Correlations between variables used in this study were rather expected. As discussed earlier in this thesis, the negative correlation between defaults and recoveries has been present in the global corporate bond markets.

Table 8   Correlation matrix

	DR	RR	GDP	UD	Equity	Spread
DR	1.000	-0.577	-0.701	-0.209	-0.239	0.659
RR		1.000	0.301	0.172	0.200	-0.713

As can be seen in the table 8, the correlation between defaults and GDP growth rate is clearly negative. Defaults rise as the economy shrinks this being vice versa during booms. Ratings have been downgraded (upgraded) more during recessions (booms) and at the same time equity markets have tended to plummet. The default spreads, in turn, widen when defaults rise. The correlation coefficients between recovery rates and macroeconomic variables support the view that defaults and recoveries are clearly negatively correlated indicating that when defaults rise (decline), recoveries tend to decline (rise).

6.3.1   *Multivariate regressions*

In order to examine the joint properties of credit variables and macroeconomic variables the multivariate regressions were run. This was implemented by using VAR methodology. VAR-models were constructed by binding credit variables and examining their lead-lag joint-time variation. Credit variables and each macroeconomic variable

separately were combined after that in order to examine how past movements in a macroeconomic variable affect on a credit variables. VAR model also incorporates the lagged value of a variable to be examined. The idea with VAR is not to make difference between dependence and independence so regressions were run for all variables separately. Whether the variables Granger-cause each other can be already seen in results and properties of causality are discussed in results as well. The results of multivariate regressions are presented below in table 9.

Table 9   Multivariate regressions

	Model 1		Model 2			Model 3		
	DR	RR	DR	RR	ΔGDP	DR	RR	ΔUD
Intercept	5.052*	-0.058	3.999	7.153	0.047	4.312*	-1.895	-0.405
DR_{t-1}	0.045	2.711	0.133	2.110	0.065	0.030	2.971	0.096
RR_{t-1}	-0.082*	0.892**	-0.092*	0.963**	0.056	-0.063	0.922**	0.005
ΔGDP_{t-1}			0.381	-2.611	0.263			
ΔUD_{t-1}						-0.948*	-0.565	-0.097
R^2 adj.	0.410	0.400	0.467	0.436	0.156	0.528	0.374	0.000
F-statistics	9.667**	9.345**	8.314**	7.432**	2.535	9.954**	5.773**	0.199

	Model 4			Model 5		
	DR	RR	ΔEquity	DR	RR	Spread
Intercept	5.280*	-0.669	79.302	4.907*	-5.380	6.250*
DR_{t-1}	-0.045	1.950	-11.197	-0.048	-0.722	0.689
RR_{t-1}	-0.083*	0.946**	-1.419	-0.082*	0.897**	-0.060
$\Delta Equity_{t-1}$	-0.002	-0.037	0.555*			
$Spread_{t-1}$				0.057	2.090	0.063
R^2 adj.	0.397	0.432	0.180	0.385	0.413	0.454
F-statistics	6.130**	7.09**	2.757	6.206**	6.853**	7.936**

*** and * designate 1% and 5% significance levels respectively*
Dependent variables are in columns and independent variables in rows
Δ designates difference, other variables are levels

In the light of previous studies the results of multivariate regressions were rather expected. As can be noticed, lagged recoveries predict default rates fairly well. Actually, the explanatory power of 41% with strongly significant F-statistic supports this relevance. Model 1 also shows us that lagged defaults do not help predicting recoveries. These results support the view that recoveries Granger cause defaults but defaults do not

recoveries. The result also indicates that declining recovery rates might indicate rising default rates next year. I also ran the regular regression without any lead-lag properties and the result showed that recovery rates significantly decline at the time default rates rise (not reported). These results might indicate that the credit cycle is not completely coherent as recoveries seem to somewhat lead defaults. Model 1 can be written as:

$$DR_t = 5.052 + 0.045DR_{t-1} - 0.082RR_{t-1}$$
$$RR_t = -0.058 + 2.711DR_{t-1} + 0.892RR_{t-1}$$

(6.4)

Incorporating GDP growth into the model somewhat raises the explanatory power although we can also conclude that GDP growth do not help predicting defaults or recoveries. Defaults or recoveries do not help predicting GDP growth rate either. The p-value for GDP growth predicting defaults when default rate is also included into model, however, was 0.075, which is very near to 5% significance level. This partially explains the high coefficient of determination. It should be mentioned that running bivariate VAR between recoveries and GDP growth (not reported) yielded the result that recovery rate was near to Granger cause GDP growth (p-value of 0.072). However, bivariate VAR between defaults and GDP growth did not showed any significance at all. This result might support the view that recoveries lead both defaults and the business cycle. This, in turn, would mean that credit downturn begins somewhat earlier than recession. The result is, however, unambiguous as the significance level in bivariate analysis did not reach the 5% significance. Model 2 can be specified as:

$$DR_t = 3.999 + 0.133DR_{t-1} - 0.092RR_{t-1} + 0.381\Delta GDP_{t-1}$$
$$RR_t = 7.153 + 2.110DR_{t-1} + 0.963RR_{t-1} - 2.611\Delta GDP_{t-1}$$
$$\Delta GDP_t = 0.047 + 0.065DR_{t-1} + 0.056RR_{t-1} + 0.263\Delta GDP_{t-1}$$

(6.5)

