COPING WITH CREDIT RISK

Essays on defaulted bonds, asset based lending and provisioning for loan losses by financial institutions

Suzanne Bijkerk

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Essays on defaulted bonds, asset based lending and provisioning for loan losses by financial institutions

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Barendrecht, oktober 2012

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Chapter 1

Introduction

"In this world nothing can be said to be certain, except death and taxes."
Benjamin Franklin (1706-1790)

1.1 Motivation and research objective

Uncertainty is part of life as the quote of Benjamin Franklin clearly states. A distinction should be made between uncertainty and risk. Uncertainty includes all facts in life that do not have a certain outcome and cannot be measured. Risk[1] is the measurable counterpart of uncertainty (Knight (2002)). This thesis is focused on risk, and more specifically on credit risk. The risks companies face can be classified broadly into two types of risks, business risks and financial risks. Business risks are the risks that are part of the core business of a company and which they use to create added value for stakeholders. Financial risks are the risks that are not based on the primary function of the company, but to which the company is exposed by the environment she has her activities in (Jorion (2007) and Duffie & Singleton (2003)). A financial intermediary is an economic agent who specializes in the activities of buying and selling (at the same time) financial claims (Freixas & Rochet (2008)). Because the primary function of financial institutions is to manage financial risks actively, the distinction between business and financial risks is not apparent for financial institutions. The risks financial institutions face can be subdivided into

[1] Another definition of risk can be found in the book by Jorion (2007), where risk is defined as "the volatility of unexpected outcomes, which can represent the value of assets, equity, or earnings". This definition has more focus on financial risks and does not explicitly mention that risks have to be measurable, but it does so implicitly. We will use the definition of Knight (2002) in this thesis.

four categories, market risk, liquidity risk, operational risk and credit risk[2]. The definitions used by regulators and academics concerning credit risk are diverse. The definition of Jorion (2007) is most appealing for this thesis "*Credit risk is the risk of financial loss owing to counterparty failure to perform its contractual obligations*". Credit risk can originate from three sources[3]:

- default risk also known as counterparty risk. The risk of defaulting by the borrower, measured by the probability of default;
- recovery risk. The risk of recovery of the original loan amount after the borrower has defaulted, measured by the loss given default or the recovery rate;
- credit exposure risk. The risk of the height of the loan amount outstanding on the moment of default of the borrower, measured by the exposure at default, limited by the credit limit;

Full mitigation of credit risk is in theory only possible through a complete contingent contract between the borrower and a financial institution. In practise and by definition[4] financial contracts are incomplete and asymmetric information gives rise to adverse selection (hidden information) and moral hazard (hidden actions). Financial institutions try to control the amount of credit risk in their loan portfolio by the implementation of a financial contract with the borrower. A financial contract between a borrower and a lender commonly states the interest rate, covenants, collateral and a credit limit. Compliance of the borrower to the conditions of this financial contract is enforced through screening and monitoring.

The research objective of this thesis is to analyze credit risk in the financial sector in three specific forms

- to explore the option to mitigate credit risks through countercyclical provisioning for loan loss reserves (chapter two and three);

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[2] Market risk, liquidity risk, operational risk and credit risk are all idiosyncratic risks, which have the property that the risks can be mitigated (in theory) by diversification. Systemic risk stands opposite to these risks and is usually defined as any risk that may affect the financial system as a whole (de Bandt & Hartmann (2000)). Systemic risk may result in contagion where the failure of one bank may propogate the entire banking industry (Freixas & Rochet (2008)).

[3] The credit risk on a loan can be quantified through the expected loss measure, being probability of default times the loss given default times the exposure at default.

[4] A complete contingent contract would specify in every possible state of nature and at every interim date the amount of repayment, the interest rate on remaining debt, the value of collateral and the actions undertaken by the borrower. By definition a complete contingent contract only exists in a world with full information on every state of nature about the implications of this state for the borrower and the financial institution. But in a perfect market, without information voids, there would be no need for financial intermediaries.

- to analyze interest setting and pricing behavior by asset based lenders in an asymmetric, dynamic market with low risk and high risk borrowers. We analyze how asset based lenders integrate the different risk profiles of borrowers in their interest setting (chapter four);
- to empirically analyze the distribution of recovery rates of defaulted bonds (chapter five);

The remainder of this introduction proceeds as follows. The next section gives an overview of the thesis and in section three I briefly discuss the contribution of this thesis to current literature.

1.2 Overview of the thesis

This thesis analyzes credit risk from three different perspectives. Chapter two and three focus on one specific form to mitigate credit risks, that is to form countercyclical provisions for loan losses. Chapter four analyzes how asset based lenders integrate credit risk in their interest rate in a dynamic market with asymmetric information and competition. In chapter five we focus on a specific part of credit risk, namely the distribution of recovery rates of defaulted bonds.

Chapter two introduces a new method of forming loan loss provisions for banks and links this provisioning method to liquidity requirements. This method is compared to current provisioning methods in literature and current regulation for banks, in the form of IFRS, Basel II and III. We discuss two loan loss provisioning methods in this chapter, Spanish statistical provisioning and Italian dynamic provisioning. The Spanish statistical provisioning method tones down the cyclical effect of loan loss provisioning and the Italian dynamic provisioning behaves acyclical[5]. We present a new method of countercyclical provisioning for loan losses to optimize the use of detailed loan loss knowledge within the banks and minimize subjectivity in provisioning. The minimization of subjectivity benefits the verifiability of the used provisions by banks and restricts the cyclicality. The new provisioning method takes into account the different distributions of high risk and low risk assets within the banks and recommends to use a multiplier γ. The multiplier γ is determined by the financial regulator to improve objectivity. This multiplier will tone down provision-

[5]The dotations to the loan loss provision do not depend on the macro-economic cycle.

ing in a recession and raise provisioning in an upturn of the business cycle. The multiplier differs from the multiplier Repullo et al. (2010) suggest. They propose a multiplier for all capital requirements, that is based on the comparison of current GDP growth to its long term trend. The multiplier we propose should not be used for the total amount of capital, but for the provisions of the specific bank. Our multiplier takes into consideration the risk profile the different banks have. Also our provisioning form does not propose the use of a specific business cycle indicator to form this countercyclical provision. We are of the opinion that the business cycle indicators that are best suited for each separate country may differ. Transferring part of this loan loss provision (α) to a Financial Market Stability Fund, governed by the financial regulator, gives recognition to the correlation between the solvency position and liquidity position of a bank. A Financial Market Stability Fund is a policy measure for a financial regulator to control the credit channel and money supply. Both Basel III and IFRS are not opposed supplementary measures by financial regulators. Although academic literature (Diamond & Rajan (2005)) recognizes the interaction between liquidity and solvency of banks, regulation like Basel III and IFRS do not incorporate this interaction in their requirements. The implementation of a Financial Market Stability Fund does recognize the correlation between the liquidity position and the solvency position of a bank and provides a verifiable and more objective method to ensure financial stability.

Chapter three tests known business cycle indicators in their ability to predict the amount of credit risk in the financial sector. The purpose of this analysis is to find a business cycle indicator or a combination of business cycle indicators that can be used to form countercyclical provisions (the proposal we introduce in chapter two). Credit risk is always present in the loan portfolio of a financial institution, but when the economic environment is in an upturn, credit risk is undervalued. In contrast credit risk is overvalued by the financial institution, when a recession arrives. The subjectivity of the valuation of credit risk, is one of the causes of procyclical behavior of financial institutions. In this chapter we use the number of bankruptcies as a percentage of domestic credit as a proxy for the amount of credit risk present in the financial sector in a country. We consider multiple business cycle indicators in their ability to forecast this proxy. We use lagged, autoregressive OLS regressions to test the correlation between the business cycle indicators and the proxy for credit risk. We run out-of-sample forecasts to determine the accuracy of the business cycle indicators to predict this proxy for credit risk. We use data concerning business cycle indicators and the number of bankruptcies in The Netherlands and The United States of America for the regressions and the forecasts. The time series of the Euro area are unfortunately too short to perform statistical tests on. We find that a combination of the credit-to-GDP gap and a stock exchange indicator, gives the best forecasts for our proxy. The use of only the credit-to-GDP gap to determine the height of the countercyclical provision, as Drehmann et al. (2010) propose, works poorly for our proxy. One-lagged indicators give the best forecasts for our proxy in The Netherlands, whereas in the United States of America, two-lagged indicators give the best results. The forecasts and regressions for The Netherlands give better results than those for the United States of America. We presume (without any further evidence) that this result might be caused by the use of our proxy (the number of bankruptcies as a percentage of domestic credit), that seems better applicable to the European funding behavior of corporations that the US corporate funding behavior, in accordance with Hackethal & Schmidt (2005). Even though the number of observations of our proxy is very limited and only available on a yearly base, the results are significant. A good indicator for the amount of credit risk in the financial sector is essential to construct a useful countercyclical provision for loan losses.

In chapter four we analyze the interest setting by asset based lenders in a dynamic market with an inelastic demand for loans. We define a dynamic market as a market where borrowers exit the market, as a result of default, and new borrowers enter the market. This chapter characterizes the complete set of Nash equilibria in a duopoly with incomplete information and learning in this dynamic market. This chapter recognizes cohorts of borrowers with a high risk profile, cohorts of borrowers with a low risk profile and two asset based lenders. The borrowers' market is characterized by adverse selection of high risk borrowers and the lack of a pure strategy equilibrium. We find that the division of borrowers can be modelled for all phases according to a defined series. Separate markets arise in which neither of the asset based lenders has an informational advantage (new borrowers' market) or one of the asset based lenders has an informational advantage (inside asset based lender). The asset based lender gains positive informational gains on the low risk borrowers in the market in which he has an informational advantage. The mixed strategy of the outside asset based lender has first order stochastic dominance over the mixed strategy of the inside asset based lender. The average interest rate the inside asset based lender offers is lower than the average interest rate the outside based lender offers over the whole range of interest rates of the mixed distribution. The mixed strategy equilibria for each new phase depends on the number of borrowers in the market, their risk profile and the probability of default of these borrowers. An increase in the amount of high risk borrowers on the market, increases adverse selection. As a result of the increased adverse selection, the informational gains for the inside asset based lender increase. The informational gains increase because the value of information with regard to the risk profile of the borrowers becomes more valuable. We find that the probability of switching for low risk borrowers depends on the relative size and riskiness of the low risk borrowers in comparison to the total market. We also find that the interest rate offered to low risk borrowers increases when the probability of default for the high risk borrowers increases.

Chapter five describes the distribution of recovery rates for defaulted commercial bonds that defaulted in the period 1981-2011. We analyze which bond characteristics influence the distribution of recovery rates. We model the different subsamples, according to these characteristics separately. We use the bond prices of all publicly available bond data of defaulted companies in the period 1981-2011 as proxies for the recovery rates of these bonds. We analyze whether the empirical subsamples are best modelled through a theoretical Beta distribution, a truncated normal or a truncated Weibull distribution. We test the goodness of fit of the theoretical distributions to the empirical data with the Kolmogorov-Smirnov test statistic and Cramer-von Mises test statistic. In accordance with Schuermann (2004) we find that a bond with a default date in a NBER recession period has a significant different recovery rate than a bond with a default date in a NBER non-recession period. Contrary to the analysis of Schuermann (2004) our analysis shows that collateral does not appear to be of significant influence on the bond recovery rate. We also analyze the percentage lifetime of the bond, this characteristic gives an indication of the timeperiod of the bond between issue date and default date in comparison to the duration of the bond (the numerator of this variable corresponds to the time to default). The percentage lifetime of a bond is always in between 0 and 1. A defaulted bond with a very low percentage lifetime is a bond that defaulted quite soon after it was issued in comparison to it's duration. The percentage lifetime is of significant influence on the bond recovery rate. We subsample the recovery rates according to their bond characteristics (NBER recession default date, percentage lifetime and collateral). We use the different subsamples to determine the goodness of fit of the theoretical distributions. We find that the different subsamples of the distribution of recovery rates of defaulted bonds are best modelled as a truncated Weibull distribution. The goodness of fit of the empirical data to the Weibull distribution increases, if the empirical data is separated according to the significant bond characteristics.

1.3 Contribution to current literature

Credit risk has been the subject of research dating back to Black & Scholes (1973), Wilcox (1973) and Merton (1974). Credit risk does not only impact financial institutions, but also financial markets and the economy as a whole. The current financial crisis has shown us that there are still voids in our knowledge concerning the influence and impact of credit risk. This thesis tries to offer a humble contribution to our knowledge on credit risk.

Chapter two presents a new method of countercyclical provisioning for loan losses to optimize the use of detailed loan loss knowledge within the banks and minimize subjectivity in provisioning. The minimization of subjectivity benefits the verifiability of the used provisions by banks and restricts the cyclicality. Transferring part of this loan loss provision (α) to a Financial Market Stability Fund, governed by the financial regulator, gives recognition to the correlation between the solvency position and liquidity position of a bank. A Financial Market Stability Fund is a policy measure for a financial regulator to control the credit channel and money supply. Although academic literature (Diamond & Rajan (2005)) recognizes the interaction between liquidity and solvency of banks, current loan loss provisioning literature does not model the interaction between bank solvency and liquidity. Our proposal for a Financial Market Stability Fund has the following advantages in comparison to current loan loss provisioning models in literature:

- The provisioning form we propose behaves counter-cyclical, instead of toning down the pro-cyclical behavior of banks concerning loan loss provisions (de

Lis et al. (2000)) or implementing an a-cyclical form of loan loss provisioning (Burroni et al. (2009));

- Our provisioning form places emphasis on the influence of loan losses on bank profits in a recession (as is shown by Bolt et al. (2011)) of the economic cycle as a disrupting factor of financial stability. Repullo et al. (2010) use a multiplier to adapt equity, we use a multiplier to enlarge or reduce the loan loss provisions;
- The use of a Financial Market Stability Fund links the risk-profile of the bank's loan portfolio, their solvency position and the bank's liquidity position. Current loan loss provisioning literature does not link the risk-profile of the bank's loan portfolio to their liquidity position, even though loan losses do inevitably cause friction within the liquidity forecast of a bank.

We also discuss the impact a Financial Market Stability Fund on current year report regulation, IFRS, and bank regulation in the form of Basel II and III in contrast to existing literature.

Chapter three analyzes business cycle indicators that are best fit to predict the amount of credit risk in the financial sector. The analysis of business cycle indicators has a long history. The classical techniques were developed by the National Bureau of Economic Research (NBER) and can be found in the articles of Mitchell (1913, 1927), Mitchell & Burns (1938) and Burns & Mitchell (1946). The classical theory of business cycles is focussed on the identification of the business cycle and the interaction between the indicators and the business cycle. We contribute to the current literature of countercyclical provisioning by the use of a different proxy for the amount of credit risk in the financial sector. We also contribute by using a different econometric approach to test the suitability of the business indicators for countercyclical provisioning. This chapter takes into consideration that bank profitability is driven by loan losses and influenced by credit risk in a recession in conformity with Bolt et al. (2011) and uses an ex post proxy for the determination of the amount of credit risk present in the financial market. Our method of research is much less sophisticated than the already present econometric methods in current literature (for example McNeil & Wendin (2007), Figlewski (2006), Koopman et al. (2009), and others). This chapter differs in two aspects from this strand of literature. Firstly the goal of this chapter is not to find an optimal method for predicting the probability of default of a loan portfolio or determining the systemic risk factors present within the corporate default rates. The goal of this chapter is to determine an indicator that can be used in a method for countercyclical provisioning by banks. We therefor use an off-the-shelf regression and an out-of-sample forecast method and do not integrate firm-specific or bank-specific determinants in our model. The second aspect that differs in our approach is the comparison between the indicators and our proxy in The Netherlands and The United States of America. In the conclusion we give a preview of how the indicators can be used to form a countercyclical provision.

Asset based lending is not a subject of extensive academic research. Asset based lending is characterized by an inelastic demand for loans and is situated in between transaction based lending and relationship lending. Small businesses with a high risk profile are the prime borrowers of asset based lenders. Current literature analyzes the consequences of relationship banking (Boot (2000), Houston and James (2001), Berger and Udell (2006)) and transaction based lending (Boot & Thakor (2000)). The close monitoring of asset based lenders brings about a steep learning curve concerning the risk profile of their borrowers, see Rajan & Winton (1995). The combination of learning by monitoring and short term contracts ensures that asset based lenders can easily adapt the loan terms based on the information they receive. The combination of a dynamic borrowers' market (where borrowers enter and default), an inelastic demand for loans and the use of convenants and collateral distinguishes asset based lenders from other financial institutions. An analysis of the combination of these market, borrower and lender characteristics is, to our knowledge, not present in current literature. We contribute to current literature by characterizing the complete set of Nash equilibria in a duopoly with incomplete information, learning and a dynamic borrowers' market. In our model there are cohorts of borrowers with a high risk profile, cohorts of borrowers with a low risk profile and two asset based lenders. The market is characterized by adverse selection of high risk borrowers and the lack of a pure strategy equilibrium. We contribute to current literature through the analysis of the division of high risk and low risk borrowers over the different periods in which asset based lenders offer interest rates. We find that the probability of switching for low risk borrowers depends on the relative size and riskiness of the low risk borrowers in comparison to the total market. We also find that the interest rate offered to low risk borrowers increases when the probability of default for the high risk borrowers increases.

The probability of default has received, in comparison to the other components of credit risk, most attention in academic literature (amongst others Wilcox (1971) and Scott (1981)). Only fairly recent the attention has shifted towards the analysis of the loss given default (amongst others Gupton et al. (2000), Gupton and Stein (2002) and Altman et al. (2003)). Our analysis contributes to current literature in two aspects. The first aspect concerns the percentage lifetime characteristic of a defaulted bond that is included in our analysis. The percentage lifetime of a defaulted bond gives an indication of the timeperiod between the default date and the issue date of the bond in comparison to it's duration (the numerator of this variable is referred to in literature as the time to default). The percentage lifetime of defaulted bonds is of significant influence on the distribution of recovery rates. This result implies a (significant) correlation between the time to default in comparison to bond duration and the loss given default of bonds. To our knowledge this correlation is not yet been analyzed in literature. The second aspect of our analysis that contributes to current literature is the result that the recovery rates of defaulted bonds are best modelled through a truncated Weibull distribution.

Chapter 2

Financial Market Stability Fund

This policy chapter introduces a new method of countercyclical loan loss provisioning for banks. This method takes into account the link between the solvency and liquidity position of banks[1].

2.1 Introduction

> "Conservatism of Dutch banks damages their shareholders. The stubbornness of the banks, which they use to hold on to their secrecy concerning the size of their VAR-provisions[2], prevents a clear assessment of the financial power of banks."

Above mentioned quote is from a Dutch newspaper, De Volkskrant (1995, 03-24), revealing the time frame in which essential decisions were made concerning accounting standards, transparency of banks and risk management. The quote was at the start of the dismissal of the formation of provisions for general banking risks (the so called VAR-provisions) by Dutch banks. The intransparency concerning these provisions and the use of these provisions for "income-smoothing" were seen as detrimental for shareholder value and other stakeholders. As a consequence VAR-provisions were no longer permitted. This and other "shareholder value enhancing" changes increased the gearing in the banking sector. In view of the current financial

[1] I would like to thank André Lucas, Maarten Pronk and Job Swank for their valuable comments on earlier versions of this chapter.

[2] This abbreviation stands for "voorziening algemene risico's" (provision general banking risks) or in plain Dutch "de stroppenpot". We refer to appendix 2A for the original quote.

turmoil the call for the strengthening of the balance sheets of banks has risen and so have the opportunities to avoid the disadvantages of the former VAR-provisions.

In the available literature there is no general agreement on the definition of financial stability. By some authors it is linked to the economy's performance (Chant (2003)), the absence of crises or instability (Crockett (1996) and Norwegian Central Bank (2003)) or the efficient performance of the financial system (Deutsche Bundesbank (2003)). The aspect of financial stability that we focus on, is managing of financial risks and absorbing shocks by the financial system (Houben et al. (2004)). One policy instrument that can be used to mitigate risks and absorb shocks is installing a financial safety net for banks. Countercyclical provisions for loan losses and the introduction of a liquidity requirement that is linked to the solvency position of the bank can be part of this financial safetynet.

Banks are known to show procyclical behavior (p.e. Borio et al. (2001), Berger & Udell (2006) and Bikker & Metzemakers (2005)): they expand lending activities and value the risks involved as low in an expansion stage of the economy and they tighten credit supply and value the risks involved as high in a recession. Countercyclical provisioning can counteract the procyclical behavior of banks. Whilst some academic papers show increased liquidity can increase banking instability (Wagner (2006)), others claim liquidity requirements may be more effective than capital buffers (Cifuentes et al. (2005)). In this chapter we discuss the influence of the liquidity requirements on the solvency of banks. We also show that our proposal for a Financial Market Stability Fund can counteract the procyclical behavior of banks and provide a financial safety net.

This chapter introduces a new method of forming loan loss provisions for banks and links this provisioning method to liquidity requirements. We present a new method of countercyclical provisioning for loan losses in this chapter to optimize the use of detailed loan loss knowledge within the banks and minimize subjectivity in provisioning. The minimization of subjectivity benefits the verifiability of the used provisions by banks and restricts the cyclicality. The new provisioning method takes into account the different distributions of high risk and low risk assets within the banks and recommends to use a multiplier γ, that is established by the financial regulator. This multiplier will tone down provisioning in a downturn of the cycle and raise provisioning in an upturn of the cycle. Our multiplier takes into consideration the risk profile the different banks have. Transferring part of this loan loss provision (α) to a Financial Market Stability Fund, governed by the financial regulator, gives recognition to the correlation between the solvency position and liquidity position of a bank. A Financial Market Stability Fund is a policy measure for a financial regulator to control the credit channel and money supply. Although academic literature (Diamond & Rajan, 2005) recognizes the interaction between liquidity and solvency of banks, current loan loss provisioning literature does not model the interaction between bank solvency and liquidity. Our proposal for a Financial Market Stability Fund has the following advantages in comparison to the current loan loss provisioning models in literature:

- The provisioning form we propose behaves counter-cyclical, instead of toning down the pro-cyclical behavior of banks concerning loan loss provisions (de Lis et al. (2000)) or implementing an a-cyclical form of loan loss provisioning (Burroni et al. (2009));
- Our provisioning form places emphasis on the influence of loan losses on bank profits in a downturn (as is shown by Bolt et al. (2011)) of the economic cycle as a disrupting factor of financial stability, contrary to adapting equity capital (Repullo et al. (2010)). We use a multiplier to enlarge or reduce the loan loss provisions;
- The use of a Financial Market Stability Fund links the risk-profile of the bank's loan portfolio, their solvency position and the bank's liquidity position. Current loan loss provisioning literature does not link the risk-profile of the bank's loan portfolio to their liquidity position, even though loan losses do inevitably cause friction within the liquidity forecast of a bank;

We also discuss the impact a Financial Market Stability Fund on current year report regulation, IFRS, and bank regulation in the form of Basel II and III in contrast to existing literature.

This chapter is structured as follows: section two discusses related literature. Section three describes the basic theoretical model that is used in this chapter and section four introduces a new form of countercyclical provisioning for banks. Section five compares Spanish statistical provisioning and Italian dynamic provisioning to the new provisioning model described in section four. The next section introduces a new form of regulation to link the solvency position of banks to their liquidity position. Section seven shows the implications of the new provision form on IFRS, Basel II and Basel III. The final section of this chapter concludes and gives indications for further research.

2.2 Related literature

The related literature for this chapter can be divided in two strands of literature. The first strand concerns recently published regulation for banks and the second strand of literature concerns the procyclicality of and provisioning for loan losses by financial institutions.

Basel III (2010) was published in December 2010 and suggests additive measures to ensure financial stability. The additive measures include limiting the definitions of tier-1 and tier-2 capital, the introduction of a Capital Conservation Buffer and two liquidity measures. Also a countercyclical capital buffer was introduced in Basel III. The aim of this countercyclical buffer is to ensure that the capital requirements take into account the macro-financial environment in which banks operate. Although Basel III only recently (December 2010) introduced the countercyclical buffer, in academic literature countercyclical capital requirements and the procyclicality of banks has already been a debated subject, well before the publication of Basel III.

Daesik & Santomero (1988) analyze the effect of bank capital regulation on risk behavior of banks. They conclude that risk-weighted capital reduces risky bank behavior if the risk weights are based on the expected return, their variance-covariance structure and the upperbound of insolvency risk. Rochet (1992) reaches a similar conclusion. If banks behave as utility maximizing portfolio managers, risk based capital requirements are a relevant instrument but only if the risk weights are proportional to the systemic risks of the assets. De Lis et al. (2000) acknowledge the procyclical behavior of bank lending and introduce a new (statistical) provisioning method for Spanish banks (this method is discussed in this chapter). After the introduction of Basel II (2006) many academic papers focus on the possibility of procyclical behavior due to Basel II. Pederzolli & Torricelli (2005) propose a forward-looking model for time-varying capital requirements, with this model they want to counteract the procyclicality of Basel II on capital requirements. Repullo & Suarez (2009) show in a dynamic equilibrium model that Basel II buffers are insufficient to prevent a significant contraction in the supply of credit at the arrival of a recession. The combination of relationship lending and the frictions in banks' access to equity markets has the potential to cause significant cyclical swings in the supply of credit. Caprio (2010) examines the countercyclical provisioning method in Spain and Colombia and concludes that these methods are not capable of preventing an asset bubble. Blundell-Wignall and Atkinson (2010) try to determine if the measures in Basel III could prevent another crisis. They conclude that Basel III has some helpful proposals, but also some major concerns with regard to the use of regulatory arbitrage by banks and the use of the shadow banking system. Drehmann et al. (2010) find that a system-wide approach for countercyclical provisioning would be better than bank-specific. De Lis & Herrero (2010) empirically compare the countercyclical provisioning methods of Spain (implemented in 2000), Colombia (implemented in 2007) and Peru (implemented in 2008). They advocate a rule-based system with the use of both provisioning and additional capital to strengthen banks' balance sheets. Marcucci and Quagliariello (2009) analyze the effect of the business cycle on bank credit risk. They find that not only the effects of the business cycle are more pronounced during recessions, but cyclicality is also higher for those banks with riskier portfolios. Bolt et al. (2011) establish the drivers for bank profitability in a recession and in an upturn of the business cycle. In an economic downturn bank profitability is primarily driven by loan losses and in an economic upturn historical long-term interest rates determine the result. Both these results advocate the use of countercyclical provisioning. Repullo and Saurina (2011) empirically assess the application of the credit-to-GDP gap to form countercyclical provisions for the UK. They conclude that the use of the credit-to-GDP gap might not dampen the procyclicality of bank capital regulation and may even exacerbate it. They also discuss some measures that might have a different outcome, for example a multiplier where they compare current GDP growth to its long term average to establish a multiplier for the capital requirements.

2.3 Balance sheet restrictions and a capital requirement

As the basis for our analysis, we use the model of Peek & Rosengren (1995) to analyze the influence of the different provisioning methods on solvency position of a bank[3]. We use a one-period model and assume that no provisioning for loan losses has occurred in the previous period[4]. We also assume that a bank cannot obtain any new equity. The bank is presumed to have one sort of asset: loans (L_t), consisting of good (low-risk) loans and bad (high-risk) loans where x is the ratio of good loans in comparison to the total amount of loans. The liability side of the balance sheet of the bank consists of equity (E_t), loan loss provisions (R_t) and deposits (D_t). The balance sheet constraint requires the asset side of the balance sheet to be equal to the liability side of the balance sheet:

$$xL_t + (1-x)L_t = E_t + R_t + D_t \tag{2.1}$$

We use the same hypothesis as Peek & Rosengren (1995) that in the loan market and deposit market the amount of deposits and loans the bank can attain, depends on the interest rate they offer borrowers (r_L) and depositors (r_D) in comparison to the mean rate in the market ($\overline{r_L}$,$\overline{r_D}$). The amount of loans and deposits a bank can attract are given by the following functions:

$$L_t = g(r_L, \overline{r_L}) \tag{2.2}$$

$$D_t = f(r_D, \overline{r_D}) \tag{2.3}$$

The Basel Committee demands a capital asset ratio (μ) based on the risk-weighted assets. The Basel Committee assigns different risk weights[5] to the different loan groups. The good loans have a risk weight of 0.5 (this is the risk weight Basel II assigns to A^+ to A^- loans) and the bad loans have a risk weight of 1.5 (this is the

[3]Peek & Rosengren (1995) use this theoretical model to show that a loss of banking capital resulting in binding capital requirements will cause a bank to behave differently than it would if the requirements were not binding. They also use the model to distinguish between the effects of loan demand shocks and bank capital constraints.

[4]See appendix 2B for a list of notation and variables.