Interestingly significant results were found when examining the interconnection between credit variables and rating revisions (i.e. up to down ratio). Like model 3 shows, up to down ratio helps predicting highly significantly default rates, although not recovery rates. This result indicates that credit rating agencies (in this case Moody's represents credit rating agencies) on average do a good job by downgrading or upgrading already before recessions or booms. While UD ratio seems to Granger cause defaults, it does not seem to Granger cause recoveries. Defaults and recoveries, in turn, do not seem to Granger-cause UD ratio at all. This also seems rational as otherwise the existence of rating agencies could be doubted. Model 3 can be rewritten as:

$$DR_t = 4.312 + 0.030DR_{t-1} - 0.063RR_{t-1} - 0.948\Delta UD_{t-1}$$
$$RR_t = -1.895 + 2.971DR_{t-1} + 0.922RR_{t-1} - 0.565\Delta UD_{t-1} \qquad (6.6)$$
$$\Delta UD_t = -0.405 + 0.096DR_{t-1} + 0.005RR_{t-1} - 0.097\Delta UD_{t-1}$$

Equities do not seem to help predicting the movements of credit variables like model 4 suggests. However, causality can be observed between lagged equity returns and equity returns. Model 4 can be specified as follows:

$$DR_t = 5.280 - 0.045DR_{t-1} - 0.083RR_{t-1} - 0.002\Delta Equity_{t-1}$$
$$RR_t = -0.669 + 1.950DR_{t-1} + 0.946RR_{t-1} - 0.037\Delta Equity_{t-1} \qquad (6.7)$$
$$\Delta Equity_t = 79.302 - 11.197DR_{t-1} - 1.419RR_{t-1} + 0.555\Delta Equity_{t-1}$$

The variable describing credit markets, default spread, do not seem to have causality with defaults and recoveries as can be seen in regression results. I also ran plain regressions without any lead-lag properties (not reported). According to results, credit variables do explain highly significantly default spread and default spread also credit variables. It seems that default spread is wide during recessions but its predicting performance is not that high a year before recession. This leaves an interesting dilemma for further studies, as with more frequent data the predicting ability of default spread might be different. Model 5 in multivariate regressions can be specified as:

$$DR_t = 4.907 - 0.0048DR_{t-1} - 0.082RR_{t-1} + 0.057Spread_{t-1}$$
$$RR_t = -5.380 - 0.722DR_{t-1} + 0.897RR_{t-1} + 2.090Spread_{t-1} \qquad (6.8)$$
$$Spread_t = 6.250 + 0.689DR_{t-1} - 0.060RR_{t-1} + 0.063Spread_{t-1}$$

In general, results support the view that credit variables are normally more tightly related to each other than to macroeconomic variables. UD ratio makes exception as can be seen, and lower ratio in previous year might indicate defaults to rise the year after that. Furthermore, it seems that lagged recoveries explain defaults, but lagged defaults do not explain recoveries. Lagged GDP growth rate did not reach significance on explaining credit variables in this phase. It should be pointed out that a high explanatory power for some regressions stems from significant relationship between credit variables. This also supports the view that credit variables are tightly related to each other.

6.3.2 Impulse response analysis and variance decompositions

The final phase in the empirical analysis deepens to examine the interconnection between GDP growth rate and credit variables. The aim is to examine more deeply the relationship between business cycle and so called credit cycle. To model specifically the GDP growth and credit variables is, actually, the most important question in this thesis as the fundamental idea was to examine and predict the movements of credit variables over business cycles. Hence, this phase asks whether the business cycle is necessary in examining the movements of credit variables over business cycle at all.

An impulse response analysis is the methodology used, and the ultimate goal is to characterize how shocks in GDP growth rate as an impulse react with default rates and recovery rates as response, respectively. Changes in defaults or recoveries are analyzed as the main question is in what direction and how much a credit variable moves when the shock in GDP growth occurs. The analysis is finalized by examining the forecast error variance decompositions in order to see how the variance in one variable's forecast errors reacts with variance in another variable's forecast error.

The result in impulse response analysis is depicted in figures 11 and 12. The vertical axe shows the unit changes in defaults or recoveries to unit shock in GDP growth. The horizontal axe shows the number of steps (years) from the shock. The black line is the response of default or recovery rate changes to shocks in GDP growth. The red dashed lines, in turn, designate the 95% confidence interval.

Orthogonal Impulse Response from GDP

95 % Bootstrap CI, 100 runs
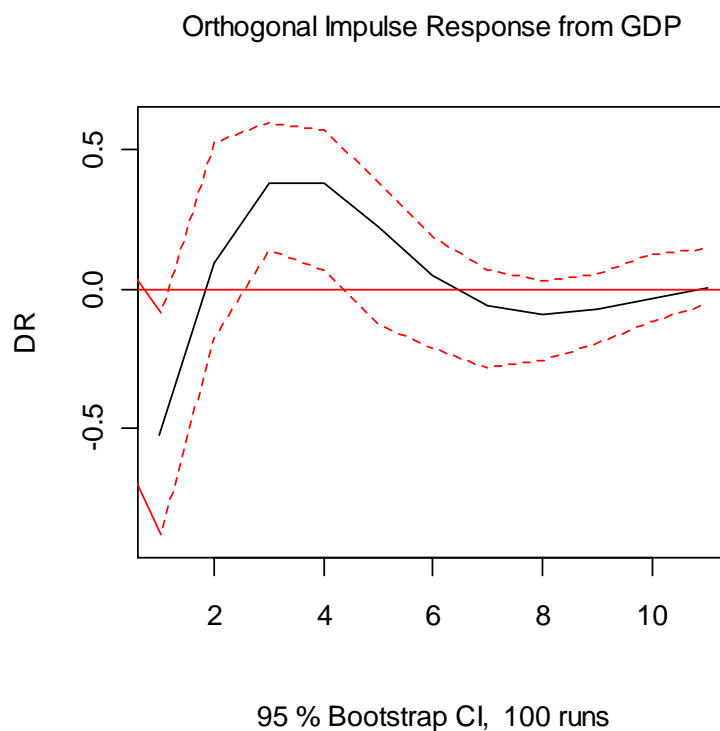
Figure 15   Impulse response from GDP growth to change in default rate

As can be seen in the figure 11, default rate reacts positively to the negative shock in GDP growth – defaults rise (they decline more slowly in the beginning, during the period examined) when GDP growth declines. In addition, after a negative shock in growth rate, defaults seem to rise steadily for a relatively long time.

Orthogonal Impulse Response from GDP

95 % Bootstrap CI, 100 runs
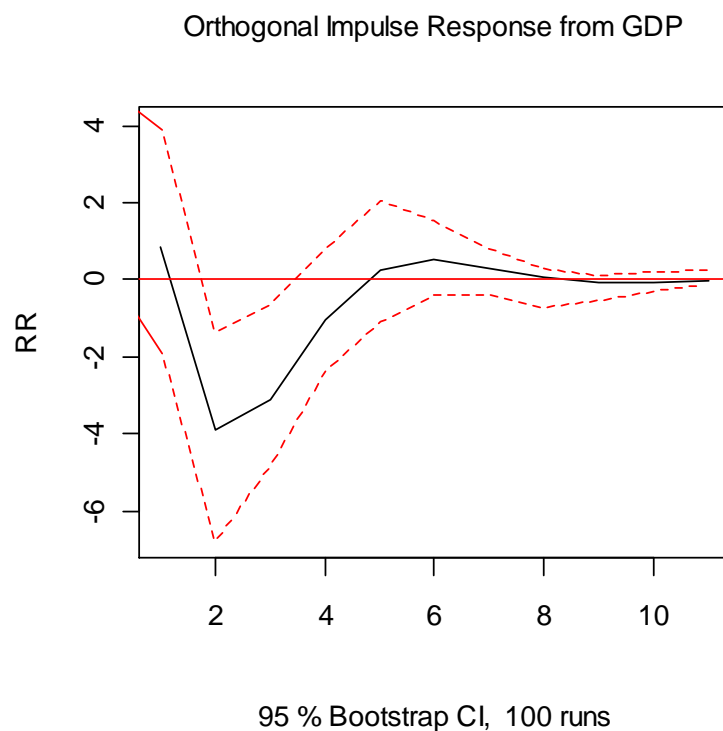
Figure 16   Impulse response from GDP growth to change in recovery rate

Response in recoveries to shock in growth rate seems rational, when also comparing this result to the results in univariate and multivariate regressions. A negative shock in GDP growth leads recoveries to decline and the pace accelerates during first years after the shock. The response in recoveries to shock in GDP growth reflects strongly the response in defaults seen. The difference, however, seems to be in how long time defaults rise compared to the declining period of recoveries. As defaults seemed to rise for a relatively long time, recoveries seem to decline for a shorter period of time, after which they start to rise again. This result is strongly in line with the result of model 1 in multivariate regressions and strengthens the view that credit cycle is not completely coherent as recoveries seem to lead defaults, as mentioned earlier. One possible explanation for this could be that recovery rates (as they are average trading prices of defaulted debt) are more dependent on financial markets and thus react more sensitively to economic changes even in the shorter term.

To summarize the impulse reaction analysis, table 10 below shows us the forecast error variance decomposition (FEVD) of credit variables for three periods ahead. Amount of variance rising from variable's own shocks compared to shocks of other variables can be seen in table 10.

Table 10   Variance decomposition between GDP growth and changes in credit va-
riables

	FEVD of Δ default rates			FEVD of Δ recovery rates		
Period	ΔGDP	ΔDR	ΔRR	ΔGDP	ΔDR	ΔRR
1	34.43 %	65.57 %	0.00 %	1.17 %	22.15 %	76.69 %
2	26.19 %	39.96 %	33.85 %	20.41 %	18.01 %	61.58 %
3	43.58 %	30.64 %	25.78 %	31.30 %	16.32 %	52.38 %

GDP growth and change in default rates are responsible for the variance of default rates in the first period. Recovery rate, in turn, seems to be exogenous. Variance breaks down more equally between each variable when period of time lengthens. All the variables seem to be somewhat responsible for the variance of recovery rates in the first period, but recovery rate is mostly responsible for it. These results support the view that the changes in recoveries stem somewhat from changes in defaults but changes in defaults stem only from defaults and GDP growth, at least during the first period. As the time interval is relatively sparse, this leaves many interesting factors for further studies.

6.4   Summary of the research results

The results reached in this chapter are in line with previous research when comparing on a broader scale. However, some results differed slightly, which can be explained by the fact that the time period used was different from time periods used in earlier studies. For instance, Altman et al. (2005) used the time period of 1982–2001, while Bruche and González-Aguado (2008) used the time period of 1981–2005. This study updated the examination about joint-time variation of defaults and recoveries as the data were examined during 1983–2009. In addition, the purpose of this study was not to concentrate on examining the U.S. bond markets but to discover global defaults and recoveries in the corporate bond markets. As the data for defaults and recoveries were global, the world GDP growth rate was also implemented and analyzed as a business cycle. These data-specific differences may also be explanation for slightly different research results. Nevertheless, the primary outcome was reached as defaults and recoveries could be said to behave similarly in the global corporate bond markets that the conclusions in previous studies found in the U.S. markets. To examine and estimate the movements of defaults and recoveries over time and business cycles, I concentrated on two different analysis – univariate and multivariate data analysis.