[5]Paragraph 66 of "International convergence of capital measurement and capital standards" A Revised Framework Comprehensive version, June 2006, Basel Committee on Banking Supervision;

risk-weight Basel II assigns to loans below BB^-). Basel III demands a total capital requirement of $\mu \geq 0.08$[6]. The capital requirement is given as follows:

$$\begin{aligned} E_t + \widetilde{R}_t &\geq \mu\left[0.5xL_t + 1.5(1-x)L_t\right] \\ &\text{or} \\ E_t + \widetilde{R}_t &\geq \mu(1.5-x)L_t \end{aligned} \tag{2.4}$$

Not all loan loss provisions (R_t) are included in the capital requirement of Basel III, those that are included are depicted by $\widetilde{R}_t$, where $\widetilde{R}_t < R_t$. According to the Basel accord a general loan loss provision can be ascribed to Tier-2 capital[7]. A loan loss provision qualifies for Tier-2 capital if it is held against future, presently unidentified losses and if it is freely available to meet loan losses which subsequently materialize[8]. A specific loan loss provision based on ex post credit risk does not qualify as Tier-2 capital. We assume that banks maximize profits (π_t) and the profits are assumed to be the difference between the interest income on loans ($r_L L_t$) and the interest costs on deposits ($r_D D_t$) and the costs of provisioning (R_t)[9]. The bank profit is stated:

$$\pi_t = r_L L_t - R_t - r_D D_t \tag{2.5}$$

The maximization problem of bank profit can be stated as a Lagrangian, where the Lagrangian multiplier λ is associated with the capital ratio constraint. If we substitute equations (2.2), (2.3) and (2.4) in equation (2.5) the profit maximizing problem is stated:

$$\max \pi = \left[r_L g(r_L, \overline{r_L}) - r_D f(r_D, \overline{r_D})\right] - R_t + \lambda\left[E_t + \widetilde{R}_t - \mu(1.5-x)L_t\right] \tag{2.6}$$

where the height of the provision R_t depends on the applied provisioning method. We assume that the capital ratio is binding, that is $\lambda \neq 0$. The capital requirement

[6] The Basel Committee demands a minimum total capital requirement of 8% of the risk-weighted assets at all times for 2013-2019 (Annex 4). The minimum total capital consists of Tier-1 capital and Tier-2 capital (page 12 part 1).

[7] Paragraph 60 and 61 of "Basel III: A global regulatory framework for more resilient banks and banking systems", December 2010, Basel Committee on Banking Supervision;

[8] General loan loss provisions can only be included in Tier-2 capital up to a maximum of 1.25 percentage points of credit risk-weighted risk assets calculated under the standardised approach. In this chapter we assume the general loan loss provisions remain under this threshold of 1.25 percentage points.

[9] We assume that in the previous period no provisioning has taken place.

μ is of negative influence on bank profit, as is shown in equation (2.6). Profit maximization and a binding capital constraint of $\mu \geq 0.08$, will bring about that the bank keeps the total capital ratio at it's minimum (that is $\mu = 0.08$). Without provisioning ($R_t = 0$) and with a binding capital ratio, the solvency of the bank is stated as follows:

$$\begin{aligned} E_t - \mu(1.5 - x)L_t &= 0 \\ E_t/D_t &= \frac{\mu(1.5 - x)}{1 - \mu(1.5 - x)} \end{aligned} \tag{2.7}$$

The ratio equity-debt in that case does not only depend on the capital asset ratio, μ, but also on the ratio good and bad loans (x).

In the different models for countercyclical provisioning discussed in the next sections different forms of credit risk are recognized:

1. ex ante credit risk (based on historical data): this is the risk of default of a specific loan subset or the total amount of loans. The measurement of this form of credit risk is based on the historical data of the bank (banks should within their measurement of these risks at least include a period that contains a recession and an upturn of the economy). When the bank issues a loan she can already, based on the historical data, determine the ex ante credit risk of the loan.

2. ex post credit risk (based on historical data): this is the risk that occurs when impairing loans during the term of the loan. The probability of default increases when it appears that the issuer of the loan has financial distress, has an actual breach of contract or another incurred act that raises the probability of default. Ex post credit risk can only be determined after the event has occurred concerning a specific loan or subset of loans.

3. estimated credit risk (based on forecasts): the bank makes an estimate of the expected credit risk based on the current loan portfolio, macro economic factors and the financial forecast.

The different provisioning methods discussed in this chapter, use these different concepts of credit risk for provisioning purposes. These different credit risk concepts contain overlap if used simultaneously.

2.4 Proposed new form of countercyclical provisioning

In this section a revised model for countercyclical provisioning based on the basic model mentioned in section three is introduced. Gideon et al. (2009) distinguish two categories of loan loss provisions: specific provisions, made for debts that have been identified as impaired or non-performing, and general provisions, made for those debts that may turn out to be non-performing based on historical data. Because the estimated credit risk is based on forecasts and estimates of future data, this specific credit risk indicator is very sensitive for subjective views. If banks were to determine the estimated credit risk for themselves, it is very likely that they will give a low estimation of this risk factor in a upturn of the economy and a high estimate in a recession. Thus applying this form of credit risk calculation to determine provisions for loan losses will only amplify the cyclicality of provisioning for loan losses. Banks with adequate risk management systems (also needed for the IRB approach of Basel II, paragraph 7) are able to determine ex ante credit risk with historical data at least containing one recent economic cycle (through-the-cycle-rating-systems). This ex ante credit risk, represented by the coefficient g, is not loan specific and states that a certain percentage of all the loans on the balance sheet of the banks will default (or result in a loss). A generic loan loss provision, based on ex ante credit risk approximations is stated as follows:

$$GR_t = g \cdot L_t$$

where GR_t is the generic loan loss provision, g the ex ante credit risk coefficient and L_t the total amount of loans on the balance sheet of the bank. The amount that periodically has to be added or released in the profit and loss account for this provision is:

$$GP_t = GR_t - GR_{t-1}$$

where GP_t is the reservation for the generic loan loss provision in the profit and loss account. An addition to or release of the provision is dependent on the coefficient g of the current and the previous year and the total amount of loans on the balance sheet current and previous year. If the economy is in an upturn and the coefficient g remains unchanged, it is likely that the amount of outstanding loans on the balance sheet of the bank rises and therefore the generic loan loss provision should also rise. It is important that the coefficient g is based on a through-the-cycle-rating-system. For a new bank with little or no historical data (more likely to appear in an upturn of the economy), there are no references available to determine g and the financial regulator should act as a determinative institution (based on data from other banks). For banks that apply the internal-rating based approach of Basel III and have a through-the-cycle-rating-system, the coefficient g is the probability of default (PD) times the loss given default (LGD).

The ex post credit risk coefficient e is based on current and historical data. This coefficient is based on the loans that the bank has yet labeled as 'bad' loans because of incurred acts (such as at this moment the issuer of the loan is already for three months in default, deteriorated financial situation of the issuer of the loan, etc.). The ex post credit risk is represented by the coefficient e and the specific loan loss provision (provision for loan losses on bad loans) is stated as follows:

$$BR_t = e \cdot (1 - x)L_t$$

where BR_t is the specific loan loss provision, e is the ex post credit risk coefficient and $(1-x)L_t$ the amount of bad loans on the balance sheet of the bank. The amount that periodically has to be reserved in the profit and loss account for this provision is:

$$BP_t = BR_t - BR_{t-1} + OL$$

where BP_t is the reservation for the specific loan loss provision in the profit and loss account and OL are the occurred losses on loans during that period that were written off from the provision. When the amount of bad loans on the balance sheet reduces (possibly in an upturn of the economy), this has a positive effect on profit. It may be clear that there is some overlap in the two provisions: the generic loan loss provision is formed for not-yet-apparent bad loans, so when these loans become apparent bad loans and they are partly or fully provisioned for (in the bad loan loss provision), they were partly already provisioned for in the generic loan loss provision.

So far nothing differs from the Statistical Provisioning method of Spain (de Lis et al. (2000)). Are the two above-mentioned provisions cyclical?

- The generic loan loss provision: g, based on the ex ante credit risk coefficient should not differ in an upturn of the economy or a recession. This coefficient is fixed and is determined by historical data of the bank concerning a complete economic cycle. The total amount of loans usually increases during an upturn of the economy and declines during a recession. So the absolute provision will increase during an upturn of the economy, but the percentage of the provision in comparison to the total amount of outstanding loans will not differ. The generic loan loss provision is not cyclical.
- The specific loan loss provision: the amount of bad loans $(1-x)L_t$ increases during a recession. The coefficient e, the ex post credit risk coefficient, might also be cyclical, because during a recession not only the probability of default increases, but also the loss given default (determined by the ex post credit risk efficient) increases. The parameter, $(1-x)L_t$, as well as the coefficient e of the provision BR_t are cyclical. The bad loan loss provision will behave cyclical: increase in a recession and decrease in an upturn of the economy.

One solution to counter this cyclical pattern of the bad loan loss provision would be to let the financial regulator establish a variable by which both provisions are to be multiplied (the multiplier γ). The financial regulator should be able to show an index which reflects the relative position of the current economy in the business cycle. The countercyclical provision should be larger in good times ($\gamma > 1$) and smaller in bad times ($0 < \gamma < 1$). The provisions should be altered in accordance with this business cycle. We refer to the use of a credit-to-GDP gap measure in Basel III[10] or chapter three of this thesis. The credit-to-GDP gap can be used to determine the multiplier γ, an index for the relative position of the current economic conditions in the business cycle. Using a multiplier $\gamma \in [0, 1]$ decreases the calculated loan loss provisions of banks. Using a multiplier $\gamma > 1$ increases the calculated loan loss provisions of banks. The multiplier, $\gamma \in [0, 1]$, decreases the calculated loan loss provisions in a recession and increases, $\gamma > 1$, the loan loss provisions in an upturn of the economy.

The advantage of using a multiplier is that the expertise within the banks, con-

[10] Guidance for national authorities operating the countercyclical capital buffer, december 2010, Basel Committee

cerning the risk profile of their loan portfolio, can be fully utilized to determine the height of both provisions and the supervisor only adjusts for the economic cycle. The use of a multiplier takes into account the riskprofile of the loan portfolio of a bank, banks with a high riskprofile have to provision more than banks with low riskprofile. The influence of the multiplier on the balance sheet of the bank is:

$$\begin{aligned} GR_t &= \gamma \cdot (g \cdot L_t) \\ BR_t &= \gamma \cdot [e \cdot (1-x)L_t] \end{aligned}$$

If we apply this provisioning method to our model, the following representation of the loan loss provisions on the balance sheet can be given:

$$\begin{aligned} R_t &= \gamma g L_t + \gamma e(1-x)L_t \\ &= (g+e-ex)\gamma L_t \end{aligned} \tag{2.8}$$

If we substitute equation (2.8) into (2.1), the amount of loans are as follows:

$$L_t = \frac{E_t + D_t}{1-(g+e-ex)\gamma} \tag{2.9}$$

Banks adapt the size of their loan portfolio to meet the Basel III requirements. If the requirements or provisions increase, the banks start deleveraging to reduce the size of their loan portfolio. If the requirements or provisions decrease, banks can expand their loanportfolio. Because the specific loan loss provision (BR_t) cannot be accounted for as capital by the Basel Accord in contrast to the general loan loss provision (GR_t), an alteration of the capital ratio occurs. If we substitute equation (2.9) into equation (2.6) and if we assume that the capital ratio is binding (that is $\lambda \neq 0$), the solvency[11] of the bank is:

$$\begin{aligned} E_t + \gamma g L_t - \mu(1.5-x)L_t &= 0 \\ E_t/D_t &= \frac{\mu(1.5-x) - g\gamma}{1-(1-x)e\gamma - \mu(1.5-x)} \end{aligned} \tag{2.10}$$

[11] We determine the influence of the different provisioning methods on solvency by determining the influence of the provisioning methods on the ratio E_t/D_t. This ratio does not include the provisions that are accounted for as Tier-2 capital ($\widetilde{R}_t$).

The multiplier influences the solvency of the bank at the margin:

$$\frac{\partial E_t/D_t}{\partial\gamma}=\frac{[g+(1-x)e]\,\mu(1.5-x)-g}{[1-(1-x)e\gamma-\mu(1.5-x)]^2}$$

The denominator of this ratio is always positive, the numerator is negative if $g<\dfrac{-(1-x)e\mu(1.5-x)}{\mu(1.5-x)-1}$. The effect of the multiplier on the bank's solvency, if the bank only has good loans ($x=1$) and a minimum capital requirement of $\mu=0.08$ is used, is

$$\frac{\partial E_t/D_t}{\partial\gamma}=\frac{-g}{1-0.5\mu}<0,\text{ if }0<g<1\text{ and }\mu=0.08 \tag{2.11}$$

The correlation between the multiplier and the solvency of the bank is negative if $g\in[0,1]$ and $\mu=0.08$. This implies that if the multiplier moves upwards (from a recession, where $0<\gamma<1$, towards an upturn of the economy, where $\gamma>1$), the solvency of the bank deteriorates and when the multiplier decreases (the economy moves from an upturn, where $\gamma>1$ to a recession, where $0<\gamma<1$), the bank solvency improves. The solvency for a bank with only good loans moves in the opposite direction of the economic cycle. When the multiplier increases, the bank has to increase her generic loan loss provisions. The generic loan loss provisions are accounted for as Tier-2 capital. The profit maximizing behavior of the bank will keep the capital requirement at $\mu=0.08$ (we refer to equation (2.6)), therefor a substitution effect occurs: the banker substitutes Tier-1 equity with the Tier-2 generic loan loss reserve. An increase in the multiplier as a consequence of profit maximizing behavior, deteriorates the solvency position of the bank.

The effect of the multiplier γ on the solvency of a bank with a lot of bad loans ($x=0$) is:

$$\frac{\partial E_t/D_t}{\partial\gamma}=\frac{1.5\mu(g+e)-g}{[1-e\gamma-1.5\mu]^2} \tag{2.12}$$

The impact of a change in the multiplier γ on the solvency position of a bank with a lot of bad loans is less obvious. If we apply the Basel capital requirement of $\mu=0.08$, the effect of the multiplier on solvency of the bank with bad loans is positive if:

$$\frac{\partial E_t/D_t}{\partial\gamma}=\frac{1.5\mu(g+e)-g}{[1-e\gamma-1.5\mu]^2}>0,\text{ if }g<\frac{1.5\mu}{1-1.5\mu}e\text{ and }\mu=0.08 \tag{2.13}$$

The condition $g<\frac{1.5\mu}{1-1.5\mu}e$ is met, if we apply the parameters of de Lis et al. (2000)

concerning ex ante credit risk, $0.005 \leq g \leq 0.01$, and ex post credit risk, $0.1 \leq e \leq 1$[12]. The correlation between the multiplier and the solvency of a bank with bad loans is positive under the mentioned conditions.

This seems a remarkable result, but this result is caused by two opposing forces. It is important to emphasize that in our model banks adapt their loan amount accordingly to their funding options. If the multiplier γ in our model increases (the economy moves from a recession, where $0 < \gamma < 1$, towards an upturn, where $\gamma > 1$), the general loan loss reserve GR_t and the specific loan loss reserve BR_t increase. The increase in the general loan loss reserve causes the same substitution effect as is present for banks with only good loans: the banks replace their equity capital (E_t decreases) with the Tier-2 general loan loss reserve to meet the minimum capital requirement of equation (2.6). An effect that is not present in the portfolio of banks with only good loans ($x = 1$) is the following. The specific loan loss reserve is not accounted for as Tier-2 capital. The increase in the specific loan loss reserve causes the bank with a lot of bad loans to adapt their loan amount accordingly: the bank with a lot of bad loans starts deleveraging (decrease in L_t and D_t). So if the multiplier moves upwards (the economy moves from a recession, where $0 < \gamma < 1$, towards an upturn, where $\gamma > 1$) banks with a lot of bad loans are forced to sell part of their loan portfolio (deleverage). We refer to this effect as the deleverage-effect. Where a bank with only good loans ($x = 1$) is only affected by the substitution-effect (as a consequence of the general loan loss reserve), the bad bank endures two effects as a result of a change in the multiplier γ: the substitution-effect (as a consequence of the general loan loss reserve) and the deleverage-effect (as a consequence of the specific loan loss reserve)[13]. The substitution-effect caused by an increase in the general loan loss reserve is dominated by the deleverage-effect caused by the increase of the specific loan loss reserve[14] as a result an increase of the multiplier γ has a positive effect on the solvency of banks with only bad loans.

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[12]If we plug in $\mu = 0.08$ and the lower boundary of e ($e = 0.1$) in the condition $g < \frac{1.5\mu}{1-1.5\mu}e$ of equation (2.13), this results in $g < 0.0136$. Because the upper boundary of g according to the conditions of de Lis et al.(2000) is 1%, the condition $g < \frac{1.5\mu}{1-1.5\mu}e$ is always met if $0.005 \leq g \leq 0.01$ and $0.1 \leq e \leq 1$.

[13]This also implies that there is a bank with a ratio of good and bad loans $x = \alpha$, where the multiplier does not influence the solvency of the bank because the negative substitution-effect is equal to the positive deleverage-effect. We did not calculate this α in this chapter.

[14]In the numerator of equation (2.13) the impact of the general loan loss reserve is less ($1.5\mu g - g$) than the impact of the specific loan loss reserve ($1.5\mu e$) under the conditions that $0.005 \leq g \leq 0.01$, and ex post credit risk, $0.1 \leq e \leq 1$.

To conclude we state that in a recession the provisions are (gradually) downsized or underestimated through the multiplier γ, this has a positive effect on the profit- and loss account and limits deleveraging by banks[15]. During a recession the occurred losses, OL, will increase and will therefore downsize profit. In an upturn of the economy the provisions are increased or overestimated through the multiplier γ, this has a negative effect on profit and will insure a larger loan loss provision. The multiplier downsizes the cyclical behavior of banks and ensures a higher provision in upturns of the economy and a lower provision in a recession, while distinguishing between banks with a lot of bad loans and banks with a lot of good loans.

2.5 Review of other models for countercyclical provisioning

2.5.1 Statistical provisioning for loan losses in Spain (de Lis et al. (2000))

De Lis et al. (2000) present a new form of provisioning for loan losses, named statistical provisioning:

> "The statistical provision is aimed at a proper accounting recognition of ex ante credit risk. Expected loan losses exist from the moment a loan is granted. This should be reflected in the risk premium included in the price of credit and hence in the income stream coming from the loan since its very beginning. Therefore it seems logical to build up the corresponding provision for loan losses also at that time."

De Lis et al. (2000) recognize three sorts of provisions for loan losses. The first one is a general provision (GR_t), which reserves a fixed amount depending on the total amount of outstanding loans (L_t). The general provision is not dependent on the downturn of upturn of the economic cycle (p.e. in a downturn of the economic

[15]If we move into a recession the multiplier decreases, causing a decrease in general and specific loan loss reserve. This will result in more free reserves for bad banks to fund their loan portfolio (or to counter the increased risk profile of their borrowers). This should counter their cyclical behavior, where the downfall of the economy increases the risk profile of their loan portfolio and banks are inclined to start deleveraging. The multiplier counters this cyclical behavior of banks.

cycle, the amount of outstanding loans will not differ as a consequence of the recession, but the acknowledged risks on these outstanding loans will). The general provision on the balance sheet can be illustrated as follows:

$$GR_t = g * L_t$$

where L_t stands for total loans and g for the parameter (between 0,5% and 1%). The annual addition to the provision in the profit& loss account can be shown as follows:

$$GP_t = g * \Delta L$$

where GP is the annual addition to the provision and ΔL is $L_t - L_{t-1}$;

The second provision is a specific provision (SR_t) which aims at covering impaired assets (ex post credit risk). The specific provision is procyclical: as the recession appears, impaired assets will increase and therefore the specific provision will need to increase. The specific provision on the balance sheet can be illustrated as follows:

$$SR_t = e * (1 - x)L_t$$

where $(1 - x)L_t$ are the impaired high risk loans and e is the parameter for ex post credit risk (between 10% and 100%). The annual addition to the provision on the profit & loss account can be given as follows:

$$SP_t = e * (1 - x)\Delta L$$

where SP_t is the annual addition to the provision.

The third provision is the statistical provision StR_t. The statistical provision is intended to anticipate the next economic cycle rather than to reflect past ones. Banks can base the statistical provision on their internal models or a standard approach to estimate Loss Given Default (LGD) and the Probability of Default (PD) in accordance with the Basel II Approach. The working paper of Banco de Espana uses other determinants, but the implication is identical: financial products are given a certain risk label corresponding with a certain percentage of provisioning (p.e. high risk, credit card balances implies 1.5% provisioning). The percentages vary from 0% to 1.5% provisioning depending on the risk category of the loan. The statistical provision on the balance sheet can be illustrated as follows:

$$StR_t = StP_t + StR_{t-1}$$

with a limit of $0 \leq StR_t \leq 3 * LR_t$, where LR_t stands for Latent Risk of outstanding loan amount. The annual addition to the provision on the profit & loss account can be given as follows:

$$StP_t = LR_t - SP_t = (s * L_t) - (1 - x)\Delta L$$

where LR_t stands for Latent Risk of outstanding loan amount and s for the average coefficient for the statistical provision (between 0% and 1.5%) and $StP_t = LR_t - SP_t$ where StP_t is the annual addition to the specific provision. Above-mentioned formula raises the specific provision (SR_t) when the expected loss on the outstanding loans (LR_t) is higher than provisioned for and decreases the specific provision (SR_t) when the expected loss on the outstanding loans (LR_t) is lower than provisioned for.

If we would apply this provisioning method to our model, the following representation can be given for the loan loss provision on the balance sheet:

$$\begin{aligned} R_t &= gL_t + e(1-x)L_t + sL_t - e(1-x)L_t \\ &= (g+s)L_t \end{aligned} \tag{2.14}$$

Notice that the specific loan loss provision for bad loans has no effect on the total amount of the loan loss provisions (so regardless of the riskprofile of a loan portfolio, the same amount is reserved). If we substitute equation (2.14) into (2.1), the amount of loans can be stated as follows:

$$L_t = \frac{E_t + D_t}{1 - (g+s)} \tag{2.15}$$

If we substitute equation (2.15) into equation (2.6) and if we assume that the capital ratio is binding (that is $\lambda \neq 0$), the solvency[16] of the bank is:

$$\begin{aligned} E_t + R_t - \mu(1.5 - x)L_t &= 0 \\ E_t/D_t &= \frac{\mu(1.5-x)-(g+s)}{1-\mu(1.5-x)} \end{aligned} \tag{2.16}$$

Effect of a change in the statistical provision on solvency of the bank at the margin is:

$$\frac{\partial(E_t/D_t)}{\partial s} = \frac{-1}{1-\mu(1.5-x)} < 0 \text{ if } x \in [0,1] \text{ and } \mu = 0.08 \tag{2.17}$$

An increase in the requested height of the statistical provision (an increase in s) has a negative effect on the solvency of the bank. The negative effect is larger for banks with more bad loans (when x moves towards 0 a bank has increasingly more bad loans). If the amount of statistical provision increases, which also accounts for the demanded capital requirement of the Basel committee, equation (2.4), the bank might have a tendency to keep a lower amount of equity on her balance sheet in comparison to the case without provisioning, equation (2.7). A substitution effect takes place.

Some remarks concerning this provisioning method are:

1. The different coefficients represent the different risks that are recognized: g stands for the ex ante credit risk, e represents the ex post credit risk and s stands for the estimated credit risk. Although not specifically mentioned in de Lis et al. (2000), it is essential that the estimated credit risk is not under the influence of bank managers themselves. Because of the biased vision of the banks concerning risk, this will not ensure the countercyclical effects of the provision. If the coefficient concerning the estimated credit risk coefficient (s) is left to decide to bank institutions, the disaster myopia of banks will remain.
2. The provisions for losses on loans the balance sheet can be represented as follows:

$$\begin{aligned} TR_t &= GR_t + SR_t + StR_t \\ &= (g+s)L_t + eL^B_{t-1} + StR_{t-1}; \end{aligned}$$

[16] We determine the influence of the different provisioning methods on solvency by determining the influence of the provisioning methods on the ratio E_t/D_t. This ratio does not include the provisions that are accounted for as Tier-2 capital ($\widetilde{R}_t$).

In the formula only the percentage of impaired high risk loans from period $t-1$ is accounted for on the balance sheet. This may have some downside effects. If in the last year a bank has not done very well and has sold more loans with a higher risk profile in period t than in previous years, the result of this raise in high risk loans will not be visible until two periods afterwards (when that period of the raise becomes $t-1$). The balance sheet does not provide a fair view of the current needed provisions for bad loans and offers banks a possibility to postpone foreseen losses on bad loans.

3. The coefficients concerning ex ante risk (g) and estimated credit risk (s) are used to provision an amount of the current outstanding loans per balance sheet date. When g is determined by a through-the-cycle calculation and s is determined based on a forecast, the coefficients g and s will include some of the same probabilities of default and losses.
4. Profit and loss account: the total amount of the addition to or release of the provisions on the balance sheet:

$$\begin{aligned} TP_t &= GP_t + SP_t + StP_t \\ &= (g+s)L_t - gL_{t-1}; \end{aligned}$$

The addition to or release of the total amount of provisions in the profit and loss account is maximized to 2.5% (maximum of g is 1%, maximum of s is 1,5%) of the change in the outstanding loan amount. The provision concerning the coefficient s does not concern the difference between the outstanding amount of loans previous year and current year, but each year the provision is build up from scratch concerning the total amount of outstanding loans current year. Also the ex post risk e and the amount of bad loans is not included in the periodic addition or release. Theoretically the amount on the balance sheet concerning $e(1-x)L_{t-1}$ will always be zero (because there is no build up of the provision in the profit and loss account). The bank does not include her ex post risk and the specific risks of her bad loans in her profit and loss account or her balance sheet. Only the change in the total loan amount determines the addition to or release of the total provision. The proportion of bad loans does not influence her balance sheet or profit and loss accounts. As a result banks with a lot of bad loans have the same provision as banks with primarily good loans. This does not seem very desirable.

2.5.2 Dynamic provisioning (Burroni et al. (2009))

Burroni et al. (2009) base their model of dynamic provisioning on the concept of expected losses. They specifically mention that this concept of expected losses is not based on the IRB-approach of Basel II, whereas in the IRB-approach the expected losses are based on the current Loss Given Default and Probability of Default. The expected losses in their model are based on long-term averages of losses recorded in the past. It is mentioned that when a bank adopts through-the-cycle-rating systems for her calculations concerning Loss Given Default and the Probability of Default, the definition for the expected losses in this model will definitely approach the definition as is mentioned in the IRB-approach. Burroni et al. (2009) state that the dynamic provision for banks is given by:

$$DP_t = (\alpha \cdot \Delta L) - SP_t \tag{2.18}$$

where α is the average long-run expected losses, ΔL is the flow of new loans and SP_t is the flow of specific provisions. Equation (2.18) concerns the income statement and not the balance sheet. The balance sheet will show a specific provision, which is not explicitly mentioned in Burroni et al. (2009), but it appears that the specific provision is formed for impaired losses (ex post credit risk). The total provisions on the balance sheet (TR_t) is the sum of the dynamic provision (DR_t) and the specific provision (SR_t) and can be stated as follows:

$$\begin{aligned} TR_t &= DR_t + SR_t \\ TR_t &= \alpha \cdot L_t \end{aligned}$$

where α is the average long-run expected losses and L_t is the total amount of loans on the balance sheet. The dynamic provision on the balance sheet can then be given as follows:

$$DR_t = (\alpha \cdot L_t) - SR_t$$

In a recession (when the specific provision SR_t will be high because of impaired losses) there will be less or no build up of the dynamic provision. In an upturn of the economy, when the specific provision is low, there will be a higher build up of the provisions until it reaches the limit of $\alpha \cdot L_t$.

If we would apply this provisioning method to our model of section (2.3), the loan loss provision on the balance sheet is:

$$R_t = aL_t \tag{2.19}$$

If we substitute equation (2.19) into (2.1), the amount of loans is:

$$L_t = \frac{E_t + D_t}{1 - a} \tag{2.20}$$

If we substitute equation (2.20) into equation (2.6) and if we assume that the capital ratio is binding (that is $\lambda \neq 0$), the solvency[17] of the bank is:

$$\begin{aligned} E_t + R_t - \mu(1.5 - x)L_t &= 0 \\ E_t/D_t &= \frac{\mu(1.5 - x) - a}{1 - \mu(1.5 - x)} \end{aligned} \tag{2.21}$$

The influence of the coefficient a on the solvency position of the bank is at the margin is:

$$\frac{\partial(E_t/D_t)}{\partial a} = \frac{-1}{1 - \mu(1.5 - x)} < 0 \text{ if } x \in [0, 1] \text{ and } \mu = 0.08 \tag{2.22}$$

An increase in the requested height of the statistical provision (an increase in a) has a negative effect on the solvency of the bank. The negative effect is larger for banks with more bad loans (when x moves towards 0 a bank has increasingly more bad loans). The effect on solvency does not differ between the statistical provision, equation (2.17), and the dynamic provision, equation (2.22). If the amount of statistical or dynamic provision increases, which also accounts for the demanded capital requirement of the Basel committee, equation (2.4), the bank might have a tendency to keep a lower amount of equity on her balance sheet in comparison to the case without provisioning, equation (2.7). A substitution effect takes place.