In univariate data analysis the goal was to find some explanatory power by examining if the lagged default rates have information on default rates, and if lagged recovery rates have information on recovery rates, respectively. The stationarity for both credit variables were tested and addressed that defaults and recoveries both were stationary as such. The univariate regressions were therefore run with level defaults and recoveries since there was no reason to use differences. The results in univariate analysis were rather strong and the evidence of their self-predicting properties was rather clear. The best fitting model for level defaults was AR(2), which showed significant predicting power according to all coefficients and information criteria. For level recoveries both the AR(2) and MA(1) parameters were identified and they were equally fitting according to significance of coefficients and information criteria as well. For both the defaults and recoveries predictability were obtained behind two years. These results show that in the longer term, both the defaults and recoveries are cyclical and their movements are somewhat invertible as both of them have self predicting properties.

As the previous research has not properly deepened into univariate properties of credit variables, the comparison was rather difficult to make. Hence, as the evidence was strong, these results ask for previous research, whether it would have been necessary to discover more credit variables as such.

The results in multivariate analysis were in line with previous research relatively well. The key foundations here were that lagged recoveries predict default rates and the credit cycle is not necessarily coherent as recoveries seem to lead defaults. This was supported by the result in regular regression analysis as well. Overall, it also seems that recoveries and defaults are closely linked, closer than they are with macroeconomic variables. These results are in line with those of Bruche and González-Aguado (2008) as well as with Altman et al. (2005). Bruche and González-Aguado stated that there is more information in recoveries about defaults and vice versa, than there is information in e.g. GDP growth about defaults. This is somewhat in line with the results presented here as recoveries seemed to Granger cause defaults but credit variables did not seem to Granger cause macroeconomics variables. Some differences might stem from different time period.

The robustness check with bivariate VAR model between defaults and GDP growth, and recoveries and GDP growth showed us results that were very near to those of Bruche and González-Aguado (2008). Recoveries were very near to Granger cause GDP growth rate as the case was with related previous research. This also strengthened the view that credit cycle is not completely coherent.

VAR model incorporating the information on rating revisions (upgrade to downgrade ratio) showed us significant results as UD ratio seemed to Granger cause defaults. UD

ratio was incorporated since it has been used for a long time as an indicator by credit rating agencies. The result supports the view that rating agencies do, on average, a good job by downgrading before recessions. As the equity index or default spread did not reach significance on one-year interval, the results leave a plenty of things to examine in further studies. By incorporating quarters could bring equity indices or default spread indicators nearer to significance.

The final phase in multivariate analysis was incorporated since impulse response analysis offers a more comprehensive view on interrelations between certain variables. Although previous research has not utilized this methodology the results showed that it was useful to apply here. Examination of shocks in GDP growth and responses in credit variables showed us, again, that defaults and recoveries are negatively correlated and response to growth rate. The result supported the conclusion made in multivariate regressions as defaults seemed to rise for a longer time than recoveries seemed to decline, after the shock in growth rate. Changes in defaults and recoveries were utilized in order to more efficiently examine the responses to shocks. Forecast error variances showed us, in turn, that in the beginning only changes in defaults and GDP growth are responsible for the variance of default rates, and recoveries do not seem to cause the variance in defaults. The results also showed that in the beginning changes in recoveries are mostly responsible for variance in themselves, but also changes in defaults explain the variance in recoveries. GDP growth rate seemed to explain only little the variance in recoveries. This result strongly indicates that defaults move more contemporaneously with GDP growth than recoveries do, when recoveries, in turn, seem to lead defaults and the business cycle.

7 CONCLUSIONS

This thesis concentrated on examining credit risk specific factors in order to understand credit markets, how credit cycle is specified and how credit cycle relates to the business cycle. The emphasis was on examining the link between default rates and recovery rates over business cycles. This viewpoint gives a broader angle for fixed income portfolio management, which is continuously disposed to credit risk especially in the corporate bond markets. The studies of defaults and recoveries have also increased partly due to the increased focus on credit risk management and as discussions on stricter capital regulations are constantly on the table, the credit risk specific factors have been examined directly or indirectly a lot. Movements of credit variables over business cycles are interesting factors also in the viewpoint of risk management practitioners.

As discussed in the beginning, various different approaches in modeling and empirically investigating credit risk specific factors exist but only the contributions during 21st century have concentrated more precisely on examining the link between defaults and recoveries. The theoretical framework has earlier based on the assumptions that default rate fluctuates over business cycles but recovery rate is just a given fraction of the face value or the market value of defaulted bond. Theoretical framework for recoveries, in other words, has not been considering that the effect of business cycles could be a reason for recovery rate fluctuations. However, recent studies of the link between defaults and recoveries have questioned this assumption. This study deepened to examine the evidence found of negatively correlated credit variables, with updated data and in the global scale.

The results attained in empirical study were very similar to those compared to Altman et al. (2005) as well as to Bruche and González-Aguado (2008), the two studies considered as remarkable contribution to the research on link between defaults and recoveries. Some differences stem, naturally, from different time periods used. Nevertheless, the movements of credit variables seemed to be tightly linked to each other. In addition, some methodologies used in this thesis differed from the methodologies used in previous research. The univariate analysis of credit variables has been on a rather little attention in previous research, and thus I concentrated deeper on examining the self-predicting performance of credit variables, on purpose. The results reached in univariate analysis also supported the view about tightly related credit variables. Earlier related studies have also left out the analysis of shocks and responses. As there has been evidence of interrelationship between credit variables and business cycle, the impulse response analysis between GDP growth and credit variables seems an obvious procedure to discover the movements of credit variables over business cycles. Besides, the

results on impulse response analysis supported greatly the results retrieved from univariate and multivariate regressions.

This thesis is, however, only a relatively broad review into credit risk research and it examines the relationships between defaults and recoveries on a relatively straightforward level. Hence, this is a fruitful ground for further examination over credit markets. Alternatives are many.

As this thesis utilized global corporate bond default and recovery data with the world GDP growth rate and provided significant results, one possible way to examine these relations more comprehensively would be to use country or region specific data. An interesting question would be that do the variables of other countries or regions help predicting world-wide defaults and recoveries, or are the U.S. specific variables (such as the U.S. GDP growth rate) the most powerful ones. This is an interesting question especially taking into account the latest discussion on the rising China and other Asian countries.

One of the limitations in this study concerned the frequency of data. In further inspections the quarterly data would be important to utilize as earlier research has somewhat utilized quarterly data as well. However, the data retrieved from Moody's did include only annual data. It is good to remember, that the most important variables used are sufficient on annual basis, although more frequent data would enable to use equity indices and default spread data more efficiently.

The methodology and models used in this study were rather straightforward econometric time series models such as AR(1), AR(2), MA(1), ARMA(1,1) and VAR(1). This stems understandably from the time frequency as it would have been useless to utilize higher-order models with annual data. However, more frequent data would allow us to model with higher orders and consider alternative models such as more developed VAR models. These would include SVAR and SVEC models. Using more frequent data would make it also interesting to structure a VAR model incorporating more variables at the same time. More comprehensive models would also include the Markov model of trend, which was briefly discussed in chapter 3.

After all, credit risk has been examined relatively narrowly in the fixed income markets and studies of relations between credit variables are a rather recent trend in the examination of credit risk. This paper updated the recent published literature about interrelations between default rates and recovery rates and provided results that are in line with previous related research. Furthermore, the examination of relations between corporate bond default rates and recovery rates offers a useful aspects and tools for fixed income portfolio management as well as for the pricing of credit risk.

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APPENDIX 1   CREDIT VARIABLE CORRELOGRAMS

Autocorrelation for DR
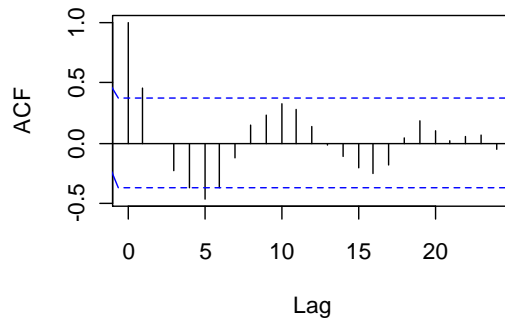
Partial autocorrelation for DR
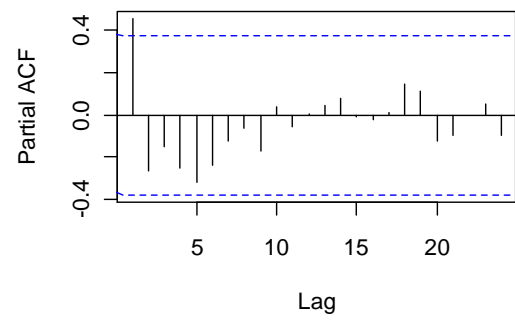
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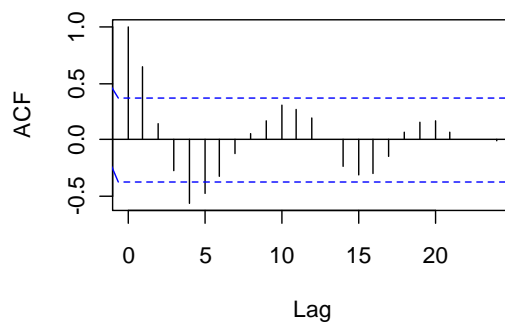
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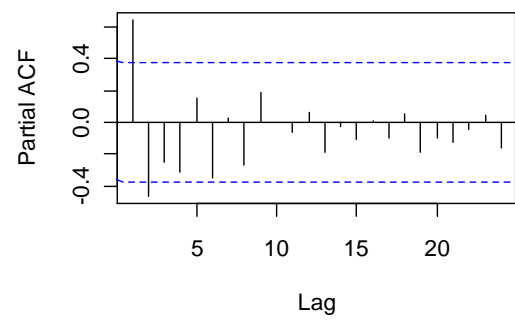
APPENDIX 2   UNIVARIATE RESIDUAL DIAGNOSTICS