[17] We determine the influence of the different provisioning methods on solvency by determining the influence of the provisioning methods on the ratio E_t/D_t. This ratio does not include the provisions that are accounted for as Tier-2 capital ($\widetilde{R}_t$).

Some remarks concerning this provisioning method can be made:

1. The amount of total provisions (TR_t) in comparison to the total amount of outstanding loans (L_t) does not change over the years (unless the coefficient α changes). The total provision therefore is not dynamic, but fixed as a percentage of the outstanding loans over the years. The coefficient α represents provisioning through the cycle and will therefor have a static coefficient through the cycle. But the loan portfolio of a bank is not static and the risk profile of this loan portfolio over time might change. This provisioning method does not take into account the changes in the risk profile of the loan portfolio of the specific bank.
2. The dotation to the provisions for loan losses is over time equal to $\alpha \cdot L_t$, regardless of the current macro-economic cycle. This type of provisioning is acyclical (regardless of macro-economic cycle) in stead of countercyclical (moving opposite of the macro-economic cycle).

If we compare the effect of the different provisioning methods (new provisioning method, statistical provisioning method and dynamic provisioning method) on the solvency of banks, it is clear that the effect of the parameter of the statistical provision, equation (2.17) and the dynamic provision, equation (2.22) is very similar. For banks with a lot of bad loans ($x = 0$) the effect of the statistical or dynamic provision is

$$\frac{\partial(E_t/D_t)}{\partial s} = \frac{\partial(E_t/D_t)}{\partial a} = \frac{-1}{1-1.5\mu} < 0 \text{ if } \mu = 0.08 \tag{2.23}$$

where for the proposed new provisioning method the effect of the multiplier for a bank with a lot of bad loans ($x = 0$) is:

$$\frac{\partial E_t/D_t}{\partial \gamma} = \frac{1.5\mu(g+e)-g}{[1-e\gamma-1.5\mu]^2} > 0, \text{ if } g < \frac{1.5\mu}{1-1.5\mu}e \text{ and } \mu = 0.08$$

The effect of the statistical and dynamic provisioning method on the solvency of a bank with bad loans is driven by the substitution effect, where an increase of the additive (!) dynamic and statistical provision increase Tier-2 capital, which can substitute (partly) Tier-1 equity capital. Our provisioning method does not demand an additive provision but enlarges or reduces the general loan loss and specific loan loss provision that are yet present within the bank. A bank with a lot of bad loans is therefor forced, when the economy moves from a downturn to an upturn (and the multiplier increases) to sell off part of its loan portfolio. Deleveraging at that moment should prevent the bank with a lot of bad loans to do so at a point in time when the recession is at it's peak. If we compare the impact of the provisioning forms on the solvency of banks with a lot of good loans ($x = 1$), the effect of the statistical and dynamic provision on the solvency of banks with a lot of good loans is:

$$\frac{\partial(E_t/D_t)}{\partial s} = \frac{\partial(E_t/D_t)}{\partial a} = \frac{-1}{1-0.5\mu} < 0 \text{ if } \mu = 0.08$$

The impact of the new provisioning form on the solvency of banks with a lot of good loans is:

$$\frac{\partial E_t/D_t}{\partial \gamma} = \frac{-g}{1-0.5\mu} < 0, \text{ if } 0 < g < 1 \text{ and } \mu = 0.08$$

it is clear that the impact of the new provisioning form on the solvency of banks with a lot of good loans ($x = 1$) is less than the impact of the statistical and dynamic provisioning form, if g is less than 1. In stead of levelling the impact of a counter-cyclical provision over the banks with different risk profiles, the new provisioning form places emphasis on the banks with the more risky portfolios. This is in conformity with Marcucci and Quagliariello (2009), who show that the procyclicality of financial institutions is higher for those financial institutions that have riskier portfolios. During the current financial crisis we also observed that financial institutions with a high risk profile (with a lot of bad loans) appeared to have larger liquidity and solvency problems[18].

2.6 Linking solvency to liquidity: Financial Market Stability Fund

The influence of provisioning on the solvency of banks is quite clear. You oblige banks to finance (a part of) their (yet apparent or still not yet apparent) losses present within the outstanding loans on the asset side with their own capital (in the form of a provision) instead of leverage. The losses on loans, yet provisioned for, will not have a profit & loss account effect[19] anymore. But the liquidity fore-

[18] Amongst others Cornett et al (2011) who show that banks with illiquid assets are more bound to deleveraging.

[19] This is only true if the realized losses are equal to the expected losses (where the provision is based on). If the realized losses are larger than the expected losses included in the provision, there will be a negative affect on the profit & loss acount.

casts based on these assets will show a gap in the (near) future, when the expected downpayments and interest payments of the outstanding loans do not generate the cash that was expected. Academic literature acknowledges the interaction between the liquidity and the solvency position within banks (Diamond & Rajan (2005)). As a consequence regulation concerning banks should not only include solvency and liquidity regulation on a stand alone base, but recognize the correlation between the two and implement this correlation into regulation.

Our proposal is to implement a Financial Market Stability Fund, managed by the financial regulator, where banks are obliged to deposit a ratio of α of their loan loss provisions. This option has no implications for the use of IFRS, because in return for their dotation to the fund, the banks receive a financial asset (concerning the Financial Market Stability Fund) on their balance sheet. These dotations are to be tax-neutral and the receivable can only be cashed in by the bank when the financial stability of the bank is at stake.

The amount to be dotated to a Financial Market Stability Fund is the factor α of the general loan loss provision and the bad loan loss provision, where $0 < \alpha < 1$. The dotation has no profit and loss effect for the bank and the financial regulator. The financial regulator will receive different accounts payable on her balance sheet. This also has a macro-economic effect:

- in an upswing of the economy, the provisions for loan losses increase and the money supply will decrease (because part of the provisions, α, are parked at the Financial Market Stability Fund). A decrease in the money supply triggers deflation in the long run. In a upturn of the economy the increase in loan loss provisions will therefore have a stabilizing effect.
- in a recession, the provisions for loan losses decrease and the money supply will increase (because part of the provisions, α, are released by the Financial Market Stability Fund). An increase in the money supply triggers inflation in the long run. The decrease of the provisions for loan losses will have a stabilizing effect on the economy in a recession.

There are some advantages of this method over a stand alone provisioning method:

1. The financial regulator has the option in case of financial distress at one bank to support that bank out of the funds of the other banks, when it appears that the financial asset of the distressed bank is not sufficient.

2. When the Financial Market Stability Fund does not cover any interest on top of the dotations of the banks, she indirectly makes banks pay for future help that might be needed by them (they pay for the put-option of always receiving government support when they are struck by financial distress);
3. The financial regulator can use the liquidity that is raised by the Financial Market Stability Fund for other short-term purposes (perhaps investments in better risk management systems for banks to further minimize risk) and also has another instrument to control the overall amount of money in the financial market. The effect of the Financial Market Stability Fund on the economy is stabilizing (in a upturn the money supply will decrease and in a downturn the money supply will increase);

If we would apply this method to our theoretical model of section (2.4), this implies that the bank has to keep an amount of αR_t on the asset side of her balance sheet, which cannot be invested in loans. The balance sheet constraint would be altered into:

$$\begin{aligned} xL_t + (1-x)L_t + \alpha R_t &= E_t + R_t + D_t \\ L_t &= E_t + (1-\alpha)R_t + D_t \end{aligned} \tag{2.24}$$

The impact of this liquidity restriction on the solvency of a bank is (substitute equation (2.24) into equation (2.6) and solve for $\lambda \neq 0$):

$$E_t/D_t = \frac{\mu(1.5-x) - (1-\alpha)\gamma g}{1-(1-x)e\gamma - \mu(1.5-x) - \alpha\gamma g}$$

$$\frac{\partial(E_t/D_t)}{\partial\alpha} = \frac{[1-(1-x)e\gamma - \gamma g]\,\gamma g}{[1-(1-x)e\gamma - \mu(1.5-x) - \alpha\gamma g]^2} \tag{2.25}$$

The impact of the dotation α on the solvency of a bank depends on the size of the parameters and the risk profile of the loan portfolio of the bank. If the bank has no bad loans in her loan portfolio ($x = 1$), the numerator of equation (2.25) is $[1+\gamma g]\,\gamma g$. The numerator and denominator of equation (2.25) are both positive. If the bank has only bad loans in her loan portfolio($x = 0$), the numerator of equation (2.25) is $[1-(e+g)\gamma]\,\gamma g$. If $(e+g)\,\gamma > 1$ the impact of α on solvency is negative. For a bad bank $(e+g)\,\gamma$ will most likely be larger than one, if γ is larger than one. So the influence of α on the solvency of a bad bank can be negative most likely in an upturn of the economy if $\gamma > 1$. The positive effect of α is caused by the fact that the money that is placed at the Central Bank, cannot be used by the financial institution to supply loans. The impact of α on the amount of loans is[20]:

$$\frac{\partial L_t}{\partial \alpha} = \frac{-\left[E_t + D_t\right]\left[(g+e-ex)\gamma\right]}{\left[1-(1-\alpha)(g+e-ex)\gamma\right]^2}$$

The impact of α on the amount of loans is negative if we apply the parameters of de Lis et al. (2000) concerning ex ante credit risk, $0.005 \leq g \leq 0.01$, and ex post credit risk, $0.1 \leq e \leq 1$, and $\left[E_t + D_t\right], \left[(g+e-ex)\gamma\right] > 0$. The impact on the loan portfolio is higher for banks with a lot of bad loans[21]. A downfall in the amount of loans, also causes a downfall in the height of the needed provisions. A downfall of loan loss provisions causes an increase in the free reserves. Free reserves are accounted for as Tier-1 capital, where general loan loss reserves are accounted for as Tier 2 capital. The bad loan loss provisions are not accounted for as capital at all, whereas the free reserves are. The dotation of a part of the loan loss provisions at the Central Bank links liquidity to solvency within the banks. It also poses liquidity and solvency restrictions on the risky behavior of banks. These restrictions should limit the consequences of high idiosyncratic risks within banks in case of a macro economic recession. These measures have a positive contribution to the financial stability of a country.

2.7 Implications for IFRS and Basel III

2.7.1 IFRS implications

The government cannot impose a countercyclical provision for loan losses under the current IFRS rules. In this subsection we will discuss how, hypothetically speaking, countercyclical provisioning could be embedded within the IFRS rules and where problems would arise[22]. The countercyclical provision as is mentioned in the previous sections, should be seen as an "additive capital requirement". The implementation of this countercyclical provision should not have any effect on profitability.

[20] We substitute equation (2.24) into equation (2.8).

[21] If $x = 0$, the denominator has a larger impact on the derivative. This causes a larger negative effect for banks with a lot of bad loans.

[22] Given the hypothetical nature of the IFRS application, this paragraph may not reflect the views of the committee members on this topic.

IAS 37 states the reporting standards for provisions, contingent liabilities and contingent assets. According to IAS 37.10 the key definition of a liability is a present obligation as a result of past events, where settlement is expected to result in an outflow of resources (payment). A contingent liability is defined as a possible obligation depending on whether some uncertain future event occurs, or a present obligation but payment is not probable or the amount cannot be measured reliably. IAS 37.86 states that a possible obligation (a contingent liability) is disclosed but not accrued. However, disclosure is not required if payment is remote. IAS 37.2 defines provisions as liabilities of uncertain timing or amount. The distinction between a liability, contingent liability and a provision is the amount of uncertainty. A liability offers the most certainty, whereas a provision offers less certainty (uncertainty concerning timing or amount) and a contingent liability offers least certainty (uncertainty concerning timing and amount). Where in these definitions do our loan loss provisions fit? IFRS does not treat the loan loss provisions as are mentioned in our proposal in section (2.4) equally, but makes a distinction between specific loan loss provisions and general loan loss provisions. We will discuss the IFRS implications of these loan loss reserves separately.

The specific loan loss provision BR_t (based on the ex post credit risk parameter) is treated by IFRS not as a provision but as the result of an impairment[23] of the loans according to IAS 39 and exposure draft IFRS 9. This impairment result is not placed at the liability side of the balance sheet, but is deducted from the loan value on the asset side of the balance sheet. The loans, L_t, are valued at amortized cost[24] and presented on the balance sheet after deduction of the specific loan loss provision

[23] IAS 39.AG84-93: "If there is objective evidence that an impairment loss on loans and receivables or held-to-maturity investments carried at amortized cost has been incurred the amount of the loss is measured as the difference between the asset's carrying amount and the present value of estimated future cash flows (excluding future credit losses that have not been incurred) discounted at the financial asset's original effective interest rate (ie the effective interest rate computed at initial recognition). The carrying amount of the asset shall be reduced either directly or through use of an allowance account. The amount of the loss shall be recognized in profit or loss."

[24] We assume that the loans fullfill the conditions that are mentioned in IFRS 9.4.2 for valuation at amortized costs: "A financial asset qualifies for amortised cost measurement only if it meets both of the following conditions: the asset is held within a business model whose objective is to hold assets in order to collect contractual cashflows; and the contractual terms of the financial asset give rise on specified dates to cashflows that are solely payments of principal and interest on the principal amount outstanding. If the loans do not meet these conditions, they have to be valued at fair value.

(BR_t)[25]. Disclosure is necessary in accordance with IFRS 7[26]. We would like to note that the character of the specific loan loss reserve (without the adjustment of a multiplier γ) behaves cyclical. In a recession the impairment of the loan portfolio of a financial institution will be large, whereas in an upturn of the economic cycle the impairment will be small.

It is clear that our general loan loss reserve, GR_t, does contain uncertainty, so the definition of a liability does not fit this loan loss reserve. Is the general loan loss provision GR_t (based on the ex ante credit risk parameter) a provision in the sense of IAS 37? IAS 37.2 states that provisions can only be recognized when, and only when the following conditions are met:

1. an entity has a present obligation (legal or constructive) as a result of a past event;
2. it is probable (i.e. more likely than not) that an outflow of resources embodying economic benefits will be required to settle the obligation; and
3. a reliable estimate can be made of the amount of the obligation.

These three conditions for the recognition of a provision are more strict than those for the recognition of a liability (present obligation as a result of past events and settlement is expected to result in an outflow of resources). The first condition concerns two requirements: there has to be a present obligation and this obligation has to be the result of a past event. A constructive obligation of the first condition is hard to prove. Enforced regulation by the financial regulator would institute a legal obligation for banks to implement our proposed method of loan loss provisioning. A legal obligation would ensure that one part of the first condition of IAS 37.2 is met. In our opinion the general loan loss reserve, provisions for losses that are yet present

[25] We are well aware that implementation of IFRS 9 may have another effect. The exposure draft of IFRS 9 imposed a new method for impairing loans and other financial instruments: the expected cash flow approach. This expected cashflow approach acknowledges and takes into account expected future credit losses on loans. The currently used incurred loss model does not take into account expected losses as a result of future events, no matter how likely. A disadvantage of this approach is that it incorporates management's estimates based on past and future loss events on existing loans (paragraph 33, FEE-EFRAC paper December 2009). When impairment is based on management's opinion concerning future loss events, management myopia might arise. The disadvantages are clearly visible: this instrument might by used by management for incomesmoothing and it has a high likelihood of procyclicality. The procyclicality will especially arise if through-the-cycle calculations are not used (for example because of a lack of historical data). The use of this method will induce more subjectivity, and therefor more cyclicality and less verifiability, into the reporting system of banks and the financial stability of the entire financial system.

[26] IFRS 7 has the objective to prescribe appropriate presentation and disclosure standards for banks and similar financial institutions, which supplements the requirements of other Standards.

within the current loan portfolio which are the result of a past event (that past event is the issuance of the loan or the signing of the loan contract). But we are aware that the "present obligation as a result of a past event"-definition should also be based on contractual terms (more specific: the contract duration) of the loans present and the period that is used to determine the ex ante credit risk parameter[27]. The second condition that concerns the probability of an outflow of resources, is questionable in combination with our proposal. The future event of a defaulting loan will not cause an outflow of resources, but it will cause a loss and a lower amount of inflow of resources (for the defaulted borrower can no longer pay the interest and the loan amount back). Without provisioning a defaulted loan has a negative effect on the solvency, profitability and liquidity of a bank. The goal of installing a general loan loss reserve is to tone down the effect of these defaults on bank liquidity and solvency. Even though loan losses do not cause an outflow of resources, IAS 37.66-68 also allows the recognition of a provision for an onerous loss-making contract[28]. Present obligations arising under onerous contracts are recognized as provisions. So if a bank has a loan contract that will result in a loss (and not an outflow of resources, but a reduction in the inflow of resources) and have a negative effect on liquidity, according to IAS 37.66-68 this could hypothetically fulfill the recognition criteria for a provision. The third condition states that a reliable estimate of the obligation should be made. The general loan loss reserve, GR_t, uses the ex ante credit risk coefficient, which is based on the historical data of the bank (banks should within their measurement of these risks at least include a period that contains a recession and an upturn of the economy). When the bank issues a loan she can already, based on the historical data, determine the ex ante credit risk of the loan. These historical data should give the bank a reliable estimate of the loan losses that are present in the portfolio. We are of the opinion that a general loan loss provision would satisfy the three conditions for recognition of IAS 37.2, if enforced regulation by the financial regulator would institute a legal obligation. We like to emphasize that our proposal

[27] If the contract duration of the present loans of a financial institution is relatively short, the present obligation does not result from a past event. The loan losses that are then captured by the general loan loss provision, are meant for loans that have a contract signing ate that lies in the future. In this chapter we assume that contract duration and the determination of the ex ante risk parameter concern teh same time period.

[28] We refer to the website http://www.iasplus.com/en/standards/standard36. An onerous contract is considered to exist if the bank has a contract under which the unavoidable costs of meeting the contractual obligations exceed the economic benefits estimated to be received. A loss-making contract that is.

for a Financial Market Stability Fund has no effect on the statement of income or the profit & loss account of financial institutions.

The financial asset that is imposed in our proposal by the Financial Market Stability Fund ($\alpha(GR_t + BR_t)$), is not influenced by IFRS and should be recognized on the asset side of the balance sheet as a financial asset.

The multiplier γ influences the height of the provision, to an extent where there is no direct link anymore between the underlying obligations ($g \cdot L_t$ and $e \cdot (1-x)L_t$) and the height of the provision. The multiplier therefore challenges the second and third recognition criterion of IAS 37.2: there is no direct link anymore between the loan losses (and the lower amount of inflow of resources) and the provision height. The reliable estimate of condition three of IAS 37.2 is influenced by the multiplier and unless the financial regulator enforces the multiplier, there is no legal or constructive obligation to form the provision in this matter. The VAR provisions of our quote in the introduction of this chapter are not recognized by IFRS on the balance sheet[29]. Without a legal obligation by the financial regulator, keeping a VAR-provision only leads to disclosure of this provision and not recognition on the balance sheet. The implementation of a Financial Market Stability Fund might not change this procedure because of the influence of the multiplier, but would ensure that financial institutions take into account the liquidity effect of loan losses on their balance sheet. The IFRS rules are not formulated to pursue macro economic goals.

2.7.2 Basel III implications

The current financial crisis forced the Basel Committee on Banking Supervision to revise the Basel II Capital Accord, leading to the introduction of Basel III (2010). Applying the revised model for countercyclical provisioning and a Financial Market Stability Fund has the following consequences for the application of the Basel II and III Accords:

- The size of the provision is not only determined by the banks, but also by the financial regulator (when determining γ based on the macro economic cycle). The financial regulator therefore has a large influence on the tier-2 capital

[29] IAS30.50 mentions that any amount set aside for general banking risks, including future losses and other unforseeable risks or contingencies shall be separately disclosed as appropriations of retained earnings. The reduction of this amount will result in an increase in the retained earnings and will not have a profit- and loss effect.

of banks. Lowering or raising the general provision directly influences tier-2 capital of the bank. Basel III requires the total capital ratio to be equal or larger than 10.5% as of 1st of January 2019. As a consequence it might be possible that the haircut of the financial regulator ($0 < \gamma < 1$) causes a bank to have a total capital ratio that is below the required 10.5%. In an upturn of the economy the financial regulator will raise the general provision ($\gamma > 1$) and theoretically it might occur that the amount of tier-2 capital of a specific bank will be larger than the amount of tier-1 capital.

- The countercyclical buffer will vary in between zero and 2.5%[30] of the risk weighted assets and the Committee diverts the responsibility for holding this buffer to the national authorities. The Committee points out that the buffer is not meant to be used as an instrument to manage economic cycles or asset prices (page 3). They do acknowledge that the buffer might have implications for monetary and fiscal policies. It is quite remarkable that a countercyclical buffer for banks is not meant to be used to manage economic cycles. This seems to contradict the very core of this measure and leaves the reader guessing what would be the use of a countercyclical buffer according to the Committee. The difference between our proposition for loan loss provisioning and the countercyclical buffer of the Basel Committee is that the Basel Committee uses the countercyclical buffer additive to other provisions and varying from zero to 2.5%. Our form of provisioning multiplies the yet apparent loan loss provisions inducing a decline or an increase of the overall provisions on the balance sheet.
- In Basel III the Committee also introduces a global liquidity standard: a Liquidity Coverage Ratio (hereafter: LCR) and a Net Stable Funding Ratio (hereafter: NSF). The LCR is meant to promote more resilience to liquidity disruptions over a thirty-day horizon and the NSF is meant to ensure that a bank links the horizon of its liabilities to the horizon of its assets and reduce the reliance on short term financing. The Committee includes Central Bank reserves as liquid assets to the extent that they can be drawn down in times of stress. This would fit the dotations to a Financial Market Stability Fund. These dotations could then be included in the determination of the LCR and

[30] We refer to the Guidance of the Basel Committee (2010), which introduces a countercyclical buffer in more detail.

the NSF for Basel III.

Whether or not the Financial Market Stability Fund would meet the Basel III requirements would depend on the multiplier chosen by the financial regulator. The correlation between solvency and liquidity positions of banks is not yet implemented in the current regulation for banks in the form of IFRS and Basel III. While recent financial crises and academic literature (Diamond & Rajan, 2005) have shown that this correlation is present, implementing measures that recognize this correlation requires legal affirmation. Not only accounting and micro-economic goals should be achieved by the regulation of Basel III and central banks, but also the macro-economic goal of financial stability. As the current financial crisis has obviously shown.

2.8 Conclusion

This chapter introduces a new method of forming loan loss provisions for banks and links this provisioning method to liquidity requirements. This method is compared to current provisioning methods in literature and current regulation for banks. We present a new method of countercyclical provisioning for loan losses to optimize the use of detailed loan loss knowledge within the banks and minimize subjectivity in provisioning. The minimization of subjectivity benefits the verifiability of the used provisions by banks and restricts the cyclicality. The new provisioning method takes into account the different distributions of high risk and low risk assets within the banks and recommends to use a multiplier γ, that is established by the financial regulator. This multiplier will tone down provisioning in a downturn of the cycle and raise provisioning in an upturn of the cycle. Transferring part of these loan loss provisions (α) to a Financial Market Stability Fund, governed by the financial regulator, gives recognition to the correlation between the solvency position and liquidity position of a bank. A Financial Market Stability Fund is a policy measure for a financial regulator to control the credit channel and money supply. Both Basel III and IFRS are not opposed supplementary measures by financial regulators. Although academic literature (Diamond & Rajan, 2005) recognizes the interaction between liquidity and solvency of banks, Basel III does not incorporate this interaction in their requirements. The implementation of a Financial Market Stability Fund does recognize the correlation between the liquidity position and the solvency position of a bank and provides a verifiable and more objective method to ensure financial stability.

One disadvantage concerning regulatory capital requirements, that remains for all provisioning methods, should not be named unmentioned. This disadvantage is well-known in accounting and is also mentioned by Laeven & Majnoni (2001), that is "income smoothing" by banks. There are several incentives for a bank to turn to the smoothing of income over several years. The incentives may have a tax origin (Rozycki, 1997) or the motivation to influence risk perceptives (Greenwald and Sinkey, 1988). Therefore it is even more important that all the coefficients that are used (γ, e and g) can be determined as objective as possible and can be verified by auditors and the financial regulator. The preference for forming provisions should therefore not be based on forecasts and forwardlooking expected losses, for these methods can be biased and manipulated (because they are not easy to verify) to become income-smoothing tools.

Complementary empirical research is necessary to determine the effect of a Financial Market Stability Fund and this new method of provisioning on financial stability. Empirical research would benefit the determination of the multiplier (γ) by the financial regulator. And as Arnold (2009) also mentions the role of accounting standards, like IFRS, and the financial crisis should be further investigated. This also includes the differentiation of the different loan loss provisions by Basel II (tier-2 and not tier-2 capital) and the influence of this differentiation on the balance sheets of banks. Another research subject can be found in quantifying the trade-off between resilience and efficiency, if policies aimed at financial stability (like a Financial Market Stability Fund) are implemented by regulators (Schinasi (2004)). This chapter does not include an analysis of the costs and benefits for individual banks or the trade off between resilience and efficiency of a financial system, though this analysis is very much needed to determine the consequences of new regulation.

2.A Appendix - Quote introduction

The quote used in the introduction of this chapter originates from the Dutch newspaper De Volkskrant (1995, 03-24) and can be found at the website:

http://www.volkskrant.nl/vk/nl/2844/Archief/archief/article/detail/398209/1995/03/24/Iris-schat-stroppenpot-banken-op-15-miljard.dhtml

The original quote in Dutch from the article named "Iris schat stroppenpot banken op 15 miljard":

> "Het conservatisme van de Nederlandse banken benadeelt hun aandeelhouders. De hardnekkigheid waarmee de banken nog vasthouden aan de geheimhouding over de omvang van hun 'stroppenpotten' verhindert een zuivere beoordeling van de financiële kracht van de banken. Van der Feen de Lille heeft de totale omvang van de vrije VAR (voorziening algemene risico's) van alle Nederlandse banken berekend op 15 miljard gulden. Dat is het saldo van toevoegingen en onttrekkingen dat de banken in de loop der jaren hebben opgebouwd. Deze reservepot is in de loop van de jaren gevuld uit de winst voor belastingen. Over de inhoud moeten de banken daarom ooit belasting betalen. De nettowaarde van de reservepot komt op 9,8 miljard gulden."

2.B Appendix - Notation

- E_t = equity
- D_t = deposits
- L_t = loans
- x = ratio of good loans in comparison to the total amount of loans
- R_t = loan loss provisions
- $\widetilde{R}_t$ = loan loss provisions that can be included in the Basel capital requirement
- r_D = interest rate on deposits
- r_L = interest rate on loans
- $\overline{r_D}$ = mean interest rate on deposits in the market
- $\overline{r_L}$ = mean interest rate on loans in the market
- μ = Basel required capital ratio on risk weighted assets
- π_t = profit
- g = parameter general provision for loan losses
- e = parameter specific provision for loan losses
- s = parameter statistical provision for loan losses
- a = parameter dynamic provision for loan losses
- γ = multiplier for loan loss provisions

Chapter 3

Empirical indicators of credit risk

The goal of this chapter is to find an empirical indicator that can be used to determine a multiplier γ for loan loss provisions to execute our proposal for a Financial Market Stability of chapter two[1]

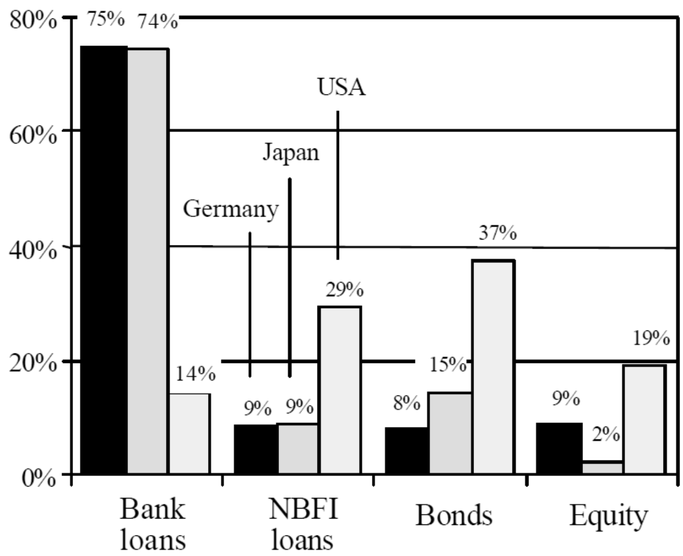
3.1 Introduction

The current financial crisis forced the Basel Committee on Banking Supervision to revise the Basel II Capital Accord to increase financial stability in future. This resulted in December 2010 in the introduction of Basel III (2010). One new measure proposed in the Basel III Accord is the installation of a countercyclical capital buffer. The countercyclical buffer is designed to ensure that banking sector capital requirements take into account the macro-financial environment in which banks operate. The Basel III Accord itself remains rather at a distance concerning the details of this countercyclical provisioning method. In chapter two of this thesis we propose a new method to model these countercyclical provisions. In this chapter we would like to determine the multiplier that can be used by a financial regulator to implement this new proposal for countercyclical provisioning.