AR(1) autocorrelations for DR
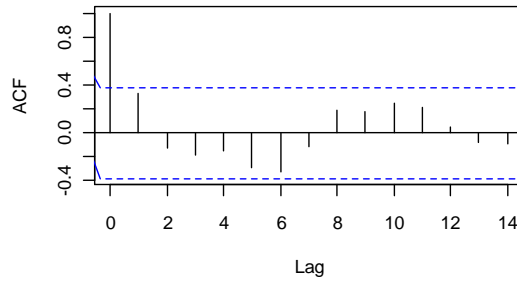
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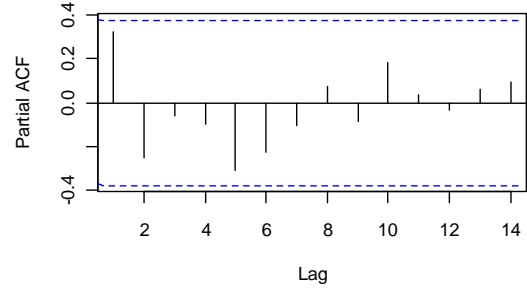
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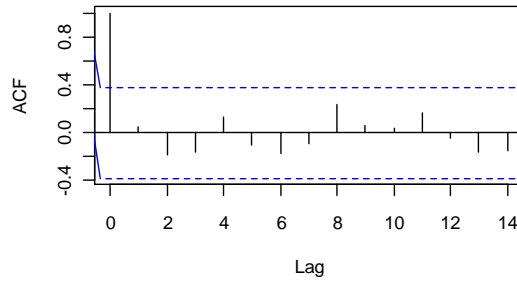
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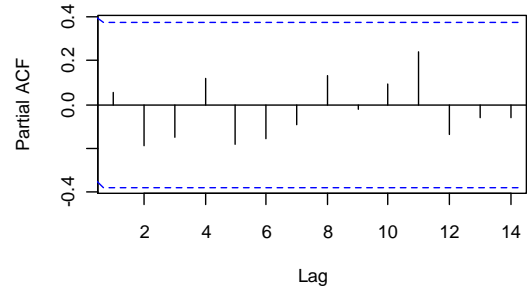
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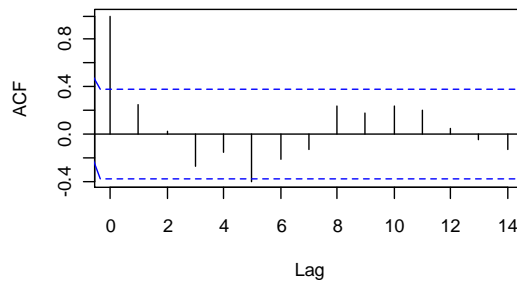
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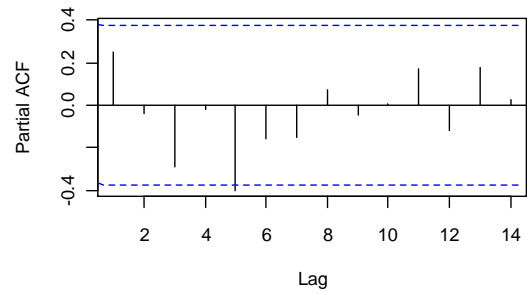
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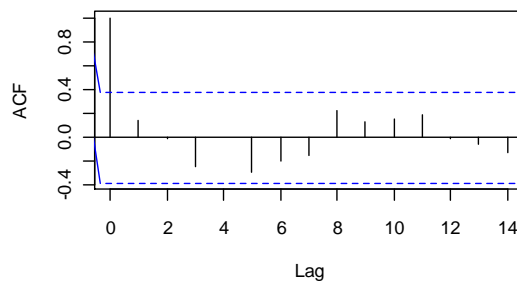
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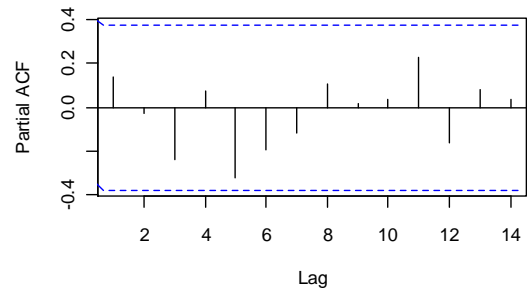
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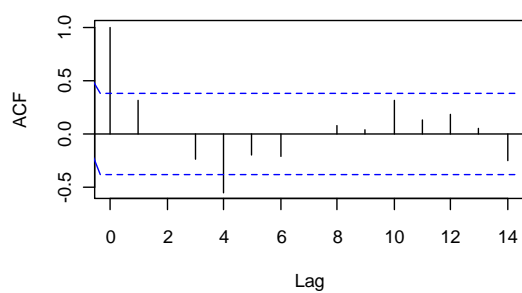
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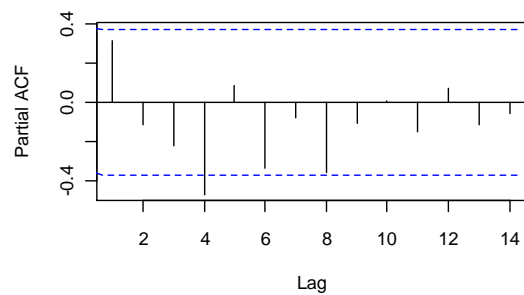
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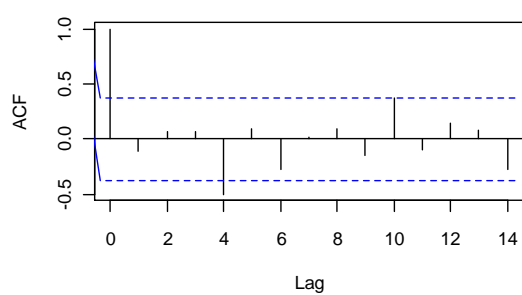
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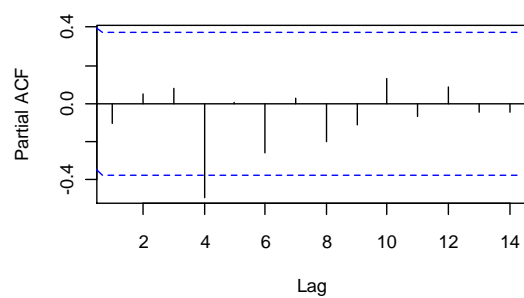
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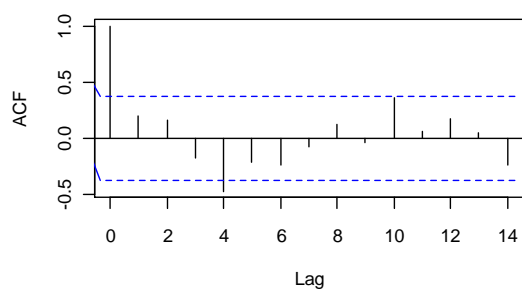
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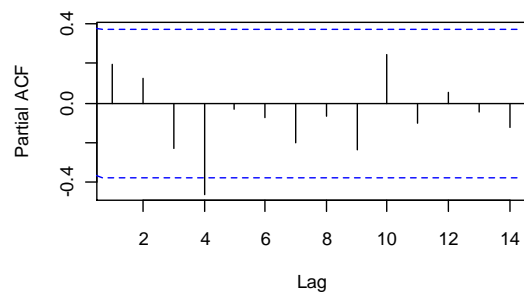
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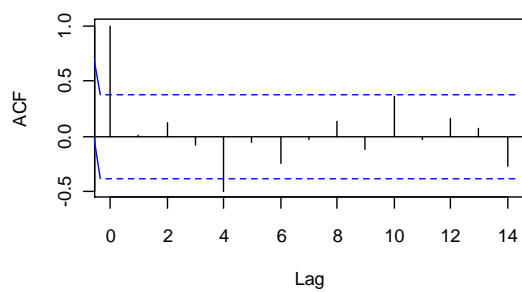
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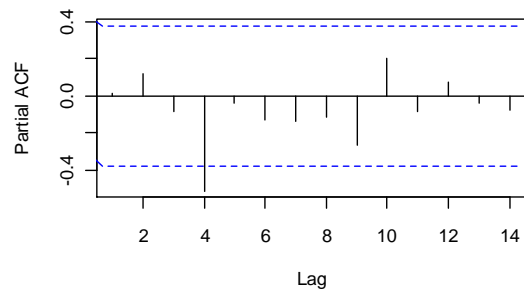
APPENDIX 3   MULTIVARIATE RESIDUAL DIAGNOSTICS

Diagram of fit and residuals for DR

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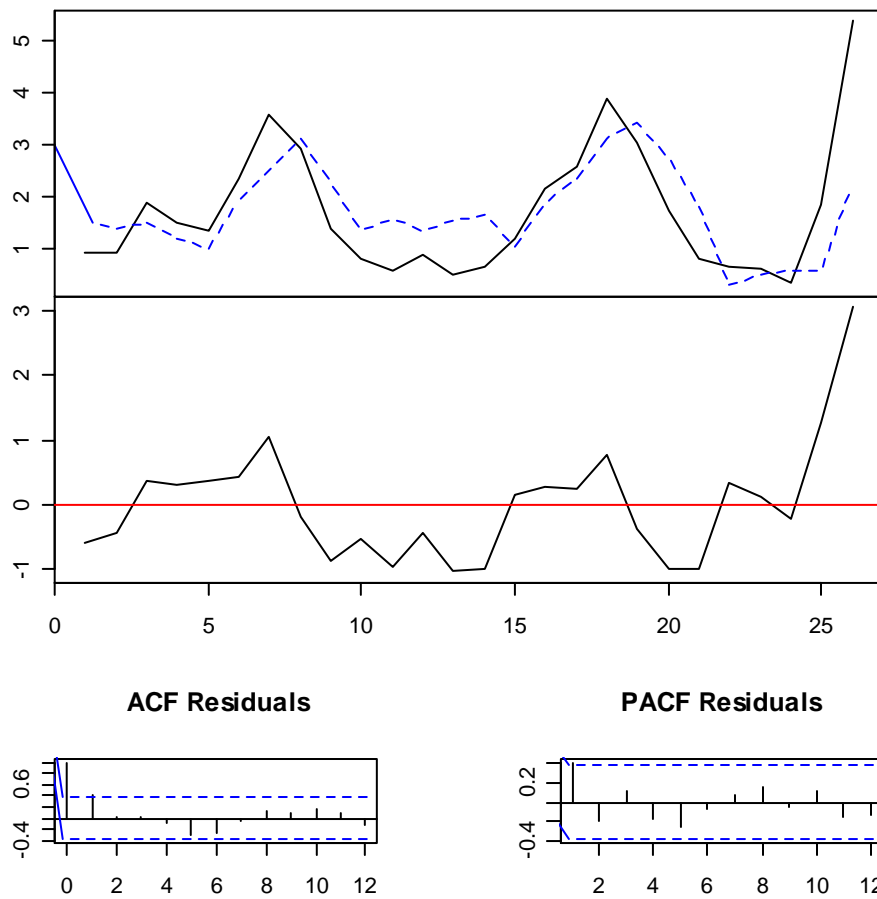
PACF Residuals