Hackethal & Schmidt (2005) show there is an essential difference between the financial resources corporations use in Europe (Germany in this case) and the United States to fund their activities. In Europe (we refer to the picture from Hackthal & Schmidt (2005)) corporations primarily use bank loans to finance their activities, in

[1] I would like to thank Anne Opschoor, Lorenzo Pozzi, André Lucas and Job Swank for their helpfull comments and advice on this chapter.

the United States corporations depend more on non-banking financial institutions (NBFI) and the bond market to fund their activities. The difference in funding of corporations between Europe and the United States of America might influence our search for an indicator for credit risk within the banking sector.



Picture from Hackethal & Schmidt (2004) concerning external long term financing (average 1995-2000)

In this chapter we use the number of bankruptcies as a percentage of domestic credit as a proxy for the amount of credit risk present in the financial sector in a country. We consider multiple business cycle indicators in their ability to forecast this proxy. We use lagged, autoregressive OLS regressions to test the correlation between the business cycle indicators and the proxy for credit risk. We run out-of-sample forecasts to determine the accuracy of the business cycle indicators to predict this proxy for credit risk. We use data concerning business cycle indicators and the number of bankruptcies in The Netherlands and The United States of America for the regressions and the forecasts. The time series of the Euro area are unfortunately too short to perform statistical tests on. We find that a combination of the credit-to-GDP gap and a stock exchange indicator, gives the best forecasts for our proxy. The use of only the credit-to-GDP gap to determine the height of the countercyclical provision, as Drehmann et al. (2010) propose, works poorly for our proxy. One-lagged indicators give the best forecasts for our proxy in The Netherlands, whereas in the United States of America, two-lagged indicators give the best results. The forecasts and regressions for The Netherlands give better results than those for the United States of America. We presume (without any further evidence) that this result might be caused by the use of our proxy (the number of bankruptcies as a percentage of domestic credit), that seems better applicable to the European funding behavior of corporations that the US corporate funding behavior, in accordance with Hackethal & Schmidt (2005). Even though the number of observations of our proxy is very limited and only available on a yearly base, the results are robust. A good indicator for the amount of credit risk in the financial sector is essential to construct a useful countercyclical provision for loan losses.

We contribute to the current literature of countercyclical provisioning by the use of a different proxy for the amount of credit risk in the financial sector. We also contribute by using a different econometric approach to test the suitability of the business indicators for countercyclical provisioning. This chapter takes into consideration that bank profitability is driven by loan losses and influenced by credit risk in a recession in conformity with Bolt et al. (2011) and uses an ex post proxy for the determination of the amount of credit risk present in the financial market. Our method of research is much less sophisticated than the already present econometric methods in current literature (for example McNeil & Wendin (2007), Figlewski et al. (2006), Koopman et al. (2009), and others). This chapter differs in two aspects from this strand of literature. Firstly the goal of this chapter is not to find an optimal method for predicting the probability of default of a loan portfolio or determining the systemic risk factors present within the corporate default rates. The goal of this chapter is to determine an indicator that can be used in a method for countercyclical provisioning by banks. We therefor use an off-the-shelf regression and an out-of-sample forecast method and do not integrate firm-specific or bank-specific determinants in our model. The second aspect that differs in our approach is the comparison between the indicators and our proxy in The Netherlands and The United States of America. In the conclusion we give a preview of how the indicators can be used to form a countercyclical provision.

This chapter is structured as follows. After this introduction, we discuss related literature in section two. Section three describes the different business cycle indicators. Section four consists of the different analyses (lagged OLS regressions and out-of-sample forecasts) for The Netherlands. The next section analyzes the US data. In the final section of this chapter we summarize our results and draw the conclusion.

3.2 Related literature

This chapter relates to three strands of literature. The first strand of literature concerns financial indicators that can forecast the downturn and upswing state of the business cycle. The history of empirical research on indicators of the business cycle is extensive. The classical techniques were developed by the National Bureau of Economic Research (NBER) and can be found in the articles of Mitchell (1913, 1927), Mitchell & Burns (1938) and Burns & Mitchell (1946). The classical theory on business cycles is focussed on the identification of the business cycle and the interaction between the indicators and the business cycle. Another aspect of business cycles that has been subject of extensive research is the decomposition of business cycles in a cyclical component and a long term trend. The cyclical fluctuations are referred to as growth cycles (Hodrick & Prescott (1981), Baxter & King (1994)). In this chapter we use a different approach and analyze the influence of the business cycle on credit risk within the financial sector. Marcucci and Quagliariello (2009) find that the impact of the business cycle on credit risk of banks is higher during a downturn of the cycle. They also find that the impact of the business cycle is higher on banks with more risky portfolios. Bolt et al. (2011) find that in a recession bank profitability is primarily driven by loan losses. This chapter differs from this strand of literature because it analyzes the influence of the business cycle on the amount of credit risk within the financial sector by using an ex-post indicator of the amount of credit risk in the financial sector. This indicator is the amount of bankruptcies within a certain time period. Koopman et al.(2009) also use the default data in relation to the business cycle, to determine the credit cycle.

The second strand of literature concerns provisioning by financial institutions and more specific countercyclical provisioning. De Lis et al. (2000) acknowledge the procyclical behavior of bank lending and provisioning and introduce a new method of countercyclical provisioning for (Spanish) banks. After the introduction of Basel II in 2004, the impact of Basel II on the procyclical behavior of banks is discussed by

Pederzolli & Torricelli (2005) and Repullo & Suarez (2009). Pederzolli & Torricelli (2005) introduce a new model for time-varying capital requirements to counteract the procyclical influence of Basel II, whereas Repullo & Suarez (2009) demonstrate the procyclical influence of Basel II in a recession. In 2010 Basel III (2010) was released with the intention to implement a countercyclical provision. The guidelines[2] of Basel III (2010) give more details for national authorities who wish to implement the countercyclical buffer. This guidance suggests to use the business cycle indicator the credit-to-GDP gap, based on the study by Drehmann et al. (2010). Drehmann et al. (2010) analyze different bottom-up (bankspecific) and top-down (countryspecific) indicators for the business cycle. They use bank charge-offs[3] and data from Senior Loan Officer Survey as a proxy for credit conditions. The authors do not use forecasts to determine the adequacy of the indicators, but use a binomial signal extraction method (p.e. Kaminsky and Reinhart (1999)). Drehmann et al. (2010) find that the credit-to-GDP ratio seems to be the best business indicator for the build-up phase of a countercyclical provision by banks. Caprio (2010) shows that even though Spain and Colombia had installed some form of countercyclical provisioning by banks, this method was not able to prevent an asset bubble. We disagree with Caprio (2010) on the goal of a countercyclical provision. A countercyclical provision installed by a bank is not meant to prevent an asset bubble. The goal of countercyclical provisioning is to downsize the impact of an exogenous shock and not to prevent the exogenous shock. Drehmann et al. (2011) conclude that credit spreads are among the best indicators to determine the release phase of countercyclical provisions.

The third strand of literature concerns that part of the econometric and finance literature engaged in finding the best method to model credit risk, integrating systemic risk into credit risk models and determining the best indicators for credit risk. Wilson (1998) develops a model for measuring expected and unexpected losses and integrates systemic risk conditional on macroeconomic circumstances into the model. Duffie et al. (2005) focus on the dynamics between firm-specific and macroeconomic variables in determining the maximum likelihood estimators for the conditional probability of default. McNeil & Wendin (2007) use a sophisticated (Bayesian) econo-

[2] "Guidance for national authorities operating the countercyclical capital buffer", Basel Committee on Banking Supervision, December 2010, Bank for International Settlements.

[3] Definition Wikipedia: A charge-off is the declaration by a creditor that an amount of debt is unlikely to be collected. This occurs when a borrower becomes severely delinquent on a debt. Traditionally, creditors will make this declaration at the point of six months without payment.

metric model to specify systemic portfolio credit risk. Figlewski et al. (2006) use a Cox intensity model to estimate the probability of default. Their model incorporates firm-specific and macroeconomic variables. Koopman et al. (2009) show that by adding an unobserved dynamic component to their intensity-based framework, the economic impact of observed macro-economic variables on default cycles and rating activity reduces considerably. Koopman et al. (2010) develop a new methodological framework to disentangle default stress as a consequence of macroeconomic variables, frailty[4] and (industry-specific) contagion. Koopman et al. (2011) propose a new framework for estimating and forecasting corporate default rates, where not only observed but also unobserved risk factors are accounted for.

3.3 Business cycle indicators

Credit risk is perhaps the most essential risk within banking. Credit risk consists of three risk factors: the probability of default of a borrower, the loss given default on a loan and the exposure at default[5]. If the objective is to protect a banking system against future loan losses, a focus on credit risk seems appropriate. Credit risk is present in the banking sector long before a financial crisis sets in. The influence of credit risk on the periodic profitability in the banking sector does not only depend on the ability of the bank to mitigate credit risk, but also on their ability to foresee losses on loans and their provisioning scheme. Using the incurred losses in a bank's profit and loss account as an indicator for the amount of credit risk in the specific bank might not be justified. A relatively small amount of incurred losses in the profit and loss account might indicate that the bank has a low risk loan portfolio or it might indicate a high risk loanportfolio and a better provisioning scheme, that mitigates the influence of the credit risk on the profits for that specific period. For both types of banks the influence on profitability might appear identical in the specific period, but the credit risk present within the two banks might be very different.

Using data on bank profits to indicate the amount of credit risk in the financial sector does not address this critique. The use of charge-offs as an indicator for credit risk or survey data of bank officials might be very sensitive to subjectivity.

[4] Frailty is autonomous default rate dynamics.

[5] Through the expected loss measure credit risk can be quantified. The expected loss on the loan consists of the probability of default times the loss given default times the exposure at default.

Although the presence of credit risk in a financial banking system is hard to observe, the result of too much credit risk is not. The number of bankruptcies in a country can be considered as an ex post indicator of the amount of credit risk present in the banking sector of this country[6]. Given the fact that almost 70%-80% of the liabilities on the balance sheet of non-financial companies consists of debt to the financial sector in Europe[7], credit risk in the financial sector becomes apparent when companies go bankrupt. Bankruptcies directly impair the capital of banks if there is no adequate provisioning scheme.

Credit risk is always present in the loan portfolio of a bank, but when the economic environment is in an upswing, credit risk is undervalued, while as the economic environment is in a downturn, credit risk is exaggerated. The outstanding loan has the same characteristics during this period, but the valuation of it's risk differs. The possible ultimate result of a loan with high credit risk is the default on this loan by the borrower. The loan loss for the bank as a consequence of the default of the borrower is not visible from macro-economic data, but the defaults followed by a bankruptcy of the borrower are. Because bankruptcies are the result of a process where banks try to keep the borrower on track by applying financial restructuring on the loan and the business of the borrower, it is obvious that a bankruptcy of a borrower is preceded by a certain time-period where credit risk on the loan is already high. The number of bankruptcies is a lagging indicator of the amount of credit risk present in the loan portfolio of a bank. When we use a business cycle indicator to determine the multiplier for the height of the loan loss provisions of banks, we want this indicator to give a timely signal of the credit risk present in the market. The business cycle indicator should be a leading indicator.

The academic literature offers many alternative business cycle indicators and their use depends on the purpose of these indicators. The indicators that can be used for determining the point in time of the credit cycle are the bottom-up and top-down indicators. Top-down indicators are indicators that are determined on a system-wide basis, where bottom-up indicators are bank specific. In this chapter we only consider top-down indicators for the following reason. A multiplier or other determinant for a countercyclical provision should not incorporate bank specific characteristics, for

[6] Koopman et al. (2011) also use this indicator to determine credit cycles.

[7] Page 48 of Schmidt et al. (1999) concerns data with regard to Germany, France and the United Kingdom over the period 1981-1996.

these characteristics are already incorporated in height of the (specific) loan loss provisions by the banks themselves. The use of the countercyclical provision is to incorporate the macroeconomic conditions of the business cycle into the provisioning scheme of banks in order to counteract their credit-risk myopia. We test the following top-down indicators in their use as a credit risk indicator:

1. Credit-to-GDP gap: Borio & Drehmann (2009) and Drehmann et al. (2010)[8];
2. Change in GDP growth: Repullo & Saurina (2011);
3. Change in M2 growth: Roubini & Backus [9];
4. Stock exchange index: Roubini & Backus [10];
5. Change in the unemployment rate: Peersman & Pozzi (2007);

We use these top-down business cycle indicators to forecast the amount of credit risk in the financial sector. We adopt the change in the number of bankruptcies as a percentage of domestic credit as a lagged proxy for the credit risk that is present in banks[11]. We apply log-linearization to this proxy, for domestic credit does not behave linear over time (the log-linearization of the number of bankruptcies as a percentage of domestic credit, is denoted as BD_t[12]). The business indicators give an indication of the different aspects of credit risk. For example domestic credit gives an indication of the amount of credit banks have supplied to the borrowers. This indicator therefore points at the exposure at default for banks. The stock exchange index gives an indication of the stockholders view on the companies. This indicator therefore signals the probability of default of the quoted companies.

The different aspects of credit risk can be quantified through the expected loss measure:

$$EL = PD \cdot LGD \cdot EAD$$

[8] For a more detailed specification of this business cycle indicator we refer to Appendix 3A.

[9] We used some of the indicators Roubini and Backus mention on their website http://people.stern.nyu.edu/nroubini/bci/bciintroduction.htm

[10] We used some of the indicators Roubini and Backus mention on their website http://people.stern.nyu.edu/nroubini/bci/bciintroduction.htm

[11] We are aware that a Dutch bank might also be influenced by the amount of bankruptcies/credit risk present in the financial market in the United States of America, for the Dutch bank might also have US assets on his balance sheet. The lack of data does not allow for corrections in this matter. We will use the number of bankruptcies as a percentage of domestic credit in The Netherlands as a lagged indicator for the amount of credit risk in the Dutch financial sector.

[12] To determine BD_t we first divide the number of bankruptcies at t by domestic credit at t. We determine the change in comparison to the previous period: (# bankruptcies at t divided by domestic credit at t) / (# bankruptcies at $t-1$ divided by domestic credit at $t-1$). BD_t is the log of this fraction. BD_t gives an indication of the growth or decline of the number of bankruptcies at t as a percentage of domestci credit in comparison to the previous period.

where EL is the expected credit loss, PD is the probability of default, LGD is the loss given default and EAD is the exposure at default[13]. The theoretical impact the business indicators have on the expected credit loss[14] are shown in Table 3.1.

Table 3.1
Impact of explanatory variables on expected loss measure
The table presents the expected theoretical effect, prior to the regressions, of the different explanatory variables on the expected loss measure (EL). The abbrevation PD represents the Probablity of Default, LGD the Loss Given Default and EAD the Exposure at Default.

Explanatory variables	Hypothetical impact on EL	Sign of hypothetical effect on EL
GDP growth	LGD	negative
Domestic credit growth	EAD	positive
Credit to GDP Gap	EAD & LGD	positive
M2 growth	EAD	positive
Unemployment rate	LGD	negative
Stock Exchange index	PD	negative

We assume that the sign of the theoretical impact of the business cycle indicators on the expected loss measure, as shown in Table 3.1 is equal to the sign of impact on our proxy for the amount of credit risk in the financial sector, (BD_t). We use these business cycle indicators to forecast our proxy (BD_t). We have very limited (yearly) data concerning our proxy (BD_t) for the United States of America and The Netherlands. The limited amount of data has implications for the econometric tests that can be executed on the residuals of the OLS regressions. Because some econometric tests for heteroskedasticity and serial correlation of the residuals cannot be used, we assume the residuals of the OLS regressions to be heteroskedastic and serially correlated. We use Heteroskedasticity and Autocorrelation Consistent (HAC, Newey-West) standard errors in our OLS regressions to counter these problems.

[13] The introduction of this thesis gives a more detailed view of the different aspects of credit risk.

[14] Domestic credit and M2 determine how much money is supplied by financial instutions in the financial system of a country, this determines primarily the exposure of banks at default. GDP and the unemployment rate give information about the turnover and costs of borrowers, and indirectly therefor in the profitability of those borrowers. These measures indicate the loss given default for financial institutions.

3.4 The Netherlands

3.4.1 Regressions 1987-2002

For the business cycle indicators of The Netherlands we use data from the World Bank concerning Gross Domestic Product (on current Local Currency Unit base), domestic credit to the private sector, money and quasi money M2 (also on Local Currency Unit base) and the unemployment rate as a percentage of the labour force. Data on the number of bankruptcies originate from Datastream and the data on the Dutch stock exchange (AEX on ultimo and average base) stems from the Dutch Central Bank website. Appendix 3B shows the origin of the used data[15], the used abbreviations and the descriptive statistics for the data of The Netherlands and the United States of America..

Appendix 3E shows the correlation matrix for the explanatory variables. Appendix 3F presents the results of the augmented Dickey-Fuller test[16], whether or not the explanatory variables and dependent variable follow a random walk (have a unit root). For The Netherlands the variables GDP_t and AA_t fail to reject the hypothesis of having a unit root. These non-stationary variables cannot be used in the analysis in their current form[17].

We run lagged OLS regressions over the period 1986-2002 to determine the correlation between our proxy for credit risk and the business cycle indicators. We use the outcome of these regressions for an out-of-sample forecast over the period 2003-2009 and compare this forecast to the actual value of the proxy for credit risk.

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[15] The unemployment rate is shown as a percentage of the total labor force of a country. Because the labor force in a country has a upgoing trend and does not behave linear, the log-linearization of the unemployment rate is used as the business cycle indicator.

[16] Tot allow for serial correlation in the error term we use the augmented Dickey-Fuller test, contrary to the Dickey-Fuller test.

[17] We perform a cointegration regression to use a stationary, linear combination of these variables in our analysis. Even though the linear combination ($DIF_t = AA_t - c - \beta GDP_t$) of the non-stationary variables is stationary, according to the Augmented Dickey-Fuller test and Ng-Perron test, we do not have an economic theory to confirm that GDP and the average value of the AEX follow the same stochastic trend. Therefore we do not include the linear combination of the variables AA_t and GDP_t in our regression model.

Table 3.2

Credit risk in The Netherlands 1986 - 2002

The table presents the results of lagged regressions of the business cycle indicators on the proxy (the log-linearisation of the number of bankruptcies as a percentage of domestic credit) for credit risk in the financial sector in The Netherlands. The HAC (Newey-West) standard errors are shown in parentheses in the table.
***, **, * denote statistically significant effects at a 1%, 5% and 10% level respectively.

Dependent variable: ln number of bankruptcies as a % of domestic credit					
	(1)	(2)	(3)	(4)	(5)
ln Bankruptcies % domestic credit (two lags)			0.089		
			(0.32)		
ln Bankruptcies % domestic credit (one lag)	0.638 ***	0.594 **			
	(0.22)	(0.23)			
ln Domestic credit growth (two lags)			-0.339		
			(0.49)		
ln Domestic credit growth (one lag)	0.014	0.294			
	(0.18)	(0.26)			
Credit to GDP Gap (lambda=100) (two lags)					0.718 *
					(0.39)
Credit to GDP Gap (lambda=100) (one lag)		1.514 ***			1.925 ***
		(0.54)			(0.45)
Credit to GDP Gap (lambda=6.25) (two lags)			2.084	1.118 ***	
			(1.40)	(0.43)	
Credit to GDP Gap (lambda=6.25) (one lag)	2.730 ***			2.507 ***	
	(0.66)			(0.57)	
ln M2 growth (two lags)			1.952		
			(2.60)		
ln M2 growth (one lag)	-1.561	-1.235			
	(2.11)	(2.07)			
ln Unemployment rate (two lags)			0.473		
			(0.74)		
ln Unemployment rate (one lag)	-0.464	-0.447			
	(0.35)	(0.44)			
ln AEX ultimo value (two lags)			-0.551 ***	-0.271 **	-0.314 **
			(0.17)	(0.11)	(0.12)
ln AEX ultimo value (one lag)	-0.199 ***	-0.129		-0.324 ***	-0.293 ***
	(0.06)	(0.11)		(0.08)	(0.11)
Constant	0.074	0.051	-0.095	0.010	0.045
	(0.14)	(0.14)	(0.17)	(0.03)	(0.05)
Summary statistics					
Regression	Lagged	Lagged	Lagged	Lagged	Lagged
Number of years	16	16	15	17	17
Adjusted R-squared	0.625	0.434	0.064	0.654	0.582
Standard error of regression	0.093	0.115	0.177	0.108	0.119
Akaike info criterion	-1.606	-1.195	-0.317	-1.370	-1.179
Schwartz criterion	-1.268	-0.857	0.014	-1.125	-0.934

Table 3.2 - *Continued*

Dependent variable: ln number of bankruptcies as a % of domestic credit				
	(6)	(7)	(8)	(9)
ln Bankruptcies % domestic credit (two lags)				
ln Bankruptcies % domestic credit (one lag)		0.444 **		
		(0.18)		
ln Domestic credit growth (two lags)	0.524			
	(0.55)			
ln Domestic credit growth (one lag)				
Credit to GDP Gap (lambda=100) (two lags)				
Credit to GDP Gap (lambda=100) (one lag)				
Credit to GDP Gap (lambda=6.25) (two lags)			0.687	
			(0.43)	
Credit to GDP Gap (lambda=6.25) (one lag)		2.912 ***	1.913 **	1.929 **
		(0.55)	(0.77)	(0.75)
ln M2 growth (two lags)				
ln M2 growth (one lag)	0.847			
	(2.19)			
ln Unemployment rate (two lags)				
ln Unemployment rate (one lag)				
ln AEX ultimo value (two lags)	-0.247			
	(0.19)			
ln AEX ultimo value (one lag)	-0.159	-0.291 ***		
	(0.22)	(0.07)		
Constant	-0.084	-0.001	-0.084 **	-0.086 **
	(0.15)	(0.03)	(0.04)	(0.04)
Summary statistics				
Summary statistics				
Regression	Lagged	Lagged	Lagged	Lagged
Number of years	15	18	19	20
Adjusted R-squared	0.025	0.650	0.285	0.283
Standard error of regression	0.149	0.107	0.154	0.151
Akaike info criterion	-0.702	-1.431	-0.764	-0.855
Schwartz criterion	-0.466	-1.233	-0.615	-0.755

The lagged OLS regressions have the following specification:

$$BD_t = c + \delta_1 BD_{t-j} + \delta_2 DC_{t-j} + \delta_3 CG100_{t-j} + \delta_4 CG625_{t-j} + \delta_5 M2_{t-j} \\ + \delta_6 UN_{t-j} + \delta_7 AU_{t-j} + \varepsilon_t \tag{3.1}$$

where BD_t is our proxy for credit risk and the abbreviations of the explanatory variables on the right hand side of the equation can be found in appendix 3B. Because of missing values (concerning the AEX and M2 data) and the limited number of observations, we only allow for a two-lagged OLS regression ($j = 2$). We also check whether the dependent variable is autoregressive, because literature indicates that credit events cluster (for example Jorion & Zhang (2007)). We perform regressions for most combinations of explanatory variables, the best and worst combinations of these regressions are shown in Table 3.2.

We use the adjusted $\overline{R}^2$, the Akaike information criterion[18] (AIC) and the Schwartz criterion[19] (SC) to determine the goodness of fit of the regressions and the number of lags in the regressions. If we compare regression (1) of Table 3.2 with only one-year lagged explanatory variables to regression (3) of Table 3.2 with only two-year lagged explanatory variables, all three test statistics[20] show that one-year lagged explanatory variables have more explanatory power than two-year lagged variables. Regression (1) including the credit-to-GDP gap with $\lambda = 6.25$ has more explanatory power than regression (2) with the credit-to-GDP gap with $\lambda = 100$ according to the same three test statistics. Regression (9) shows the explanatory power of the credit-to-GDP gap (with $\lambda = 6.25$), as is suggested in Drehmann et

[18] The Akaike information criterion can be given as follows:

$$AIC = \ln(\frac{\sum \widehat{\varepsilon}^2}{N}) + \frac{2k}{N}$$

where $\sum \widehat{\varepsilon}^2$ is the sum of the squared residuals. AIC penalizes the addition of right-hand-side variables more heavily than the adjusted R squared. The lower the AIC the better the explanatory value of the right-hand side variables (Pindyck & Rubinfeld (1998)).

[19] The Schwartz criterion can be given as follows:

$$SC = \ln(\frac{\sum \widehat{\varepsilon}^2}{N}) + \frac{k \ln N}{N}$$

where $\sum \widehat{\varepsilon}^2$ is the sum of the squared residuals. SC penalizes the addition of right-hand-side variables more heavily than the adjusted R squared. The lower the SC the better the explanatory value of the right-hand side variables (Pindyck & Rubinfeld (1998)).

[20] That is: $\overline{R}^2$ is closer to one, AIC and SC are of lower value

al. (2010) as a variable that can be used to determine the countercyclical provision for financial institutions. The explanatory power of regression (9) is very limited in comparison to the other regressions. According to the adjusted $\overline{R}^2$ regressions (4) and (7) of Table 3.2 have the most explanatory power. These regressions include combinations of the variables $CG100_t, CG625_t$ and AU_t. The Akaike information criterion and the Schwartz criterion suggest that regression (1) and (7) have the most explanatory power. Regressions (1) and (7) are autoregressive and also include the variables $CG625_t$ and AU_t. In our analysis some macro-economic business indicators are significant in the regressions of Table 3.2, research by Koopman et al (2009) has shown that adding an unobserved dynamic component[21] might influence the significance of the macro-economic variables we use, negatively. We are aware of this omission in our analysis.

3.4.2 Forecasts 2003-2009

From the regressions in previous subsection, we determine the out-of-sample forecasts for our proxy BD_t and compare these out-of-sample forecasts for the period 2003-2009 to our actual values of BD_t. We use an ex post forecast concerning the period 2003-2009, where the actual values of the dependent variable are already known. We use a static forecasting model and not a dynamic forecasting model, because the data are stationary and it concerns an out-of-sample forecast. We test this forecast by using the root mean squared error of the forecast and the Theil inequality coefficient[22]. Table 3.3 shows the test statistics for these forecasts based on our regressions of Table 3.2. Figure 3.1 shows the forecast graphs, where the forecasted value of BD_t is compared to the actual value of BD_t.

The forecasts based on the indicators of regression (3) and (9) perform worst for our out-of-sample forecast. Again the forecast based on the credit-to-GDP gap (with $\lambda = 6.25$), regression (9), as proposed by Drehmann et al. (2010), does not

[21] This component can be interpreted as an omitted systematic credit risk factor.

[22] Theil's inequality coefficient, U, is used to evaluate forecasts and is given as follows:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\ln BNKDC_t^s - \ln BNKDC_t^a)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\ln BNKDC_t^s)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\ln BNKDC_t^a)^2}}$$

where $\ln BNKDC_t^s$ is the forecasted value of our dependent variable and $\ln BNKDC_t^a$ is the actual value of our dependent variable. If $U = 0$ the forecast is a perfect fit for the actual values and if $U = 1$ the model has no predictive value (Pindyck & Rubinfeld (1998)).

seem to predict our proxy for the amount of credit risk in the financial sector very well. Forecast (9) shows little variance over the course of the time period and in 2009 the forecast based on this estimation appears to have a downward trend, whilst our proxy still shows an increase in the amount of credit risk in the financial sector. The dependent variables of regression (4) and (5) give the best forecasts according to our test statistics (rms error is closest to zero and the same is true for Theil's inequality coefficient).

Table 3.3

Test statistics out-of-sample forecasts The Netherlands 2003 - 2009

The table presents the test statistics of the out-of-sample forecasts based on the regression results show n in Table (3.2). The forecastnumbers in this table correspond to the regression numbers of Table (3.2).