Diagram of fit and residuals for RR
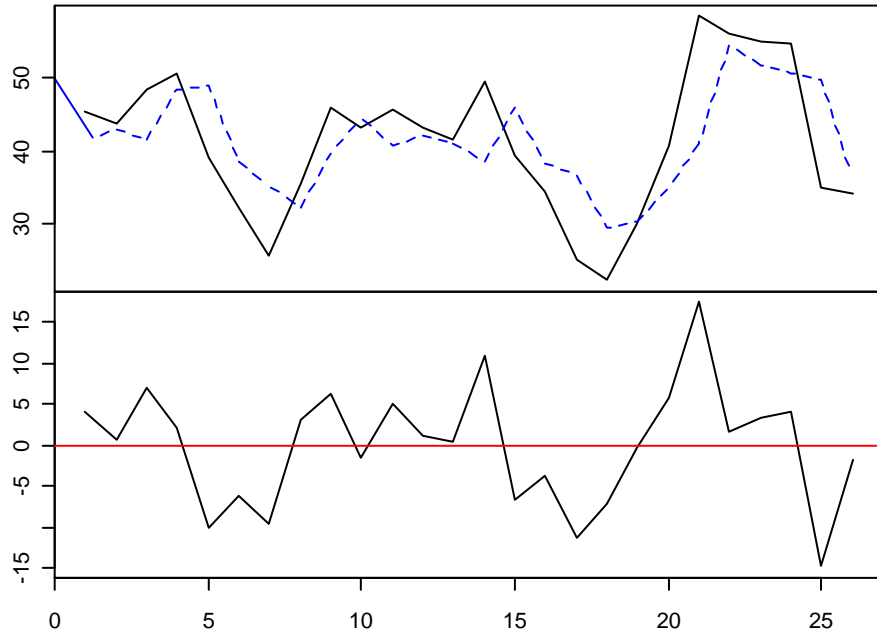
ACF Residuals
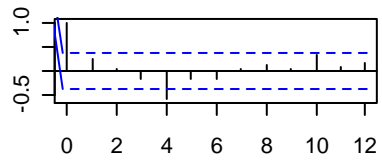
PACF Residuals
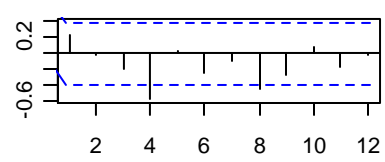
Model 4 acf for DR
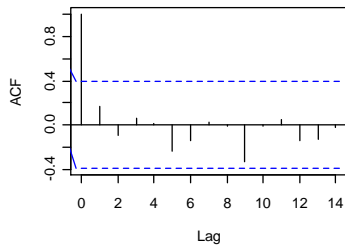
Model 4 acf for RR
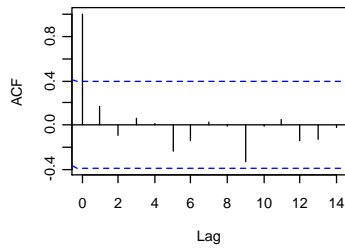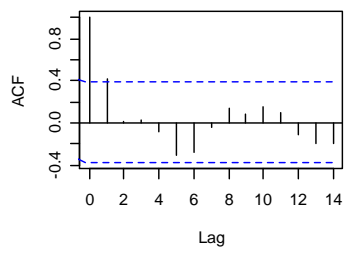
Model 4 acf for S&P500
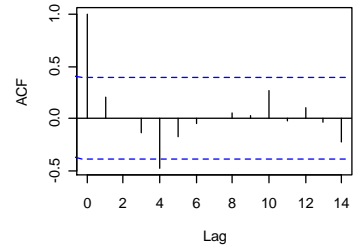
Model 4 pacf for DR
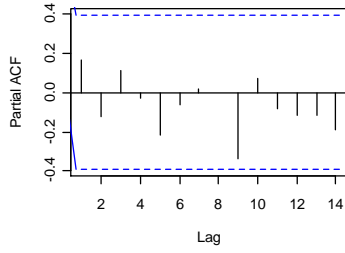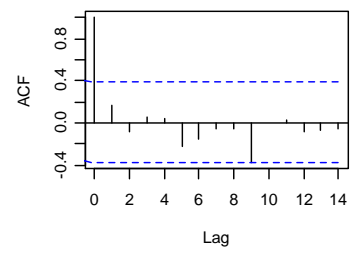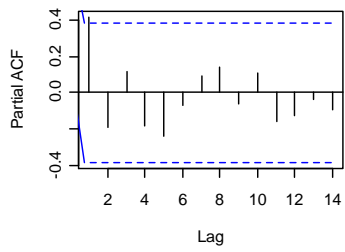
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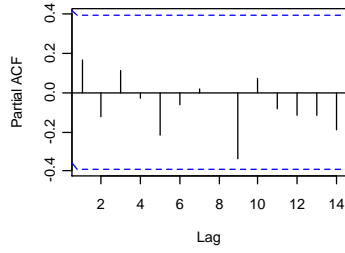
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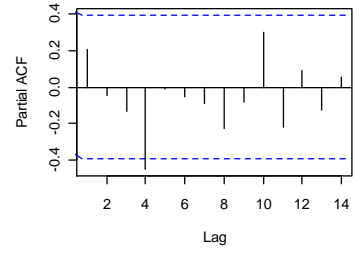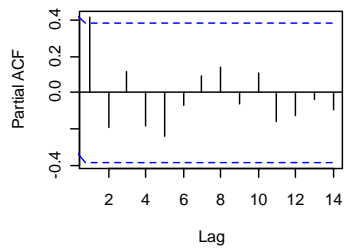
Model 5 acf for DR
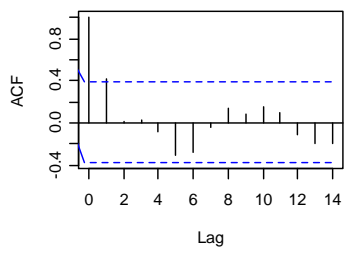
Model 5 acf for RR

Model 5 acf for Spread

Model 5 pacf for DR

Model 5 pacf for RR

Model 5 pacf for Spread