	Forecast corresponding to regressions Table (3.2)				
	(1)	(2)	(3)	(4)	(5)
Root mean squared error	0.192	0.181	0.284	0.121	0.124
Theil's inequality coefficent	0.515	0.532	0.679	0.330	0.318
Bias proportion	0.277	0.140	0.118	0.123	0.315
Variance proportion	0.498	0.657	0.015	0.385	0.194
Covariance proportion	0.226	0.202	0.867	0.492	0.491

	Forecast corresponding to regressions Table (3.2)			
	(6)	(7)	(8)	(9)
Root mean squared error	0.178	0.162	0.236	0.250
Theil's inequality coefficent	0.554	0.458	0.691	0.718
Bias proportion	0.246	0.004	0.125	0.110
Variance proportion	0.614	0.309	0.499	0.382
Covariance proportion	0.139	0.687	0.376	0.508

The forecasts with the best test statistics are generated by a combination of the business cycle indicators $CG625_{t-1}, CG625_{t-2}$ or $CG100_{t-1}, CG100_{t-2}$ and AU_{t-1} and AU_{t-2}. The negative impact of the explanatory variable AU_t is in conformity with our theoretical assumption (we refer to Table 3.1), as is the positive empirical impact of the explanatory variables $CG625_t$ and $CG100_t$. These explanatory variables combine the three different aspects of credit risk (probability of default, AU_t, and exposure at default & loss given default, $CG625_t$). Without further proof, it might be true that in order to have a fair view on the amount of credit risk in the financial sector, one should use indicators that combine all the different aspects of credit risk to get the best forecast.

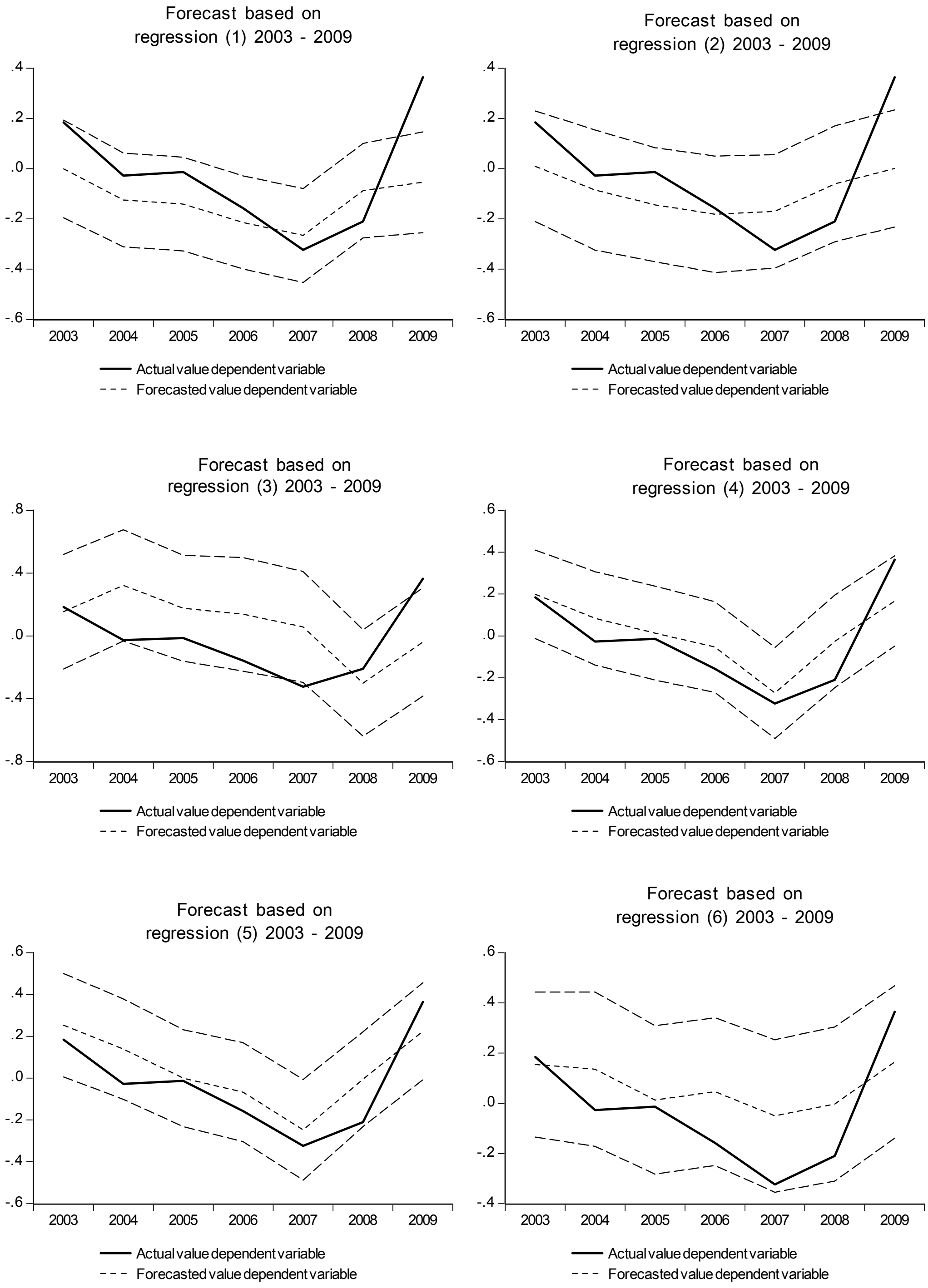
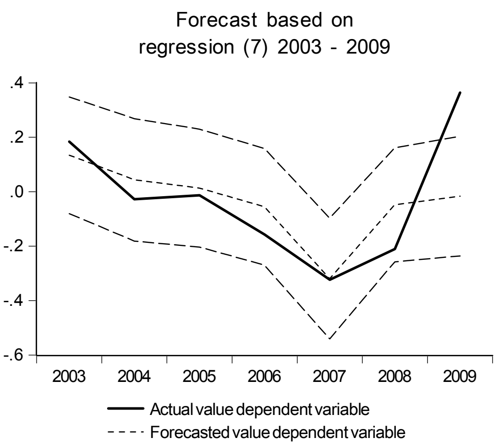
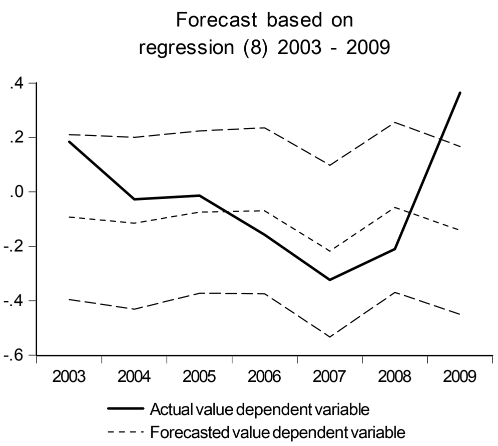


Figure 3.1 - Forecast graphs The Netherlands 2003 - 2009





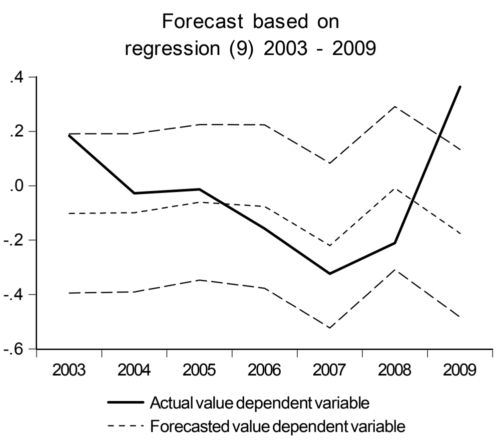


Figure 3.1 - Forecast graphs The Netherlands 2003 - 2009 (continued)

3.5 The United States of America

3.5.1 Regressions 1982-2002

For the Unites States of America we use data from the American Bankruptcy Institute concerning the number of business filings for bankruptcy on a year base. Data concerning GDP, M2, unemployment and domestic credit originate from the Worldbank. The data concerning the New York Stock Exchange index and the S&P500 listings are from Datastream. The number of business filings for bankruptcy as a percentage of domestic credit is used as a dependent variable for the amount of credit risk present in the financial sector. Appendix 3B shows the origin of the used data[23], the used abbreviations and the descriptive statistics for the data of The United States of America (hereafter: USA). The correlation matrix[24] of the explanatory variables is shown in appendix 3E. We use an Augmented Dickey-Fuller test[25] to test whether the used explanatory variables have a unit root (follow a random walk). The results of the Augmented Dickey-Fuller test can be found in appendix 3F. For the USA the variables $CG100_t$, $M2_t$ and SP_t fail to reject the hypothesis of having a unit root. These non-stationary variables cannot be used in the regressions in their current form[26].

We run lagged OLS regressions over the period 1983-2002. We use these regressions to make an out-of-sample forecast for the period 2003-2009 and compare this forecast to the actual value of the proxy for credit risk.

[23] The unemployment rate is shown as a percentage of the total labor force of a country. Because the labor force in a country has a upgoing trend and does not behave linear, the log-linearization of the unemployment rate is used as the business cycle indicator.

[24] In order to prevent multicollinearity, if two variables are highly correlated, we only use one of those variables in the regression.

[25] Tot allow for serial correlation in the error term we use the augmented Dickey-Fuller test in stead of the Dickey-Fuller test.

[26] We perform a cointegration regression to use a stationary, linear combination of these variables in our analysis. Even though the linear combination ($DIF_t = SP_t - c - \beta M2_t - \gamma CG100_t$) of the non-stationary variables is stationary, according to the Augmented Dickey-Fuller test and Ng-Perron test, we do not have an economic theory to confirm that M2, the credit-to-GDP gap (with $\lambda = 100$) and the S&P500 listings follow the same stochastic trend. Therefore we will not include the variables $CG100_t$, $M2_t$ and SP_t in our regression model.

Table 3.4

Credit risk in United States of America 1983 - 2002

The table presents the results of lagged regressions of the business cycle indicators on the proxy (the log-linearisation of the number of bankruptcies as a percentage of domestic credit) for credit risk in the financial sector in The Netherlands. The HAC (New ey-West) standard errors are show n in parentheses in the table. ***, **, * denote statistically significant effects at a 1%, 5% and 10% level respectively.

Dependent variable: ln number of bankruptcies as a % of domestic credit					
	(1)	(2)	(3)	(4)	(5)
ln Bankruptcies % domestic credit (two lags)		-0.243			
		(0.21)			
ln Bankruptcies % domestic credit (one lag)	0.159				
	(0.27)				
ln GDP growth (two lags)		5.092 ***	3.779 ***	3.458 ***	4.905 ***
		(1.10)	(1.14)	(1.03)	(1.25)
ln GDP growth (one lag)	3.774 *		2.312	2.160 *	
	(2.02)		(1.66)	(1.26)	
ln Domestic credit growth (two lags)		-0.675	0.373	0.578	-0.803 **
		(0.52)	(0.68)	(0.55)	(0.39)
ln Domestic credit growth (one lag)	-0.573		-0.632		
	(1.38)		(0.98)		
Credit to GDP Gap (lambda=6.25) (two lags)		1.055 *			1.435 **
		(0.62)			(0.60)
Credit to GDP Gap (lambda=6.25) (one lag)	0.956		1.053	0.749	
	(0.98)		(0.82)	(0.50)	
ln Unemployment rate (two lags)		0.272			0.029
		(0.30)			(0.23)
ln Unemployment rate (one lag)	0.211		0.308	0.395	
	(0.41)		(0.34)	(0.29)	
ln New York Stock Exchange index movement (two lags)		-0.529 **	-0.606 **	-0.601 **	-0.523 ***
		(0.24)	(0.31)	(0.30)	(0.19)
ln New York Stock Exchange index movement (one lag)	-0.157		-0.438	-0.521 **	
	(0.24)		(0.28)	(0.24)	
Constant	-0.257	-0.322 ***	-0.335 ***	-0.371 ***	-0.282 ***
	(0.17)	(0.07)	(0.12)	(0.10)	(0.08)
Summary statistics					
Regression	Lagged	Lagged	Lagged	Lagged	Lagged
Number of years	21	20	20	20	20
Adjusted R-squared	-0.156	0.439	0.468	0.487	0.425
Standard error of regression	0.126	0.088	0.086	0.084	0.089
Akaike info criterion	-1.048	-1.754	-1.774	-1.822	-1.754
Schwartz criterion	-0.700	-1.405	-1.326	-1.424	-1.455

Table 3.4 - *Continued*

Dependent variable: ln number of bankruptcies as a % of domestic credit					
	(6)	(7)	(8)	(9)	(10)
ln Bankruptcies % domestic credit (two lags)					
ln Bankruptcies % domestic credit (one lag)					
ln GDP growth (two lags)	4.004 ***		4.766 ***		
	(0.51)		(0.56)		
ln GDP growth (one lag)					
ln Domestic credit growth (two lags)		0.957	-0.817 **		
		(0.77)	(0.39)		
ln Domestic credit growth (one lag)					
Credit to GDP Gap (lambda=6.25) (two lags)	0.826 **		1.444 **	0.522	
	(0.34)		(0.58)	(0.67)	
Credit to GDP Gap (lambda=6.25) (one lag)	0.599			1.029 *	0.277
	(0.43)			(0.54)	(0.36)
ln Unemployment rate (two lags)					
ln Unemployment rate (one lag)					
ln New York Stock Exchange index movement (two lags)	-0.688 ***	-0.622 ***	-0.525 ***	-0.627 **	
	(0.19)	(0.23)	(0.17)	(0.25)	
ln New York Stock Exchange index movement (one lag)	-0.422 **	-0.428		-0.461 ***	
	(0.16)	(0.39)		(0.16)	
Constant	-0.236 ***	-0.091 **	-0.273 ***	0.002	-0.121 ***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Summary statistics					
Regression	Lagged	Lagged	Lagged	Lagged	Lagged
Number of years	20	20	20	20	21
Adjusted R-squared	0.523	0.153	0.463	0.171	-0.042
Standard error of regression	0.081	0.108	0.086	0.107	0.119
Akaike info criterion	-1.942	-1.434	-1.853	-1.419	-1.322
Schwartz criterion	-1.643	-1.235	-1.604	-1.170	-1.223

The lagged OLS regressions have the following specification:

$$BD_t = c + \delta_1 BD_{t-j} + \delta_2 GDP_{t-j} + \delta_4 CGP625_{t-j} + \delta_2 DC_{t-j} \\ + \delta_6 UN_{t-j} + \delta_7 NY_{t-j} + \varepsilon_t \tag{3.2}$$

where BD_t is our proxy for credit risk and the abbreviations of the explanatory variables on the right handside of the equation can be found in appendix 3B. Because of the limited number of observations, we only allow for a two–period lagged OLS regression ($j = 2$). We perform regressions for most combinations of explanatory variables, the best and worst combinations of these regressions are shown in Table 3.4.

We use the adjusted $\overline{R}^2$, the Akaike information criterion (AIC) and the Schwartz criterion (SC) to determine the number of lags of the regressed explanatory variables and the explanatory power of the regressions. If we compare regression (1) with all one-year lagged variables to regression (2) with all two-year lagged variables, it is clearly visible that the one-lagged variables have very little explanatory power for the USA. The Akaike information criterion and the Schwartz criterion of regression (2) are of lower value than the test statistics of regression (1). This is a different result in comparison to Table 3.2. In The Netherlands the one-year lagged variables have more explanatory power than the two-year lagged variables. One theory concerning this result is that this difference might be caused by the different funding structures of companies in both countries. Hackethal & Schmidt (1999) find that German companies are primarily financed through bank loans, where US companies are primarily funded through non-bank loans and bonds. When a company goes into default on its debt, it does not automatically imply that this company will go bankrupt. Perhaps the debtholders of US companies are less likely to aim at a bankruptcy than are the debtholders of the German companies (or in our chapter: Dutch companies). Or the timeline between default and bankruptcy is different for the different debtholders in the US and Germany. We do not have evidence on a possible explanation for the found difference between the USA and The Netherlands. Regression (10) shows the explanatory power of the credit-to-GDP gap (with $\lambda = 6.25$), as suggested by Drehmann et al. (2010). The explanatory power of solely the credit-to-GDP gap is in both countries (The Netherlands & The USA) small. If we analyze all regressions of the USA, regression (6) and (8) have the best test statistics. These results appear to be quite similar to the regressions in previous section: these regressions also use the variables $CG625_{t-j}$ and NY_{t-j}. Another difference in the USA is that the variable GDP_{t-j} has significant explanatory power. In The Netherlands this variable could not be used in the regressions because of non-stationarity. In our analysis some macro-economic business indicators are significant in the regression, research by Koopman et al (2009) has shown that adding an unobserved dynamic component[27] might influence the significance of the macro-economic variables we use negatively. We are aware of this omission in our analysis.

3.5.2 Forecasts 2003-2009

From the regressions in previous subsection, we determine the out-of-sample forecasts for our proxy BD_t. We compare these out-of-sample forecasts for the period 2003-2009 to our actual values of BD_t. We use an ex post forecast concerning the period 2003-2009, where the actual values of the dependent variable are already known. We use a static forecasting model and not dynamic forecasting model, because the data are stationary and it concerns an out-of-sample forecast. We test this forecast by using the root mean squared error of the forecast and the Theil inequality coefficient. Table 3.5 shows the test statistics for these forecasts and Figure 3.2 the forecast graphs, where the forecasted value of BD_t is compared to the actual value of BD_t.

[27] This component can be interpreted as an omitted systematic credit risk factor.

Table 3.5

Test statistics out-of-sample forecasts The United States of America 2003 - 2009

The table presents the test statistics of the out-of-sample forecasts based on the regression results show n in Table (3.4). The forecastnumbers in this table correspond to the regression numbers of Table (3.4).

	Forecast corresponding to regressions Table (3.4)				
	(1)	(2)	(3)	(4)	(5)
Root mean squared error	0.413	0.365	0.372	0.393	0.364
Theil's inequality coefficent	0.780	0.637	0.733	0.749	0.667
Bias proportion	0.104	0.154	0.047	0.039	0.153
Variance proportion	0.646	0.551	0.669	0.515	0.739
Covariance proportion	0.250	0.294	0.284	0.446	0.108

	Forecast corresponding to regressions Table (3.4)				
	(6)	(7)	(8)	(9)	(10)
Root mean squared error	0.358	0.392	0.364	0.381	0.413
Theil's inequality coefficent	0.713	0.756	0.665	0.702	0.802
Bias proportion	0.049	0.025	0.152	0.004	0.105
Variance proportion	0.747	0.514	0.738	0.419	0.833
Covariance proportion	0.204	0.460	0.110	0.577	0.062

The out-of-sample forecast based on the one-lagged variables (1) and the out-of-sample forecast (10) based on solely the credit-to-GDP gap (with $\lambda = 6.25$) perform worst according to our test statistics.

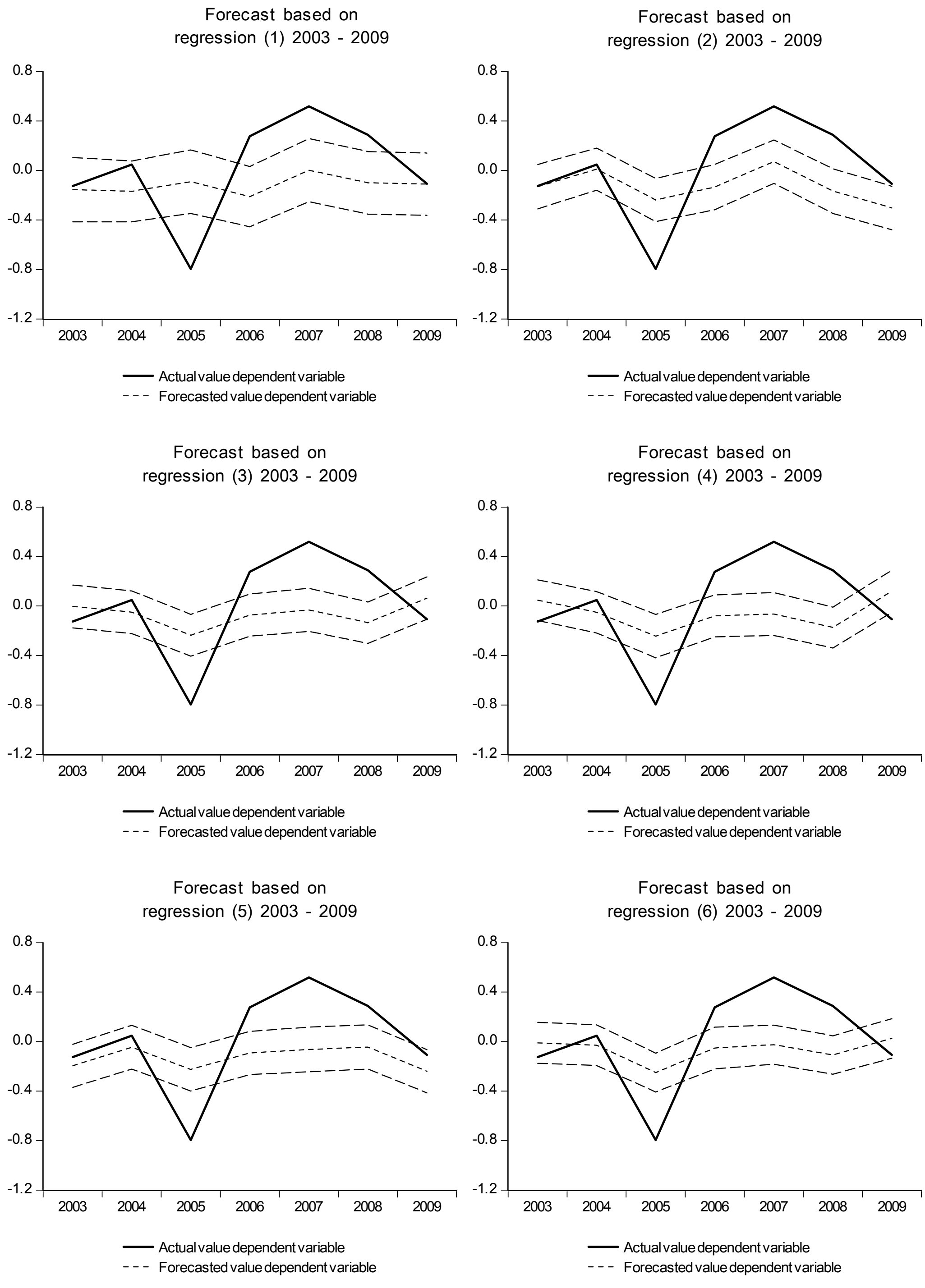


Figure 3.2 - Forecast graphs United States of America 2003 - 2009

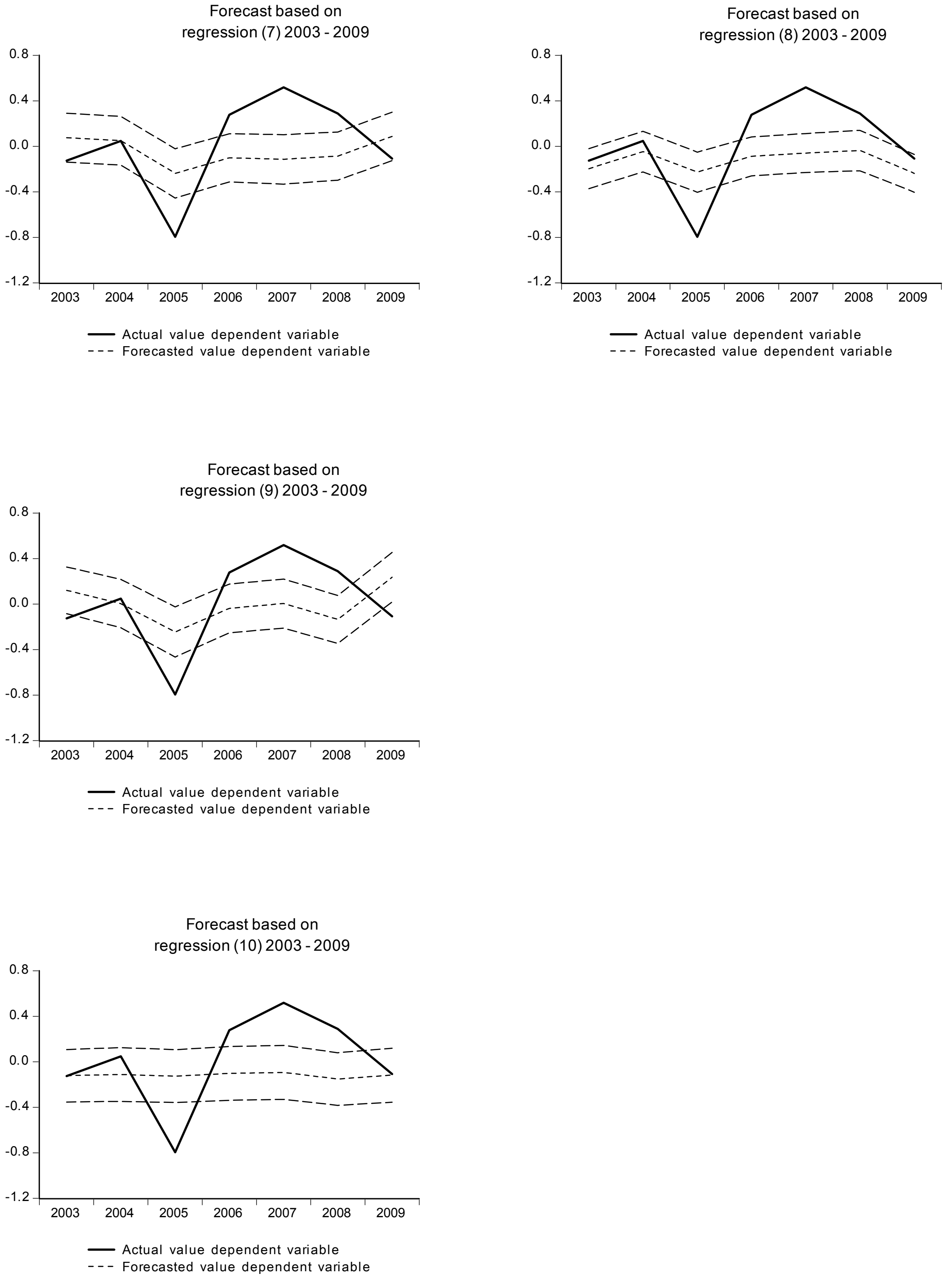


Figure 3.2 - Forecast graphs United States of America 2003 - 2009 (continued)

This is in conformity with the explanatory power of these regressions in Table 3.4. The out-of-sample forecasts for the Netherlands (Table 3.3) on average perform better than those of the USA (Table 3.5). We do not have a clear explanation for this result. But we are aware that country-specific insolvency laws and the entity type of businesses influence our proxy for credit risk. Also the registration of bankruptcy filings and the reason to file for bankruptcy influence our proxy for credit risk.

The forecasts with two-lagged variables (2) give a better forecast than those with one-lagged variables (1) in the USA, this is in conformity with regression results. The forecasts that include the variables $CG625_{t-j}$, NY_{t-j} and GDP_{t-j}, forecast (6) and (8), give the best forecast of our proxy BD_t according to the test statistics of Table 3.5. This result is in conformity with the regressions of (3.4) and the results of the forecasts in The Netherlands. The positive correlation between the GDP growth and the number of bankruptcies as a percentage of domestic credit is not in accordance with our hypothetical impact of Table 3.1. This result would imply that an increase in GDP correlates with an increase in the number of bankruptcies as a percentage of domestic credit. We do not have an economic interpretation for this result. The best forecasts for the USA include the variables concerning the stock exchange market and the credit-to-GDP gap. These significant variables do show the same sign as was theoretically predicted in Table 3.1. The combination of these variables covers all three aspects of credit risk of the expected loss measure.

The actual data on the proxy for credit risk for The Netherlands (BD_t) and the USA (BD_t) differ. The Dutch data show an increasing actual value of our proxy for credit risk from the period 2007 onwards (Figure 3.1), but the actual USA data show a decreasing proxy (Figure 3.2). If we compare this trend to the known shocks within the financial sector during this period in the USA[28], it seems quite peculiar that the proxy for credit risk has a downward trend in the USA. One explanation for this result might be consistent with the outcome of our analyses, where the proxy of the USA is more lagged than that of The Netherlands. As a consequence the known shocks from 2007 onwards, will not appear in the actual data concerning our proxy before 2009. Another explanation might be that, although the proxy seems to work well for The Netherlands, it is less applicable to the situation of the USA

[28]In September 2008 Lehman Brothers Holding Inc. goes bankrupt and in the first quarter of 2009 the Case-Shiller US National Home Price Index has a decline of 18.9%.

as a consequence of a different funding structure of US companies[29].

3.6 Conclusion

Basel III imposes the use of a countercyclical provision by financial institutions. The goal of the countercyclical provision is to promote a more resilient banking sector and improve the banking sector's stability. Loan losses as an eventual outcome of credit risk, have impact on the liquidity, profitability and solvency position of banks[30]. In order to improve stability in the banking sector, the indicator that is used for countercyclical provisioning should give a good indication of the amount of credit risk in the banking sector. This indicator should be determined on a top-down basis and indicate credit risk without being distracted by the provisioning scheme of a specific bank. An empirical indicator to determine the height of the countercyclical provision should be timely, consistent and give an indication of the amount of credit risk in the financial sector. We use the change in the number of bankruptcies as a percentage of domestic credit, BD_t, as a proxy of the amount of credit risk in the financial sector. We analyze the correlation between BD_t and different top-down business cycle indicators from literature. We find that a combination of the credit-to-GDP gap and the stock exchange rate gives the best forecast of BD_t in the Netherlands. When we include the indicator GDP growth in the forecast for the United States of America, the forecast improves. The number of lags of the indicators, that best predict our proxy, differ for the United States and The Netherlands. Our proxy for credit risk BD_t appears to be more lagged in the United States than in The Netherlands. The limited amount of observations for our proxy BD_t limits our analysis. We conclude that the best forecasts combine indicators of all three aspects of credit risk (probability of default, exposure at default and loss given default). The forecasts of credit risk in The Netherlands are more accurate than the forecasts of credit risk in The United States of America. One explanation for this result might be the different funding structure of US companies in comparison to Dutch companies, that are primarily funded by bank loans[31]. If this explanation is valid, a different

[29] Hackethal & Schmidt (1999) find that German companies are primarily financed through bank loans, where US companies are primarily funded through non-bank loans and bonds.

[30] We refer to Bolt et al. (2011).

[31] Hackethal & Schmidt (1999) find that German companies are primarily financed through bank loans, where US companies are primarily funded through non-bank loans and bonds.

proxy for the amount of credit risk in the US financial sector should be used in the analysis for the United States of America.

In this chapter we analyze the indicators for the amount of credit risk present in the financial sector of a country, with the purpose of using these indicators to form a countercyclical provision for loan losses. When a policy rule changes, for example by the implementation of a countercyclical provision, the optimization rule of the financial institutions might also change. This could result in a change in the variables we use in this chapter. This phenomenon is known as the Lucas critique (1976). We do not have any information or assumptions on how the optimization rule of financial institutions might change and influence our results.

Analysis of the effect of our proposal for countercyclical provisioning is only possible with detailed information concerning the current loan loss provisions in the aggregated financial sector. For The Netherlands we have some empirical data on the aggregated financial sector, but the details are very limited. If we would use our indicators for credit risk from regression (4) from Table 3.2 to determine a multiplier $\gamma \in [0.9, 1.1]$ from the regression (4) formula:

$$cr_t = 0.010 + 1.118 \cdot CG625_{t-2} + 2.507 \cdot CG625_{t-1} - 0.271 \cdot AU_{t-2} - 0.324 \cdot AU_{t-1}$$

where cr_t is our indicator for credit risk and the result of the regression formula. We choose our multiplier γ according to this indicator cr_t[32] and the result is shown in Figure (3.3):

[32] According to the formula:

$$\gamma_t = \gamma_{\min} + \left(\frac{cr_t - cr_{\min}}{e(cr)}\right) \cdot (\gamma_{\max} - \gamma_{\min})$$

where γ_t is the multiplier at t, $\gamma_{\min}$ is the minimum value of the multiplier (in this case we chose 0.9) and $\gamma_{\max}$ is the maximum value of the multiplier (in this case we chose 1.1). The parameter cr_t is the result of our regression formula at t, $cr_{\min}$ is the minimum value of the regression result over the timeperiod (1991-2009 for The Netherlands) and $e(cr)$ is the average value of cr over the timeperiod (1991-2009 for The Netherlands).

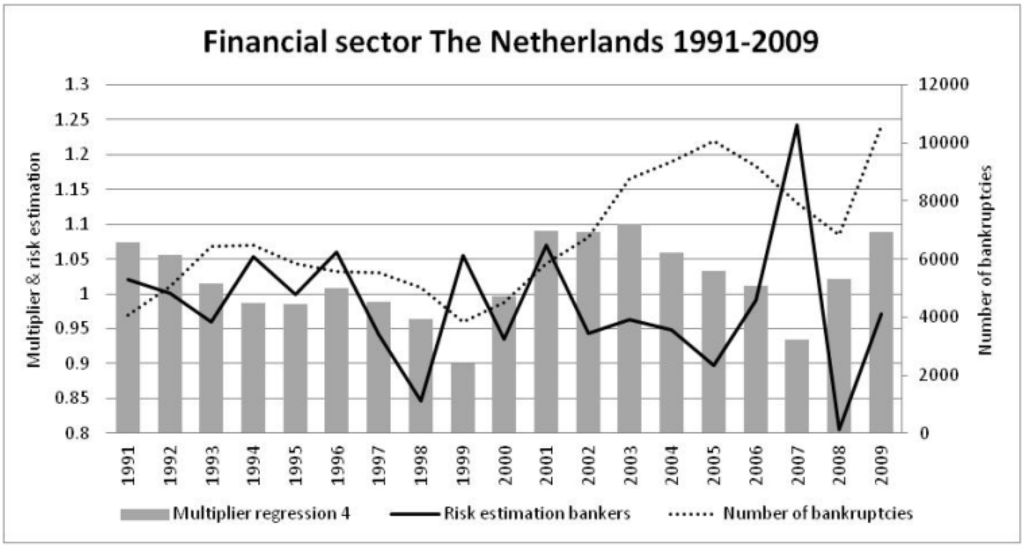


Figure 3.3 Multiplier for The Netherlands based on regression (4)

We do not have detailed information on the loan loss provisions of Dutch banks, but Figure (3.3) does show the number of bankruptcies and the risk estimation of bankers. The risk estimation of bankers is variable that is determined by dividing the risk weighted assets by the total asset amount on the balance sheet. This variable gives an indication of the perceived risk profile of the assets by banks.

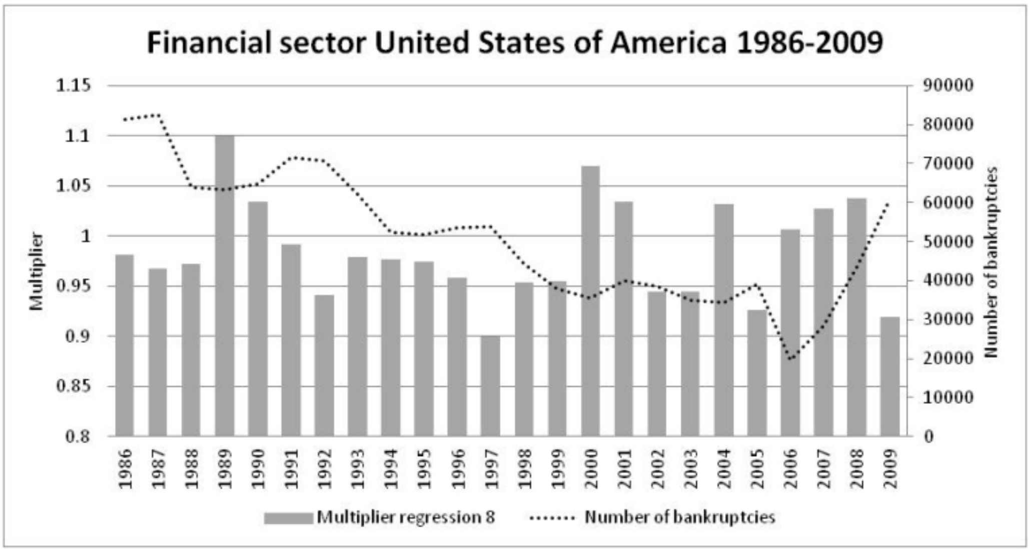


Figure 3.4 Multiplier for The USA based on regression (8)

For the USA we do not have information concerning the risk-weighted assets on the aggregated balance sheet of the financial sector. For future research the estimation of the amount of credit risk in the financial sector could be improved by a dataset that would have more observations over a longer timeperiod to increase the predictive value of the forecasts. Also aggregated bank data with concern to non-performing loans, defaulted loans and loan losses could improve our analysis.

3.A Appendix - Credit-to-GDP gap

Basel III (2010)[33] suggests the credit-to-GDP gap as an indicator variable to determine where the economy is in the economic cycle. Drehmann et al. (2010) primarily focus on choosing a variable that signals the time to build up and release capital buffers. Basel III gives a very detailed description how to determine the credit-to-GDP gap[34]. We have to determine the credit-to-GDP trend, that is the sustainable average of the ratio of credit-to-GDP. This can be done by using a Hodrick-Prescott filter, the assumption behind this filter is that it divides the original series y_t in a trend (τ_t) and the cycle (c_t). Hodrick and Prescott (1981) obtain the trend by solving the following optimization problem:

$$\min \sum_{t=1}^{\tau}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{\tau-1}(\tau_{t+1} - 2\tau_t + \tau_{t-1})^2 \tag{3.3}$$

where the first term penalizes the variance of the difference between the original series and the trend (that is the cyclical component $c_t = y_t - \tau_t$) and the second term penalizes the growth rate of the trend component (3-period based). Drehmann et al. (2010) use a λ of $1,600$ to determine the trend in the Hodrick and Prescott filter, because the trend of the credit cycle covers a longer period (according to Drehmann et al. (2010) a business cycle covers 4 to 8 years and a credit cycle is three to four times longer than the business cycle). Drehmann et al. (2010) test different λ's. They find that a λ of $125,000$ or $400,000$ (that is approx. 3^4 or 4^4 times $1,600$) performs best in determining the trend. We have to adjust the λ for yearly data concerning GDP and credit in stead of quarterly data. Ravn & Uhlig (1997) suggest to use a λ of 6.25 for yearly data where other authors suggest a λ of 100 (Backus & Kehoe (1992)) or a λ of 400 (Correia et al. (1992) and Cooley & Ohanian (1991)). We will use a λ of 100 and a λ of 6.25 to determine the credit to GDP gap.

[33] Annex 1 of "Guidance for national authorities operating the countercyclical capital buffer", Basel Committee on Banking Supervision, Bank for International Settlements, December 2010

[34] Annex 1 of "Guidance for national authorities operating the countercyclical capital buffer", Basel Committee on Banking Supervision, Bank for International Settlements, December 2010

3.B Appendix - Descriptive statistics

Descriptive statistics empirical data

Table 3B.1
Origin of empirical data

This table presents the origin of our empirical data. Domestic credit to the private sector refers to financial resources provided to the private sector, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises. The number of bankruptcies concern only business filings in the analysis of this chapter, not the non-business or consumer filings.

The Netherlands 1981 - 2009		The USA 1981 - 2009	
Datatype	Origin	Datatype	Origin
Number of bankruptcies	Datastream	Number of bankruptcies	American Bankruptcy Institute
Gross Domestic Product	World Bank	Gross Domestic Product	World Bank
Money and Quasi-money (M2)	World Bank	Money and Quasi-money (M2)	World Bank
Domestic Credit	World Bank	Domestic Credit	World Bank
Unemploymentrate	World Bank	Unemploymentrate	World Bank
AEX average index value	Dutch Central Bank	New York Stock Exchange index	Datastream
AEX ultimo index value	Dutch Central Bank	S&P 500 index	Datastream

Table 3B.2
Variable description

This table presents the used abbreviations, the description of the variables and their calculation (if applicable). Domestic credit to private sector refers to financial resources provided to the private sector, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises. The number of bankruptcies concern only business filings in the analysis of this chapter, not the non-business or consumer filings.

The Netherlands & The United States of America 1981 - 2009

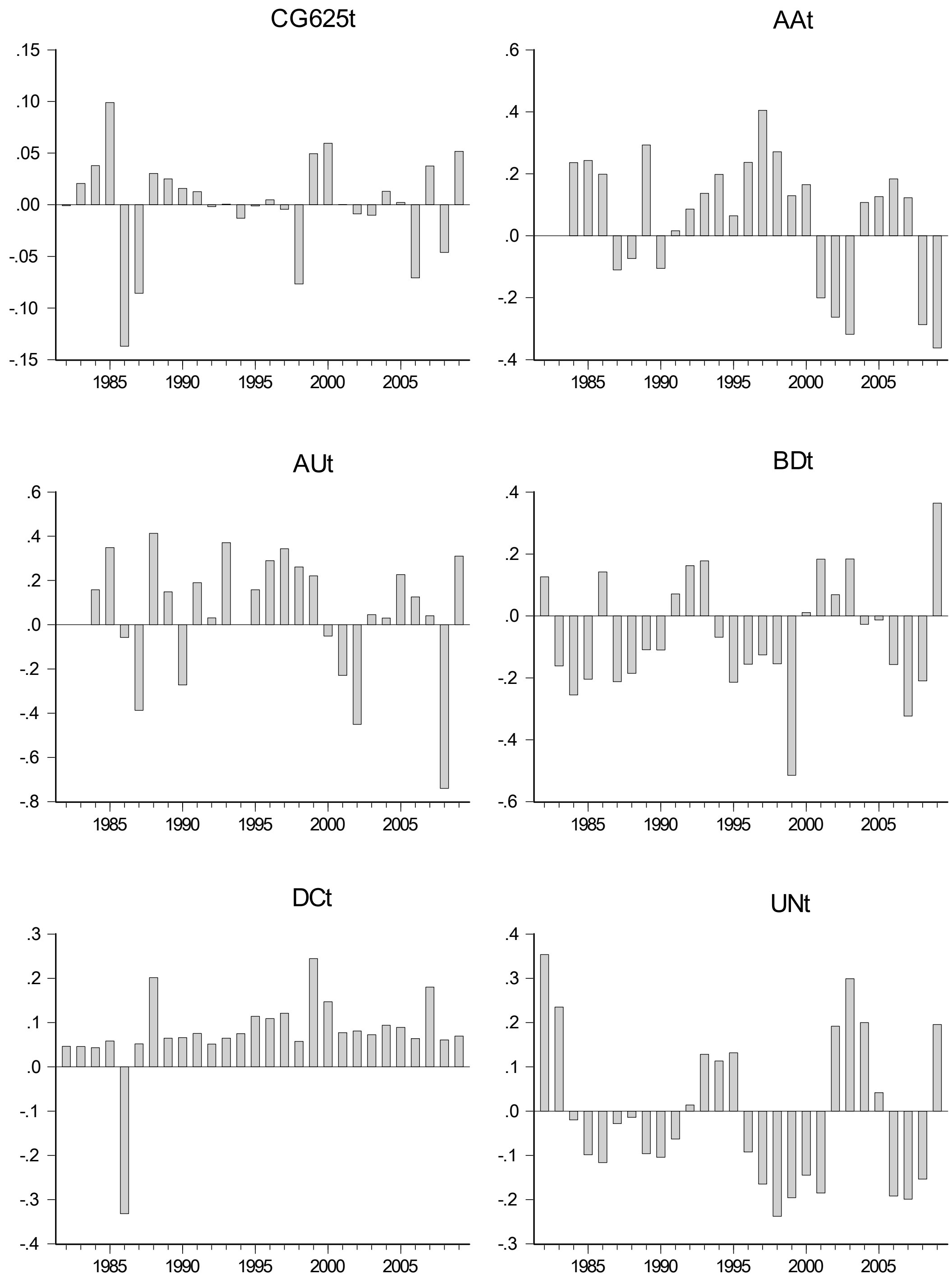
Variable	Variable description
BD	Log-linearisation of the number of bankruptcies as a percentage of domestic credit, ln(BNKDCt/BNKDCt-1)
GDP	Log-linearisation of Gross Domestic Product, ln(GDPt/GDPt-1)
M2	Log-linearisation of Money and Quasi-money (M2), ln(M2t/M2t-1)
DC	Log-linearisation of Domestic Credit, ln(DOMCRt/DOMCRt-1)
CG100	Credit to GDP Gap with a lambda of 100, appendix 3A
CG625	Credit to GDP Gap with a lambda of 6.25, appendix 3A
UN	Log-linearisation of the unemploymentrate, ln(UNEMPLt/UNEMPLt-1)
AA	Log-linearisation of the average value of the Amsterdam Stock Exchange Index, ln(AEXt/AEXt-1)
AU	Log-linearisation of the ultimo value of the Amsterdam Stock Exchange Index, ln(AEXt/AEXt-1)
NY	Log-linearisation of New York Stock Exchange Index, ln(NYSEt/NYSEt-1)
SP	Log-linearisation of S&P 500 Index, ln(SPt/SPt-1)

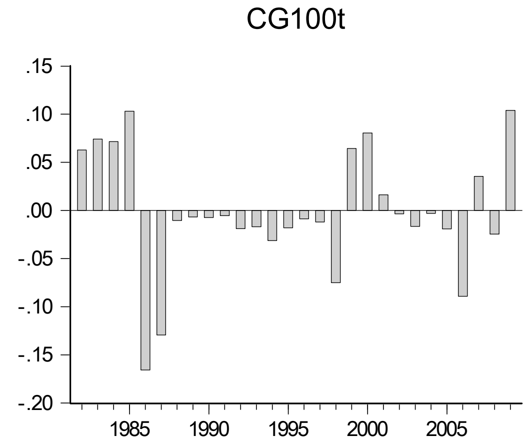
Table 3B.3
Descriptive statistics

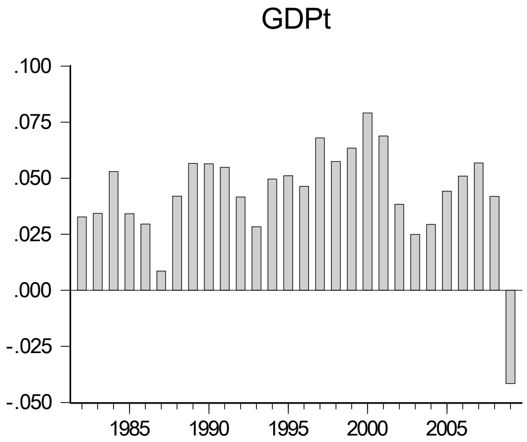
The table presents the descriptive statistics of the empirical data of the Netherlands and the United States of America.

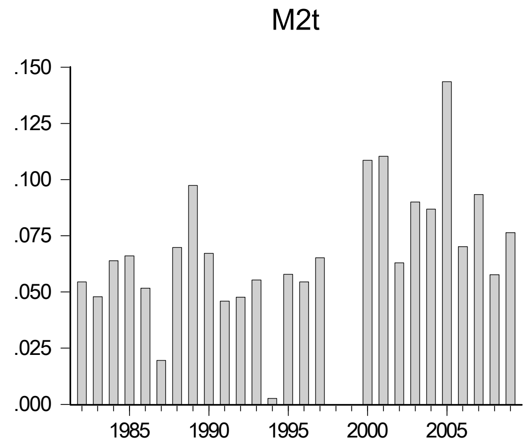
	The Netherlands 1981 - 2009				The USA 1981 - 2009			
Variable	No. of observations	Mean	Median	St. deviation	No. of observations	Mean	Median	St. deviation
BD	28	-0.061	-0.110	0.191	29	-0.075	-0.081	0.239
GDP	28	0.043	0.045	0.023	29	0.053	0.056	0.022
M2	28	0.075	0.071	0.094	29	0.058	0.072	0.037
DC	28	-0.002	-0.008	0.064	29	0.080	0.086	0.052
CG100	28	0.000	0.001	0.048	29	0.000	-0.005	0.064
CG625	26	0.068	0.065	0.029	29	0.000	-0.002	0.047
UN	28	-0.007	-0.046	0.168	28	0.007	-0.039	0.153
AA	26	0.058	0.124	0.209				
AU	26	0.059	0.137	0.281				
NY					29	0.075	0.090	0.179
SP					29	0.074	0.122	0.180

3.C Appendix - Business cycle indicators and BD_t NL (1981-2010)

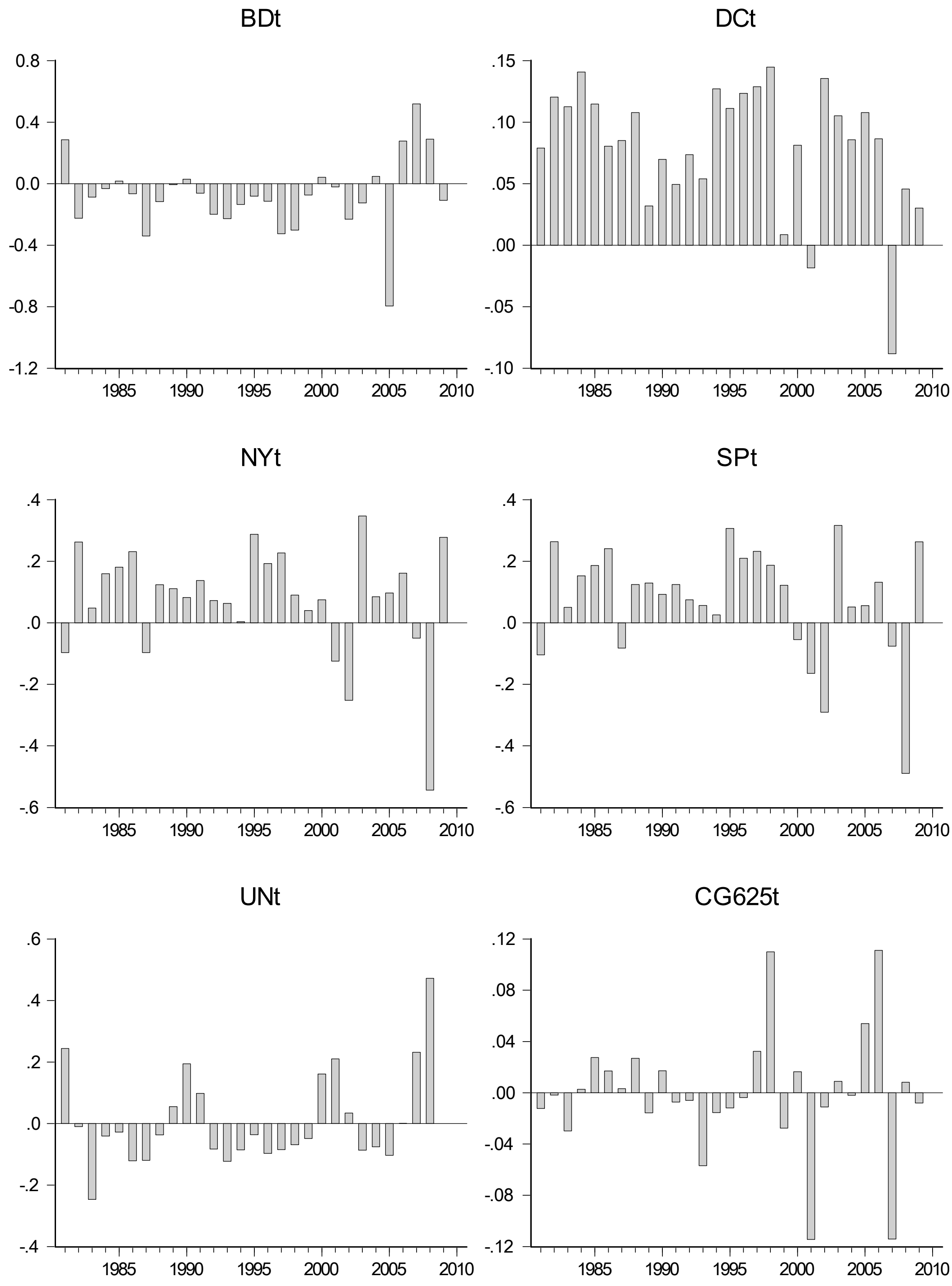


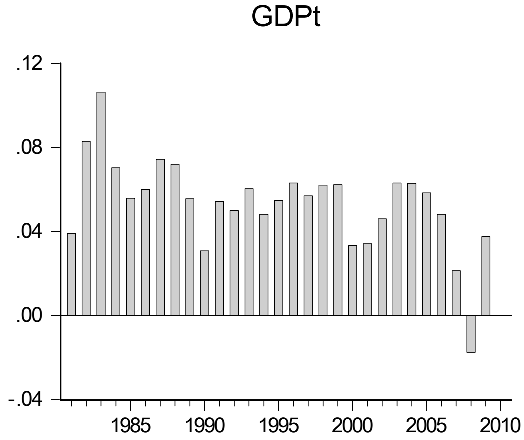

CG100t
.15
.10
.05
.00
-.05
-.10
-.15
-.20
1985
1990
1995
2000
2005

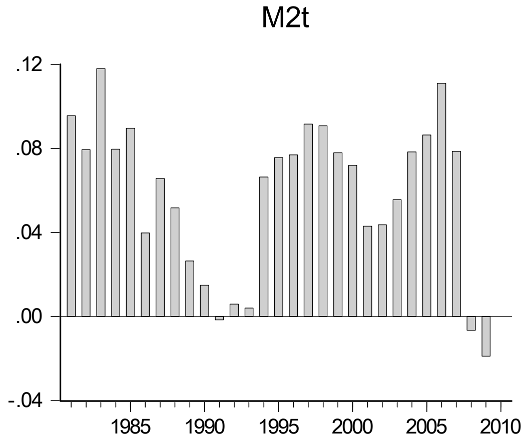

GDPt
.100
.075
.050
.025
.000
-.025
-.050
1985
1990
1995
2000
2005


M2t
.150
.125
.100
.075
.050
.025
.000
1985
1990
1995
2000
2005

3.D Appendix - Business cycle indicators and BD_t USA (1981-2010)




GDPt
.12
.08
.04
.00
-.04
1985
1990
1995
2000
2005
2010


M2t
.12
.08
.04
.00
-.04
1985
1990
1995
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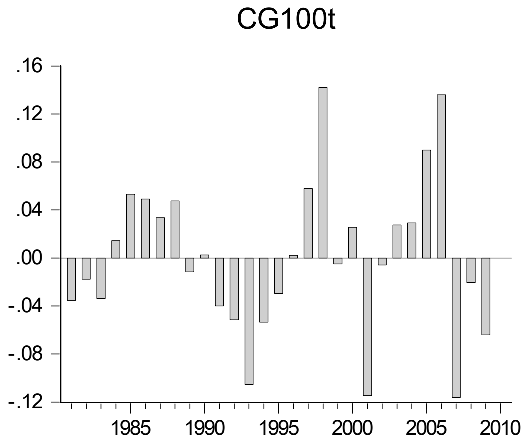
2010


CG100t
.16
.12
.08
.04
.00
-.04
-.08
-.12
1985
1990
1995
2000
2005
2010

3.E Appendix - Correlation matrices empirical data

Correlation matrices dependent and explanatory variables

The table presents the correlation betw een the dependent variable and the explanatory variables. For The Netherlands the correlation betw een the variables GDP and UN is high. For The USA the correlation betw een GDP, NY, SP and UN is high. The correlation betw een BD, DC, GDP and UN is also high.

The Netherlands

	CG100	CG625	AA	AU	BD	DC	GDP	M2	UN
CG100	1.00								
CG625	**0.94**	1.00							
AA	-0.05	0.08	1.00						
AU	0.30	0.43	**0.52**	1.00					
BD	0.04	-0.07	-0.41	0.06	1.00				
DC	**0.54**	**0.64**	-0.09	0.18	-0.32	1.00			
GDP	0.01	0.10	0.49	-0.07	-0.43	0.23	1.00		
M2	0.37	0.36	-0.05	0.14	0.14	0.23	0.21	1.00	
UN	0.08	0.09	-0.39	0.12	0.45	0.06	**-0.56**	-0.10	1.00

The United States of America

	CG100	CG625	BD	DC	GDP	M2	NY	SP	UN
CG100	1.00								
CG625	**0.93**	1.00							
BD	-0.31	-0.29	1.00						
DC	**0.58**	**0.66**	**-0.53**	1.00					
GDP	0.23	0.15	**-0.51**	0.47	1.00				
M2	0.42	0.27	-0.03	0.31	0.45	1.00			
NY	0.31	0.27	-0.28	0.34	**0.62**	0.32	1.00		
SP	0.34	0.31	-0.29	0.35	**0.63**	0.30	**0.97**	1.00	
UN	-0.31	-0.24	**0.62**	**-0.52**	**-0.87**	-0.37	**-0.62**	**-0.64**	1.00

3.F Appendix - Augmented Dickey-Fuller test

Augmented Dickey-Fuller Test (Unit Root Test)

The table presents the results of the Augmented Dickey-Fuller test. The null hypothesis that the variable has a unit root is tested.
*** is rejection on a 1% level, ** on a 5%-level and * on a 10%-level.

The Netherlands			
Variables	ADF test statistic	ADF Critical Value	Conclusion
BD	-3.64 **	T < CV	Rejects H0
GDP	0.73	T > CV	Fails to reject H0
DC	-4.93 ***	T < CV	Rejects H0
CG100	-3.69 **	T < CV	Rejects H0
CG625	-5.28 ***	T < CV	Rejects H0
M2	-4.10 **	T < CV	Rejects H0
UN	-4.01 **	T < CV	Rejects H0
AA	-2.70	T > CV	Fails to reject H0
AU	-4.84 ***	T < CV	Rejects H0

The United States of America			
Variables	ADF test statistic	ADF Critical Value	Conclusion
BD	-4.26 **	T < CV	Rejects H0
GDP	-3.72 **	T < CV	Rejects H0
DC	-3.89 **	T < CV	Rejects H0
CG100	-1.72	T > CV	Fails to reject H0
CG625	-5.66 ***	T < CV	Rejects H0
M2	-1.90	T > CV	Fails to reject H0
UN	-3.46 *	T < CV	Rejects H0
NY	-4.78 ***	T < CV	Rejects H0
SP	-1.76	T > CV	Fails to reject H0

Chapter 4

Mixed strategy equilibria in asset based lending

Chapter is based on joint work with Casper G. de Vries

4.1 Introduction

Asset based lending is a specific form of transaction based lending. Asset based lenders supply credit to companies with a high risk profile, based on the collateral they supply. Asset based lenders accept accounts receivable, inventory or other (short-term) assets as collateral. In The Netherlands asset based lending by banks is usually done by a separate bank entity, for this activity requires separate skills and constitutes a different risk class from standard bank lending. Although asset based lending is classed as transaction-based lending, during the term of the lending contract, the asset based lender does gain "soft" information concerning the risk profile of the borrower. The article of Rajan & Winton (1995) suggests that the inspection of collateral itself may give the lender additional information about the borrower. Because asset based lenders use factual information and "soft" information to gain a view on the risk profile of their borrowers, asset based lending can be situated in between relationship lending and transaction-based lending. Rajan & Winton (1995) also find empirical evidence that shows that firms deplete their collateral when they are in trouble, rather than in good times. The asset based lending market can therefore be characterized as a "lender-of last resort" market where the companies that apply for asset based lending have very limited access to other sources of funding. This causes an inelastic demand for asset based loans.

Asset based lending has not received much attention in academic literature. One reason might be, because it is situated in between relationship lending and transaction based lending. The asset based lending market is a very specific market with high risk profile borrowers who are very sensitive to differences in interest rates between the different providers of loans. Asset based lenders rely even more than their banking colleagues on screening and monitoring to distinguish between the risk profiles of their borrowers.

We analyze interest rate setting behavior by asset based lenders in a dynamic market (with in- and outflow of borrowers) with an inelastic demand for loans. This chapter characterizes the complete set of Nash equilibria in a duopoly with incomplete information, learning and a dynamic borrowers' market with the entry and exit through default. In this dynamic market there are cohorts of borrowers with a high risk profile and cohorts of borrowers with a low risk profile and two asset based lenders. The market is characterized by adverse selection of high risk borrowers and the lack of a pure strategy equilibrium. We find that the division of borrowers can be modelled for all phases according to a series. Separate markets arise in which neither of the asset based lenders has an informational advantage (new borrowers' market) or one of the asset based lenders has an informational advantage (inside asset based lender). The asset based lender receives positive informational gains on the low risk borrowers in the market in which he has an informational advantage. The mixed strategy of the outside asset based lender has stochastic dominance over the mixed strategy of the inside asset based lender. The average interest rate the inside asset based lender offers is smaller than the average interest rate the outside based lender offers over the whole range of interest rates of the mixed distribution. The mixed strategy equilibria for each new phase depend on the number of borrowers in the market, their risk profile and the probability of default of these borrowers. An increase in the amount of high risk borrowers on the market, increases adverse selection. As a consequence of the increased adverse selection the informational gains for the inside asset based lender increase (the value of information concerning the risk profile of the borrowers becomes more valuable). We find that the probability of switching for low risk borrowers depends on the relative size and riskiness of the low risk borrowers in comparison to the total market. We also find that the interest rate offered to low risk borrowers increases when the probability of default for the high risk borrowers increases. This chapter differs from the current literature with respect to the game setup where an inelastic demand for asset based loans is combined with heterogeneous borrowers, learning by lending, a repeated game and a dynamic borrowers' market (entry and default to mimic a dynamic market). We think this game setup fits the practice of asset based lending better than current literature.

The remainder of this chapter is organized as follows. In section two we discuss related literature and section three outlines the framework of the model. From section four onwards we discuss the different stages and equilibria in the different phases of the game. The first phase of our model analyzes the symmetric case where both asset based lenders have no information concerning the borrower's type. The following phases are characterized by inside information concerning the risk profile of their borrowers and a lack of information concerning the borrowers of the competing asset based lender and the new borrowers on the market. The implications for the asset based lending market are derived in section eight. Conclusions are in section nine.

4.2 Related literature

The related literature can be divided into two separate strands. The first strand of literature concerns small business lending and transaction based lending. The second strand of literature concerns adverse selection in markets and more specific in the strategic banking literature.

According to Berger & Udell (2002) and Udell (2008) small business lending by financial intermediaries can be categorized into four main distinct lending technologies: Financial statement lending, asset based lending, credit scoring and relationship lending. The first three lending technologies are commonly referred to as transactions-based lending. Because lending decisions are based on factual information that is relatively easily available and does not rely on 'soft' data gathered over the course of a relationship. Relationship lending primarily focuses on the relationship between the lender (the bank) and her borrower. Transaction-based lending focuses on arm's length lending by banks (Boot & Thakor (2000)). The relationship over time between a bank and her borrower can facilitate monitoring and screening and resolve asymmetric information. But the relationship can also lead to an ex post information monopoly, where the outside banks are uninformed. This phenomenon is known as the hold-up or lock-in problem. It places all bargaining power with the bank and was first described by Williamson (1975) and Klein et al. (1978).

Boot (2000) shows that relationship banking is vulnerable to soft-budget constraint. Relationship lending may lead to perverse ex ante incentives on the part of borrowers, when the borrower threatens to go into default, if no extra liquidity is offered. Empirical evidence from Houston & James (2001) and Berger & Udell (2006) stresses three important determinants of borrowers involved in relationship lending. The age of a firm, the size of a firm and the type of business are determinative for relationship borrowing. Smaller and younger firms and firms that have more intangible assets are more likely to be involved in relationship banking.

Even though asset based lending is part of transaction based lending, close monitoring does cause asset based lenders to have a steep learning curve concerning the risk profile of their borrowers (Rajan & Winton (1995)). The combination of learning by monitoring and short term contracts ensures that asset based lenders can easily adapt the loan terms based on the information they receive. Contrary to Boot et al. (1991) we treat the risk profile of borrowers and the value of collateral as exogenous in this chapter[1]. We assume that the borrowers of asset based lenders are more rigid in their investment and financing opportunities, creating an exogenous risk profile and a very inelastic demand for asset based loans.

Stiglitz & Weiss (1981), Narasimhan (1988) and Hillman & Riley (1989) are amongst the first to explore the consequences of mixed strategy equilibria in markets with adverse selection (banking game, promotional strategies and politically contestable rents). Stiglitz & Weiss (1981) show that in a one-period model an increasing interest rate and an increasing demand for collateral may increase the riskiness of a bank portfolio. Imperfect information between borrowers and lenders causes adverse selection. If a credit supplier is unable to distinguish between the risk profiles of borrowers, he will set the interest rate too high and attract the high risk borrowers. The imperfect information also causes credit rationing, where credit suppliers keep the offered interest rates high although they still have loanable funds

[1] In section 4.8 we relax the assumption of exogenous collateral.

available. Our paper expands this adverse selection problem to a repeated game with imperfect information regarding different borrower cohorts, an exogenous risk profile, entry and default of borrowers and an inelastic demand for loans.

Our analysis also builds on a framework used by von Thadden (2004) to analyze repeated bank lending under asymmetric information. Our framework also resembles that of Kofman and Nini (2006) to analyze insurance markets. The memo by von Thadden (2004) corrects a misdirected analysis by Sharpe (1990). Albeit the fact that the failure of pure strategy equilibria already followed from the Kunreather and Pauly (1985) analysis. The difference between our model and that of von Thadden (2004) and Kofman and Nini (2006) concerns the information bankers have concerning their clientele. In our model the asset based lender, who supplies the loan, learns the borrower's type, while the outside asset based lender does not. In the model of von Thadden (2001) both bankers receive a signal concerning the quality of the borrower. Kofman and Nini (2006) consider the case where only the informed insurer receives a signal of the borrowers type. Our model does not include signals, but there is learning due to repeated interaction. After having observed the borrower for one period the asset based lender becomes perfectly informed and learns the borrower's type. Outside asset based lenders do not observe the risk profile of the borrower.

From the second phase onwards the results resemble those of the model of sales equilibria of Varian (1980) and Baye et al. (1992). There are mixed strategies to balance the repelling forces of charging high interest rates versus the loss of borrowers. Mixed strategy equilibria in a banking environment with adverse selection have also been studied by Dell'Ariccia et al. (1999), Dell'Ariccia (2000) and Marquez (2002). These papers focus on the entry of new bankers in the market and the role of insider information on the structure of the banking industry. Our model differs from these papers because it takes into consideration the dynamics within the borrowers' market (entry & default) and the influence of a repeated game setup on the equilibria. We do not analyze the structure of the banking industry, but we focus on the division of borrowers on the borrowers' market instead.

Berger et al. (2011) find evidence in empirics that bankers use collateral to mitigate adverse selection. Bester (1985) reaches the same conclusion through a theoretical model. Ortiz-Molina & Penas (2008) empirically show that the maturity of a loan is used to mitigate adverse selection. Boot & Thakor (1994) show in an infinitely repeated credit market game without learning but with moral hazard, that the costs of borrowing in the later stages of a bank-borrower relationship are lower than in the early stages. Our model fits the practise of asset based lending better than current literature, because it combines the specific market characteristics of asset based lending best (an inelastic borrower demand for loans, the entry and default of borrowers and an exogenous risk profile of the borrower).

4.3 Preliminaries

Consider two types of borrowers:

1. Low risk (LR) borrowers: these borrowers are startup companies, companies in a growth market or capital intensive companies. The shortage of liquidity and/or solvency for these borrowers is usually temporarily and/or is not (yet) the consequence of a non-profitable business model;
2. High risk (HR) borrowers: these borrowers have a high risk profile because they are active in a declining market, have a declining market share or a declining profitability. A replacement market, mismanagement or other internal or external factors may cause the low profitability, low solvency and/ or low liquidity position of these borrowers. High risk borrowers have a higher probability of default than low risk borrowers;

In conformity with relationship banking, asset based lenders initially do not know the risk profile of the borrower when they enter into a one period-contract with the borrower. The asset based lender learns the risk profile of the borrower during the first contract period. If the borrower switches to another asset based lender, we assume that this information is lost. For the clientele that remains with the asset based lender that initially supplied the loan, the asset based lender can distinguish between the high and low risk borrowers. Hence the asset based lender may differentiate between the types and offer a different interest rate to the two types. The borrowers that fail in each period are replaced by new entrants. The demand for asset based loans is inelastic. This captures the feature that young and small firms have very little other alternative sources for financing.

Adverse selection (hidden information) is of greater importance to asset based lending than moral hazard (hidden actions), because contracts, collateral and monitoring constrain the borrower in exercising moral hazard[2]. But before contracts are signed, an asset based lender has to get a clear view of the risk profile of a borrower. Although there are asset audits and other screening devices, these devices are usually aimed at determining the value of collateral. The risk profile of a borrower still remains subjective and is based on information concerning the market of the borrower, management of the company and the feasibility of budgets and business plans. In a highly competitive asset based lending market, adverse selection is the larger of the two problems stemming from asymmetric information.

Consider the strategic choices by two asset based lenders who compete for borrowers. The funding side is left exogenous. There are two type of borrowers, high risk and low risk borrowers. The high risk borrowers default with probability H and the low risk borrowers default with probability L, $1 > H > L > 0$. Note that this implies

$$\frac{L}{(1-L)} < \frac{H}{(1-H)} \tag{4.1}$$

Default rates are assumed to be uncorrelated across borrowers. After one period the asset based lenders (hereafter: ABL's) learn the type of their own clientele. If borrowers migrate from one lender to the other, this information is lost. Thus once clients have been with a specific ABL, there is asymmetric information between the lenders. Borrowers are assumed to always know their type. There exists an adverse selection issue as lenders know the type of their current borrowers, while they cannot distinguish between high risk and low risk types that migrate from one ABL to the other ABL.

Every borrower wants to borrow just one unit of working capital. If the borrower is successful, the ABL makes gross interest rate R minus its cost of obtaining funding and providing the loan B. The net return for the ABL in this case is:

$$t = R - B > 0 \tag{4.2}$$

[2]Contracts contain covenants that include for example an obligatory check by an auditor, all sort of restraints on equity, the amount of dividend that can be distributed and also information obligations like running all transactions exclusively through the bankaccount of the lender.

The return for the asset based lender if the borrower fails is:

$$f = -1 + C - B < 0 \tag{4.3}$$

where C is the value of collateral the asset based lender has secured on the loan. If the borrower fails, the asset based lender looses the loan amount (-1) and the costs for funding the loan (B), but this is partly compensated by the value of collateral (C). We assume that the costs for lending B are equal for all asset based lenders. In the first part of this chapter we assume t is endogenous and can be influenced by the asset based lender, while other variables are exogenous. At a later stage we also investigate how equilibria might be affected if the collateral value C is endogenous.

We consider a duopoly of two asset based lenders, ABL 1 and ABL2. For simplicity, the borrowers' market consists of cohorts of perfectly divisible low and high risk borrowers. We ignore the integer problem. This can be easily taken care of, but complicates notation unnecessarily. For simplicity two divisible cohorts low risk borrowers and two divisible cohorts high risk borrowers are present in the borrowers' market. Let K and k be the high risk borrowers of ABL1, where capital letters denote the number of borrowers whose type is known to the ABL1. The k borrowers are first time high risk borrowers who can not be differentiated from first time low risk borrowers, denoted as m. The low risk borrowers who are identified as such by ABL1 are denoted by M. Similarly, the high risk and low risk agents of ABL2 are denoted by Q, q and W and w respectively.

Consider one of these quantities, say M. After one period the expected number of low risk firms that survives is $(1-L)M$. On the basis of the law of large numbers, we assume that this also equals the actual number of low risk firms of ABL1 that survive. Similar survival numbers apply for the other firms, i.e. $(1 - H)Q$ high risk firms survive at ABL2. For simplicity we assume that the total number of market participants is constant. But from the setup above, it is clear that one could easily cope with changes in the size of the market. The model has the following other assumptions, in accordance with Von Thadden (2004):

1. there are no long-term contracting possibilities;
2. profits are distributed each period (no retained earnings);
3. the borrower has no own funds, but has to borrow from competing ABL's;
4. one borrower can only receive financing from one bank.

These assumptions reflect the characteristic that asset based borrowers typically have few outside financing options but to go to an ABL. The asset based lenders can distinguish between the competitor's borrowers (switchers) and new borrowers. We show that the ABL's on the new borrowers' market follow a pure strategy Nash equilibrium in the initial phase and use marginal cost pricing. We assume that the discount factor the asset based lenders use is sufficiently different from one to ensure that trigger strategies do not impose a tacit collusion equilibrium[3]. We first discuss the initial phase in the asset based lending game, when both asset based lenders do not yet have information concerning the risk profile of the borrowers. Then we discuss generically the events in any subsequent period after exit, entry and switching has taken place. Furthermore we assume that ABL's know whether a borrower is a first time borrower in the ABL market or not. The subscripts at parameters indicate ABL1 or ABL2 and the superscripts at parameters indicate the subgroup of borrowers that the parameter refers to (where H indicates high risk borrowers, L low risk borrowers, N new borrowers on the market and C borrowers of the competing ABL).

4.4 Initial Phase

When the market for asset based lending is initiated, the two ABL's do not possess any information regarding the clientele quality. Hence we start of with two cohorts of high risk borrowers, k and q, and two cohorts of low risk borrowers, m and w. The ABL's cannot differentiate between the borrowers and will therefore offer one interest rate to the complete set of borrowers. Denote by t_1 the net interest rate ABL1 is offering, recall (4.2), and t_2 is the interest rate ABL2 is offering. Note that ABL1 breaks even if

$$t_1\left[(1-L)m+(1-H)k\right]+f\left[Lm+Hk\right]=0$$

[3]The articles of Baye & Morgan (1999) and Fudenberg & Maskin (1986) show that a host of other equilibria may be maintained by trigger strategies in infinitely repeated games according to the folk theorem. Two asset based lenders in a price setting environment in an infinite game might be quite likely to have a Nash equilibrium known as tacit collusion, but this possibility is not considered here.

Solving for t_1 then gives:

$$\widehat{t} = t_1 = t_2 = \frac{-f\,[Lm + Hk]}{(1-L)m + (1-H)k} > 0 \tag{4.4}$$

This pure strategy Nash equilibrium where both asset based lenders offer the same interest rate, is the unique equilibrium in the initial phase.

Note that if $t_1 > t_2$, then the entire market is captured by ABL2 and vice versa if $t_1 < t_2$. If $t_1 > \widehat{t}$, then ABL2 has an incentive to raise the interest rate above $\widehat{t}$ but below the interest rate ABL1 is charging, say to $t_1 - \varepsilon > \widehat{t}$. But then ABL1 has an incentive to undercut ABL2 to capture the entire market, while still pricing above $\widehat{t}$ to make a profit. Hence, pricing by deviating above $\widehat{t}$ from equation (4.4) is not in the interest of the ABL's. Deviating by pricing below $\widehat{t}$ is also not of interest to the ABL's, since it would capture the whole market with probability one. But any price below $\widehat{t}$ would result in a loss for the ABL. The break even price $\widehat{t}$ is the unique symmetric pure strategy Nash equilibrium. This equilibrium with marginal cost pricing and zero profits is also known as the Bertrand (1883) paradox.

4.5 Division of borrowers

The information asymmetry and the in- and outflow of borrowers from phase 2 onwards causes a separation of the borrowers in separate markets:

1. A borrowers' market where asset based lender 1 is the inside asset based lender with the information advantage (K & M);
2. A borrowers' market where asset based lender 2 is the inside asset based lender with the information advantage (Q & W);
3. The new borrowers' market with the inflow of new borrowers (k, m, q & w respectively).

The ABL's distinguish between the interest rates they charge on the different markets, according to the size of the market and the available information concerning this market. This also implies that the borrowers in one market cannot use the offered interest rates on another market. Competition over the borrowers only takes place within the markets. ABL's use the information asymmetry to make positive returns. The ABL's have an incentive to differentiate between the different groups of borrowers. This phenomenon is known as the lock-in problem, first described by

Williamson (1975) and Klein et al. (1978).

From the second phase onwards, three interest rates are offered to the borrowers on the markets with information asymmetry (so excluding the new borrowers' market):

1. t^C - this is the interest rate the outside asset based lender offers to the borrowers from the competitor's market;
2. t^L - this is the interest rate the inside asset based lender offers his low risk borrowers on the market in which he has an information advantage;
3. t^H - this is the interest rate the inside asset based lender offers his high risk borrowers on the market in which he has an information advantage.

The inside asset based lender is the asset based lender with the information advantage on the market. Borrowers switch asset based lender, if the offered interest rate by the outside asset based lender is less than the interest rate that the inside asset based lender offers. There are three possibilities:

1. $t^C < t^L$ - all borrowers switch to the outside asset based lender;
2. $t^L \leq t^C < t^H$ - only the high risk borrowers switch to the outside asset based lender;
3. $t^C \geq t^H$ - none of the borrowers switches to the outside asset based lender;

These possible combinations of relative interest rates and the specific entry and default of borrowers in the markets, determine the division of borrowers from the second phase onwards. The division of borrowers between the asset based lenders follows a series. This series can be described as follows:

Proposition 1 *The division of borrowers amongst the two asset based lenders, after the default and entry of borrowers, in phases* $[2, \infty)$ *can be presented as follows:*

	B_1	B_2
High risk borrowers (H)	$K + k = 1 + \omega$	$Q + q = 1 - \omega$
Low risk borrowers (L)	$M + m = 1 + \gamma$	$W + w = 1 - \gamma$

where $\omega \in \{0, (1-H)^n\}$ *and* $\gamma \in \{0, (1-L)^n\}$. *If* $\omega = 0$ *and* $\gamma = 0$, *you have an equal division of the borrowers and a symmetric equilibrium. If* $n = 1$ *(that is* $\omega = (1-H)$ *and* $\gamma = (1-L)$*), you will have a winner division of the borrowers and an asymmetric equilibrium. All the other division possibilities of borrowers in the subsequent stages are combinations of the above mentioned series where* $n \in \mathbb{N}\backslash\{0\}$

(all positive integers excluding zero). These possibilities result in an asymmetric division of borrowers. When we differentiate between the new borrowers and the existing borrowers, the division of existing borrowers amongst both asset based lenders can be represented as follows:

	B_1	B_2
High risk borrowers (H)	$K = (1 - H) + \omega$	$Q = (1 - H) - \omega$
Low risk borrowers (L)	$M = (1 - L) + \gamma$	$W = (1 - L) - \gamma$

This division of existing borrowers is used by the asset based lenders to determine their strategy for setting the interest rate for existing borrowers and the borrowers of the competing asset based lender.

Proof. *Proof by induction, appendix 4A* ■

The entry and default of borrowers every period and the equal division of the new borrowers on the asset based lending market, causes the configuration where one asset based lender serves all low risk borrowers and the other asset based lender serves all high risk borrowers to be absent. The amount of borrowers one ABL has in the following phases is dependent on the outcome of the mixed strategy played in phase two and the following phases. Regardless of the specific division of borrowers in a phase, one can determine the equilibrium interest setting strategies.

4.6 Market for entrants k, m, q and w subsequent periods $[2, \infty)$

In any subsequent period, the ABL's have information regarding the previous period clientele. Recall that existing clientele is denoted by capital letters, lower case letters refer to entrants on the ABL market. The generic quantities of firms applying for a loan are K, k and M, m for ABL1 and Q, q and W, w for ABL2. Note that these quantities refer to the number of firms at the start of a new period after the failing firms have exited the market. Each period these quantities may be different. In the previous section we described in detail how these quantities may develop due to entry and exit. Note that we do not require symmetric quantities of (K, M, Q, W) firms across the two ABL's. Due to the entry and exit of borrowers in all phases after the first phase, there will be $2H$ high risk borrowers and $2L$ low risk borrowers in the new borrowers' market every phase. Given the absence of information, the market for entrants is characterized by the pricing to entrants in accordance with the initial phase where both asset based lenders offer an interest rate equal to equation (4.4). This pricing strategy will result in a pure strategy Nash equilibrium where both asset based lenders will receive an equal part of the new borrowers' market ($k = q = H$ and $m = w = L$).

4.7 Market for surviving borrowers K, M, Q and W subsequent periods $[2,\infty)$

The market for surviving borrowers from the initial phase, can be subdivided in the inside market for ABL1 with K high risk borrowers and M low risk borrowers and the inside market for ABL2 with Q high risk borrowers and W low risk borrowers. The inside market for ABL1 with K high risk borrowers and M low risk borrowers is the market where ABL1 has an information advantage and ABL2 is the outside asset based lender who cannot distinguish between the low and high risk borrowers in the portfolio of ABL1. The borrowers' market with Q high risk borrowers and W low risk borrowers has the exact opposite information distribution: ABL1 is the outside asset based lender on this market and ABL2 has inside information on the risk profile of the borrowers on this market. The pricing strategy for a high risk borrower on both markets is identical with only the differentiation in the asset based lender, which is opposite. For this reason, we will not distinguish between the high risk borrowers on both markets, but only between the pricing strategy for the high risk borrowers and the pricing strategy for the low risk borrowers.

4.7.1 Pricing strategy high risk borrowers K and Q

On the market with K high risk borrowers, ABL1 has inside information and can distinguish the high risk borrowers K from the low risk borrowers M. ABL1 charges the high risk borrowers an interest rate t_1^H at least as large so not to make a loss, i.e.

$$t_1^H(1-H)K + fHK \geq 0$$

or

$$t_1^H \geq -f\frac{H}{(1-H)} > 0 \tag{4.5}$$

The high risk borrowers of ABL1 will switch asset based lender if they can receive a lower interest rate at ABL2. The mixed strategy equilibria, as are shown in the following section, show that the outside asset based lender, here ABL2, will charge an interest rate to the borrowers of the inside asset based lender, here ABL1, that is below or equal to t_1^H. The strategy of offering an interest rate to your high risk borrowers of t_1^H will always result in zero profit. If $t_1^H = -f\frac{H}{(1-H)}$, profit for ABL1 is zero, because the loan is priced at marginal costs. And if $t_1^H > -f\frac{H}{(1-H)}$, profit for ABL1 is also zero, because the outside asset based lender will receive your high risk borrowers. Following the strategy of charging t_1^H according to equation (4.5) to your high risk borrowers is a Nash equilibrium, where deviating would result in a lower than zero return.

On the market with Q high risk borrowers, ABL2 follows the same strategy as ABL1 concerning her high risk borrowers. Once ABL2 distinguishes its high risk borrowers, it charges these agents an interest rate t_2^H at least so large as not to make a loss, resulting in the pricing strategy for high risk borrowers equal to:

$$t_2^H = t_1^H \geq -f\frac{H}{(1-H)} > 0 \tag{4.6}$$

Following the strategy of charging t_2^H according to equation (4.6) to your high risk borrowers is a Nash equilibrium, where deviating would result in a lower than zero return. The strategy of ABL2 is identical to the strategy of ABL1 concerning the high risk borrowers. This strategy is independent of the amount of high risk borrowers on the borrowers' market.

4.7.2 Pricing strategy low risk borrowers M and W

On the market with M low risk borrowers, ABL1 is in competition with ABL2 who wants to lure away these good quality borrowers. ABL1 has inside information concerning the risk profile of the M low risk borrowers and ABL2 can only distinguish between the borrowers from ABL1 and the new entrants in the market. ABL2 cannot distinguish between the risk profiles of the borrowers of ABL1. As we will see, the high risk firms often have an incentive to switch. In practice it is often seen that borrowers that come from the opponent are offered a discount vis à vis existing borrowers. The analysis in this subsection reveals that sometimes there is a discount for borrowers that switch in our theoretical model and sometimes not. Two repelling forces determine whether or not there is a discount: more borrowers (quantity effect) versus higher pricing (price effect). Because of the separate markets, it suffices to describe one market of existing low risk firms (M). The analysis for the complementary market (W) being analogous. The equilibrium is similar in spirit to the asymmetric equilibrium strategies in Varian (1980), Hillman and Riley (1989) and Baye et al. (1992) describing the expenditures for winning politically contestable rent, except that the direction of bidding is downward rather than upward.

Suppose ABL1 uses a mixed pricing strategy for her low risk borrowers M. Let $B_1(t_2)$ denote the pricing strategy of ABL1 concerning her low risk borrowers. The probability that ABL1 charges her low risk borrowers an interest rate A that is less or equal to the interest rate ABL2 charges all her borrowers, t_2, can be denoted as:

$$B_1(t_2) = \Pr\{A \leq t_2\}.$$

From the point of view of ABL2, the net interest rate that ABL1 will charge to her low risk borrowers is the random variable A. If ABL2 sets an interest rate t_2 for the borrowers of ABL1, the low risk borrowers will switch to ABL2 with probability

$$\Pr\{A > t_2\} = 1 - B_1(t_2).$$

As we will see $t_2 \leq -fH/(1-H)$, it then follows from equation (4.5) that the high risk firms from ABL1 will always switch. This implies that ABL2 always gets the high risk borrowers from ABL1. The low risk borrowers also switch over to ABL2 in the case that t_2 undercuts the price that ABL1 charges its existing low risk clientele. The fact that the high risk borrowers always switch is a case of adverse selection.

Since ABL2 cannot distinguish between the high risk borrowers and low risk borrowers who switch from ABL1 to ABL2 (it has no informational advantage), ABL2 is expected to break even on it's pricing strategy t_2 to lure away borrowers from ABL1. This break even condition reads

$$\begin{aligned} 0 &= [1 - B_1(t_2)] \times \{[HK + LM] f + [(1-H) K + (1-L) M] t_2\} \\ &+ B_1(t_2) \times \{HKf + (1-H) Kt_2\}. \end{aligned} \tag{4.7}$$

Note that the payoff to winning over the switchers is determined by the proportion of failures, respectively H and L for the high and low risk borrowers, and the complementary proportion of successes, respectively $(1-H)$ and $(1-L)$. From equation (4.7) we can solve for the equilibrium mixed pricing strategy of ABL1

$$B_1(t_2) = 1 - \frac{K[-Hf - (1-H) t_2]}{M[Lf + (1-L) t_2]}. \tag{4.8}$$

At the upperboundary of t, $\bar{t}$, the cumulative probability $B_1(\bar{t}) = 1$, which is the case when

$$Hf + (1-H)\bar{t} = 0$$

or

$$\bar{t} = -f\frac{H}{(1-H)} > 0 \tag{4.9}$$

Note that since $H > L$, the denominator of equation (4.8) is:

$$M\left[Lf + (1-L)\bar{t}\right] = M\left[fL - f(1-L)\frac{H}{(1-H)}\right] > 0$$

whereas M is also larger than zero. At the lower end of the support of t, $\underline{t}$, the cumulative probability $B_1(\underline{t}) = 0$. Solving equation (4.8) for $\underline{t}$

$$\underline{t} = -f\frac{HK + LM}{(1-H) K + (1-L) M} > 0 \tag{4.10}$$

Check that $0 < \underline{t} < \bar{t}$

$$\frac{HK + LM}{(1-H) K + (1-L) M} < \frac{H}{(1-H)}$$

which is equivalent to

$$H(1-H)K + L(1-H)M < H(1-H) K + H(1-L) M$$

or

$$\frac{L}{(1-L)} < \frac{H}{(1-H)}$$

which holds by assumption, we refer to equation (4.1). Because $f < 0$ both $\bar{t}, \underline{t} > 0$, it also holds that density

$$\begin{aligned} b_1(t_2) &= \frac{K}{M}\frac{(1-H)}{Lf+(1-L)t_2} - \frac{K}{M}\frac{Hf+(1-H)t_2}{(Lf+(1-L)t_2)^2}(1-L) \\ &= \frac{K(L-H)f}{M[Lf+(1-L)t_2]^2} > 0 \end{aligned}$$

Hence, $B_1(t_2)$ is a well defined continuous distribution function.

Next we turn to the pricing strategy by which ABL2 sets its interest rate s for borrowers that are lured away from ABL1. Thus let U denote the pricing strategy of ABL2 to lure away existing borrowers of ABL1, i.e. K and M. From the point of view of ABL1, s charged by ABL2 is a random interest rate S. The pricing strategy of ABL2 can be denoted as

$$U_2(t_1) = \Pr\{S \leq t_1\} \tag{4.11}$$

From the point of view of ABL1, the interest rate S that ABL2 charges, captures his low risk borrowers if ABL1 charges a interest rate t_1 to his low risk borrowers such that the interest rate S is less or equal to t_1 as denoted in (4.11). In this case the return for ABL1 on his low risk borrowers is zero, as they have switched to be served by ABL2.

The expected payoff for ABL1 from charging t_1 to his M low risk borrowers is

$$[1-U_2(t_1)] \times \{LMf + (1-L)Mt_1\} + U_2(t_1) \times 0$$

Since ABL1 has an informational advantage over ABL2, his expected payoff is positive, say $c > 0$. We can then solve for the pricing strategy $U_2(t_1)$:

$$U_2(t_1) = 1 - \frac{c/M}{Lf+(1-L)t_1} \tag{4.12}$$

Given the continuous pricing strategy $B_1(t_2)$ of ABL1, if ABL2 prices at the lower bound $t_1 = \underline{t}$, it is sure to receive all the M and K firms, and hence has no incentive to undercut since at $\underline{t}$ from (4.10) ABL2 just breaks even:

$$[HK + LM]\, f + [(1-H)\, K + (1-L)\, M]\, \underline{t} = 0$$

Thus at any $a < \underline{t}$, ABL2 would make a loss. It also has no incentive to increase the lower end of the support of U above $\underline{t}$ given the strategy $B_1(t_2)$ by ABL1. Raising the support by ABL2 does not increase its profits, see (4.7). Thus we can determine c from equation (4.12) and the fact that $U_2(\underline{t}) = 0$. If we solve for $U_2(\underline{t}) = 0$, we can determine:

$$Lf + (1-L)\, \underline{t} - c/M = 0$$

or

$$\begin{aligned} c &= LMf - f\frac{HK + LM}{(1-H)\, K + (1-L)\, M}(1-L)\, M \\ &= \frac{KM(L-H)f}{(1-H)\, K + (1-L)\, M} > 0 \end{aligned} \tag{4.13}$$

Note that the density on $[\underline{t}, \overline{t})$ reads

$$u_2(t_1) = \frac{K(L-H)(1-L)f}{[(1-H)\, K + (1-L)\, M]\, [Lf + (1-L)\, t_1]^2} > 0.$$

At the upper boundary $t_1 = \overline{t}$, one can show that if one substitutes (4.9) and (4.13) into (4.12), the outcome of the pricing strategy at the upperboundary is:

$$\begin{aligned} U_2(\overline{t}) &= 1 - \frac{c/M}{Lf + (1-L)\, \overline{t}} \\ &= \frac{(1-L)\, M}{(1-H)\, K + (1-L)\, M} < 1 \end{aligned}$$

It follows that with probability

$$\frac{(1-H)K}{(1-H)\, K + (1-L)\, M}$$

ABL2 bids at the upper boundary $\overline{t}$. Note that this is a masspoint. At the other points on the distribution $[\underline{t}, \overline{t})$, the mixed strategy $U_2(t_1)$ is continuous and there is no mass at any particular point. When ABL2 prices at the upper bound, ABL2 only wins over the existing high risk borrowers K from ABL1. This masspoint at the upperboundary guarantees ABL1 its informational rents $c > 0$ on its current low risk borrowers M.

Proposition 2 *The equilibrium mixed strategies for the inside asset based lender* $B_1(t_2)$ *and the outside asset based lender* $U_2(t_1)$ *on the existing borrowers' market with* K *high risk borrowers and* M *low risk borrowers can be summarized as follows:*

$$B_1(t) = 1 - \frac{K[-Hf - (1-H)t]}{M[Lf + (1-L)t]}$$

on $t \in [\underline{t}, \overline{t}]$ *for the low risk borrowers (inside asset based lender)*

$$U_2(t) = 1 - \frac{K(L-H)f}{[K(1-H) + M(1-L)][Lf + (1-L)t]}$$

on $t \in [\underline{t}, \overline{t})$ *for competing ABL's borrowers (outside asset based lender)*

and $U_2(\overline{t}) = 1$

where $B_1(t)$ *is the strategy of the inside asset based lender to set the interest rate for her low risk borrowers and* $U_2(t)$ *is the strategy for the outside asset based lender to set the interest rate for all borrowers on this market. The informational rents the inside asset based lender can earn on his low risk borrowers are equal to* $c = \frac{KM(L-H)f}{(1-H)K+(1-L)M}$.

Proof. *By induction as shown above.* ■

These mixed strategies are comparable to the strategies from Narasimhan (1988), Dell'Ariccia et al. (1999) and Marquez (2002). These mixed strategies can be depicted as shown in Figure 4.1:

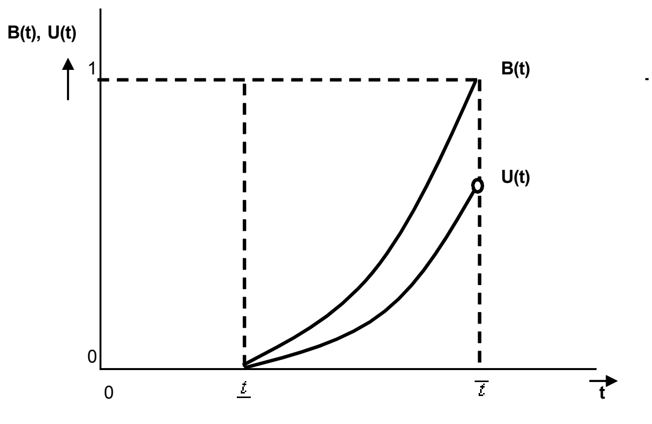


Figure 4.1: Mixed strategy equilibrium

The strategies for the market with Q high risk borrowers and W low risk borrowers where ABL2 is the inside asset based lender and ABL1 the outside asset based lender, can be analogously analyzed. Without further ado we can state the pricing strategies adopted for the low risk borrowers W. Denote the respective pricing strategies by ABL1 and ABL2 by $G(.)$ and $Z(.)$. Then in analogy with the above, one finds

$$\begin{aligned}
G_1(t) &= 1 - \frac{Q(L-H)f}{[Q(1-H)+W(1-L)]\,[Lf+(1-L)t]} \\
\text{on } t &\in [\underline{t},\bar{t}) \text{ for competing banker's borrowers (outside asset based lender)} \\
Z_2(t) &= 1 + \frac{Q\,[Hf+(1-H)\,t]}{W\,[Lf+(1-L)\,t]} \\
\text{on } t &\in [\underline{t},\bar{t}] \text{ for the low risk borrowers (inside asset based lender)} \\
\text{and } Z_2(\bar{t}) &= 1
\end{aligned}$$

The expected informational rents of ABL2 on its advantage of being able to identify its Q and W borrowers, are:

$$\frac{QW(L-H)f}{(1-H)\,Q+(1-L)\,W} > 0$$

4.7.3 Uniqueness of the mixed strategy equilibrium

The mixed strategy equilibrium of proposition one is comparable to the unique mixed strategy equilibria of theorem one from Baye et al. (1992) in the Varian model of sales. Uniqueness follows by arguments similar to lemmas 12, 15, and theorem 1 in Baye et al. (1992). Both asset based lenders play the same continuous mixed strategy over the interval $[\underline{t},\bar{t}]$ and randomize their interest rate over this interval where the outside asset based lender has a mass point at the upper boundary $\bar{t}$. This is in accordance with theorem 1 of of Baye et al. (1992). We have shown that the condition mentioned in lemma 15 (at least two firms randomize continuously on $[\underline{t},\bar{t}]$) is met, because asset based lenders cannot gain return when deviating from their strategy $B_1(t)$ or $U_2(t)$. Two repelling forces block a pure strategy equilibrium: on the one hand the ABL's like to charge a low interest rate to capture the low risk borrowers (quantity effect), on the other hand a low interest rate implies a loss of revenue and given a set of borrowers, one likes to maximize revenue by charging a high interest rate (price effect). The uniqueness follows from the fact that the two distributions follow from solving the two profit conditions. One shows these distributions are the solution of a differential equation and showing that bidding outside the respective supports yields no gain, this is in conformity with lemma 12 of Baye et al. (1992).

4.8 Implications for asset based lending market

The implications in this subsection for the asset based lending market are presented from the point of view where ABL1 is the inside asset based lender and ABL2 is the outside asset based lender (the market with K high risk borrowers and M low risk borrowers). But these implications are also valid for the existing borrowers' market with Q high risk borrowers and W low risk borrowers.

4.8.1 First order stochastic dominance

The outside asset based lender has first order stochastic dominance on the interval $[\underline{t}, \overline{t}]$:

$$\frac{B_1(t)}{U_2(t)} = \frac{K(1-H) + M(1-L)}{M(1-L)} > 1$$

so that

$$B_1(t) = \left[1 + \frac{K(1-H)}{M(1-L)}\right] U_2(t) \qquad \text{on the interval } [\underline{t}, \overline{t}]$$

It follows that

$$U_2(t) \leq B_1(t) \qquad \text{on the interval } [\underline{t}, \overline{t}] \tag{4.14}$$

The outside asset based lender's strategy $U_2(t)$ stochastically dominates the mixed strategy of the inside asset based lender $B_1(t)$. This implies that over the interval $[\underline{t}, \overline{t}]$ a borrower weakly prefers the inside asset based lender over the outside asset based lender. This is in conformity with the article of Narasimhan (1988), who shows first order stochastic dominance in a promotional pricesetting game by firms. The stochastic dominance also follows from Theorem 2 of Baye et al. (1992). Furthermore, for the densities one shows that on $[\underline{t}, \overline{t})$

$$u_2(t) = \frac{(1-L)M}{(1-H)\,K + (1-L)\,M} b_1(t).$$

So that except at $\bar{t}$

$$u_2(t) < b_1(t) \qquad \text{on the interval } [\underline{t}, \bar{t})$$

4.8.2 Expected interest rate

The average interest rate the outside asset based lender offers, is (because of first order stochastic dominance) over the interval $[\underline{t}, \bar{t})$ higher than the average interest rate the inside asset based lender is charging. To determine the average interest rate the outside asset based lender charges the low risk borrowers, we have to take into consideration the masspoint that is present at the upper boundary of t:

$$\begin{aligned}
\mu_2 &= \int_{\underline{t}}^{\bar{t}} t \cdot u_2(t)dt + \left[1 - U_2(\bar{t})\right]\bar{t} \\
&= -f\left[\frac{K(L-H)\ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| + (LM+HK)(1-L)}{(1-L)\left[K(1-H)+M(1-L)\right]}\right] > 0.
\end{aligned}$$

where $\frac{K(1-H)}{K(1-H)+M(1-L)} < 1$, $\ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| < 0$ and $K(L-H)\ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| > 0$ (for $(L-H)$ is also smaller than zero). This implies that the numerator is above zero, as is the denominator, and because $f < 0$, the average interest rate the outside asset based lender charges, μ_2, is always larger than zero. The average interest rate the inside asset based lender charges the low risk borrowers on the same market is:

$$\begin{aligned}
\mu_1 &= \int_{\underline{t}}^{\bar{t}} t \cdot b_1(t)dt; \\
&= -f\left[\frac{K(L-H)\ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| + LM(1-L)}{(1-L)^2 M}\right] > 0.
\end{aligned}$$

The average interest rate the inside asset based lender charges is also always larger than zero. When we compare the two average interest rates:

$$\begin{aligned}
\frac{\mu_1}{\mu_2} &= \frac{\left[K(1-H)+M(1-L)\right]\left[(1-L)LM + \ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| K(L-H)\right]}{M(1-L)\left[(LM+HK)(1-L) + \ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| K(L-H)\right]} < 1 \\
\mu_1 &< \mu_2
\end{aligned} \tag{4.15}$$

This is in conformity with first order stochastic dominance[4].

4.8.3 Probability of switching

The borrowers of the inside asset based lender will switch if the interest rate the outside asset based lender (determined according to mixed strategy $U_2(t)$) offers is lower than the interest rate their current asset based lender (according to mixed strategy $B_1(t)$) offers. The probability of switching for a low risk borrower can be determined as follows:

$$\begin{aligned}
\Pr\{T^2 &< T^1\} = \int_{\underline{t}}^{\bar{t}} U_2(t) \cdot b_1(t) dt \\
&= \int_{\underline{t}}^{\bar{t}} (1 - \frac{K(L-H)f}{[K(1-H)+M(1-L)]\,[Lf+(1-L)t]}) \cdot \frac{K}{M} \frac{(L-H)f}{[Lf+(1-L)t]^2} dt \\
&= \frac{1}{2} \frac{M(1-L)}{K(1-H)+M(1-L)}
\end{aligned}$$

The masspoint at $\bar{t} = 1 - \frac{M(1-L)}{K(1-H)+M(1-L)}$ is at the upperboundary of t. The probability of switching $\Pr(T^2 < T^1)$ is half the size of one minus this masspoint.

The intuition behind this switching probability can be explained by analyzing the two extreme cases concerning the difference in the mixed strategies between the inside and the outside asset based lender. There are two extreme combinations of the mixed strategies of the outside and inside asset based lender. One extreme case is that the number of high risk borrowers K is very small relative to M and adverse selection is very small for the outside asset based lender. In that case both ABL's use approximately the same distribution to determine their interest rates, $B_1(t) \approx U_2(t)$, we refer to equation (4.14). Thus the probability of the low risk borrowers switching approaches 50%.

The opposite extreme case appears if the amount of low risk borrowers M in comparison to the amount of high risk borrowers K is very small and adverse selection is very high for the outside asset based lender. The inside asset based lender offers an interest rate on the interval $[\underline{t}, \bar{t}]$ according to $B_1(t)$ and the outside asset based

[4] Proof: $[K(1-H)+M(1-L)]\left[(1-L)LM + \ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| K(L-H)\right] < M(1-L)\left[(LM+HK)(1-L) + \ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right| K(L-H)\right]$, if $(L-H)K\left[(1-L)M + (1-H)K \ln\left|\frac{K(1-H)}{K(1-H)+M(1-L)}\right|\right] < 0$.
This expression is true, because $(L-H)$ is always smaller than zero.

lender has a masspoint close to one at $\bar{t}$ (almost a pure strategy in which the outside asset based lender offers $\bar{t}$ to all the borrowers of ABL1). The outside asset based lender primarily offers the borrowers in the market an interest rate approximately close to $\bar{t}$. In this extreme case the probability of the low risk borrowers switching from the inside asset based lender to the outside asset based lender is near zero. The more the cumulative distribution of the outside asset based lender deviates from the distribution of the inside asset based lender, the lower the probability of switching of the low risk borrowers. The probability of switching is determined by the distance between the distributions of the outside and the inside asset based lender. We arrive at the following conclusion

Proposition 3 *The probability of switching for low risk borrowers is equal to*

$$\Pr(T^2 < T^1) = \frac{1}{2}\frac{M(1-L)}{K(1-H) + M(1-L)} \tag{4.16}$$

The probability of switching depends on the adverse selection that is present in the borrowers' market. The more adverse selection that is present within the market, the higher the average interest rate the outside asset based lender will charge and the lower the probability of switching for low risk borrower. High risk borrowers present in the market prevent the low risk borrowers from switching.

4.8.4 Influence of the size of the borrowers' market on the strategies of the asset based lenders

Increase in the amount of low risk borrowers M on the market

An increase in the amount of low risk borrowers on the market influences the interest rates that both asset based lenders offer. It also influences the probability of switching of the borrowers. The upperboundary of the distribution of interest rates ($\bar{t} = -f\frac{H}{(1-H)}$) is not affected by the size of the market. The lower boundary of the distribution of interest rates however, is affected by the amount of low risk and high risk borrowers ($\underline{t} = -f\frac{HK+LM}{(1-H)K+(1-L)M}$). If the amount of low risk borrowers increases on the market, the lower boundary of offered interest rates moves downwards. Both asset based lenders will randomize their interest rates over a larger interval. This is depicted in Figure 4.2[5].

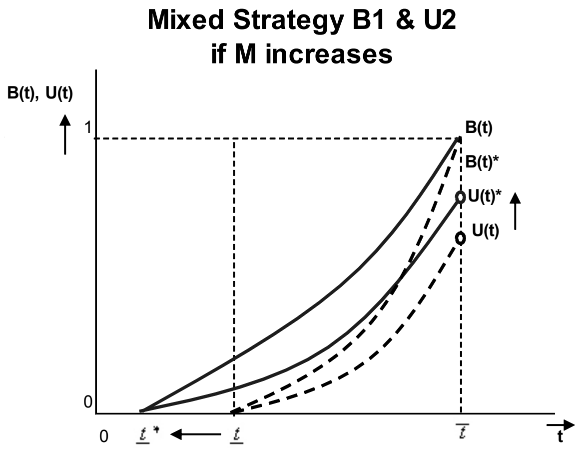


Figure 4.2: Influence of an increase in M on the mixed strategies $B_1(t)$ and $U_2(t)$

When the number of low risk borrowers on the market increases, adverse selection for the outside ABL decreases. Because the overall riskprofile of the borrowers' market decreases, the outside ABL charges $\bar{t}$ with lower probability. The mixed strategy of the outside asset based lender moves towards the mixed strategy of the inside asset based lender. The probability of switching therefore increases. The low risk borrower is more likely to choose the outside asset based lender based on the interest rates. The informational rents ($c = \frac{KM(L-H)f}{(1-H)K+(1-L)M}$) on the low risk borrowers of the inside asset based lender increase, because the quantity effect dominates the price effect. Ergo the larger amount of low risk borrowers compensates for the lower margin per low risk borrower.

Proposition 4 *If the amount of low risk borrowers on the market increases, the probability of switching for low risk borrowers increases. Due to the reduction in adverse selection, the outside ABL can price more competitively. Nevertheless the informational rents of the inside asset based lender are positively influenced. An increase of the amount of low risk borrowers on the market has a positive influence on the dynamics on the market (more frequent switching of low risk borrowers). The quantity effect dominates the price effect and increases the informational rents for the asset based lender. Ergo the larger amount of low risk borrowers compensates*

[5] Appendix 4B shows the derivatives of the mixed strategies.

for the lower margin per low risk borrower.

Increase in the amount of high risk borrowers K on the market

An increase in the amount of high risk borrowers on the market has the opposite effect on the interest rates that are charged by both asset based lenders. The lower boundary of the charged interest rates ($\underline{t} = -f\frac{HK+LM}{(1-H)K+(1-L)M}$) moves upward. This upward movement is caused by an increase of total market risk. Because of the increase in the amount of high risk borrowers, the adverse selection for the outside ABL increases. This can be depicted as follows[6]:

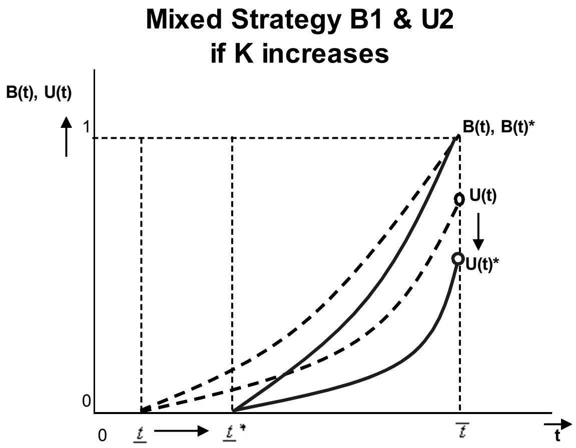


Figure 4.3: Influence of an increase in K on the mixed strategies $B_1(t)$ and $U_2(t)$

The increase in adverse selection forces the outside ABL to charge the upper-boundary of the interest rate ($\bar{t}$) more often. Because the outside ABL charges on average higher interest rates, the probability of switching decreases. Low risk borrowers are less likely to switch from the inside asset based lender to the outside asset based lender. The decrease in the probability of switching of the low risk borrowers has a positive impact on the informational rents the inside asset based lender receives ($c = \frac{KM(L-H)f}{(1-H)K+(1-L)M}$).

Proposition 5 *When the amount of high risk borrowers on the market increases, adverse selection increases for the outside ABL. The increased adverse selection causes the outside ABL to charge on average higher interest rates. The higher inter-*

[6] Appendix 4B shows the derivatives of the mixed strategies.

est rates charged by the outside ABL, decrease the probability of switching for the low risk borrowers. As a consequence the informational rents for the inside asset based lender increase. The relatively smaller amount of low risk borrowers (quantity effect) is compensated by the higher margin per low risk borrower (price effect), resulting in higher informational rents for the inside ABL.

4.8.5 Influence of the probability of default on the strategies of the asset based lenders

Increase in the probability of default of the low risk borrowers L

An exogenous shock that deteriorates the probability of default for low risk borrowers influences the two mixed strategies. If the exogenous shock causes the probability of default of the low risk borrowers to rise, this influences the mixed strategies of the asset based lenders as is depicted in Figure 4.4[7].

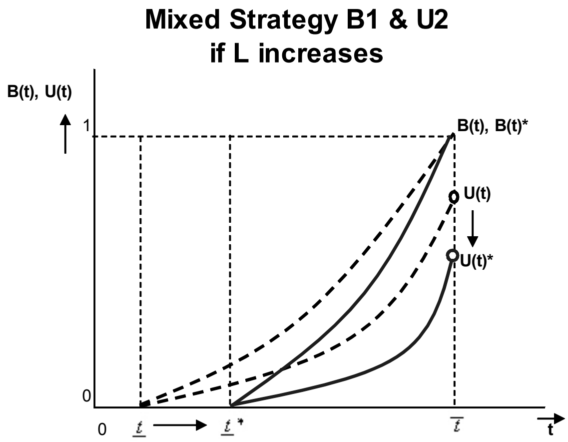


Figure 4.4: Influence of an increase in L on the mixed strategies $B_1(t)$ and $U_2(t)$

The increase in the probability of default of the low risk borrowers causes an overall increase of market risk. This effect brings both asset based lenders to charge a higher weighted average interest rate (the lower boundary of the interest rate, $\underline{t}$, moves upward). The masspoint on the upperboundary $\bar{t}$ of the outside asset based lender becomes larger. The outside asset based lender charges the upperboundary of the interest rate with higher probability. As a consequence the probability of

[7] Appendix 4B shows the derivatives of the mixed strategies.

switching of the low risk borrowers decreases. The increased probability of default of the low risk borrowers influences the informational rents of the inside asset based lender negatively.

Proposition 6 *An increase in the probability of default of low risk borrowers causes both asset based lenders to charge a higher average interest rate. The outside asset based lender charges the upperboundary of the distribution of interest rates, $\bar{t}$, more often. As a consequence the probability of switching of the low risk borrowers decreases. The informational rents of the inside asset based lender are negatively influenced by the increase in the default probability.*

Increase in the probability of default of the high risk borrowers H

If an exogenous shock increases the probability of default of the high risk borrowers (H) on the market, the influence on the mixed strategies of both asset based lenders can be depicted as shown in Figure (4.5)[8].

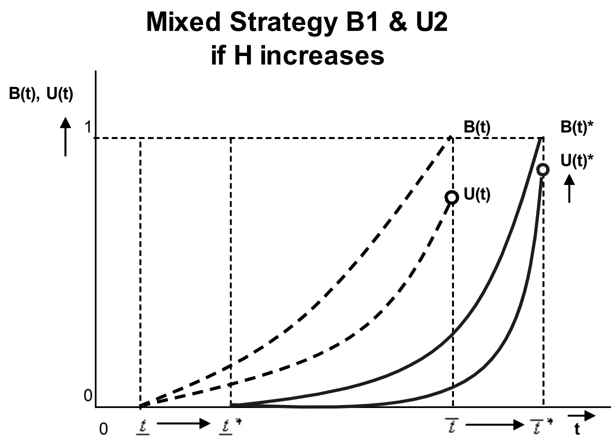


Figure 4.5: Influence of an increase in H on the mixed strategies $B_1(t)$ and $U_2(t)$

The increase in the probability of default of high risk borrowers causes an increase of the overall risk on the borrowers' market. The interest rate interval, $[\underline{t}, \bar{t}]$ and $[\underline{t}, \bar{t})$, of the mixed strategies of both asset based lenders moves upward. The low risk borrowers become more attractive in comparison to the high risk borrowers. The relative increased attractiveness of the low risk borrowers, causes the outside asset

[8]Appendix 4B shows the derivatives of the mixed strategies.

based lender to charge the upperboundary of the interest rate interval, $\bar{t}$, with smaller probability. The difference between the interest rate the inside asset based lender offers and the interest rate the outside asset based lender offers, becomes smaller. The mixed strategy of the outside asset based lender approaches the mixed strategy of the inside asset based lender. Because the outside asset based lender charges the upperboundary of the interest rate interval, $\bar{t}$, with smaller probability, the probability of switching increases. The increase in H also increases adverse selection. The increased adverse selection has a positive influence on the informational rents of the inside asset based lender.

If an exogenous shock increases the probability of default of high risk borrowers, for example because of a financial crisis, the average interest rate for the low risk borrowers increases. The intuition behind this result is as follows. The outside asset based lender cannot distinguish between the borrowers on the market. The outside asset based lender only knows that the probability of default for the high risk borrowers has increased. This causes the overall risk profile of the borrowers' market for the outside asset based lender to increase. In accordance the outside asset based lender adapts his strategy and charges higher interest rates to the borrowers' market. The inside asset based lender responds opportunistic and also raises the interest rate for his low risk borrowers. The inside asset based lender gains higher informational rents on his low risk borrowers (price effect). The asset based lenders transfer the costs from the overall increased risk level of the borrowers' market onto the low risk borrowers.

Proposition 7 *An increase in the probability of default of high risk borrowers causes an increase of the overall risk on the borrowers' market. The distribution of interest rates,* $[\underline{t}, \bar{t}]$ *and* $[\underline{t}, \bar{t})$, *of the mixed strategies of both asset based lenders moves upward. The probability of switching increases and the informational rents for the inside asset based lender are positively influenced (price-effect). The asset based lenders transfer the costs from the overall increased risk level of the borrowers' market onto the low risk borrowers.*

4.8.6 Bargaining power asset based lenders after one period

Rajan (1992) shows that informed banks have bargaining power over the firm's profits, once projects have begun. In this subsection we analyze if implementing

Rajan's (1992) bargaining power of banks onto our theoretical model would effect our results. In our model Rajan's (1992) bargaining power for bankers would apply to the periods $[2, \infty)$, because in the first period the projects have not yet begun. In our theoretical model the asset based lender uses his bargaining power to improve his profits. The inside asset based lender has two options to improve his profits. He can increase the interest rate he charges his borrowers or he can demand more collateral for the same loan. The option of demanding a higher interest rate was discussed in previous sections of this chapter. The adverse selection in our model and the informational advantage of the inside asset based lender forces both asset based lenders to apply a mixed strategy to their low risk borrowers and the borrowers of the outside asset based lender.

After learning the type of a borrower in the initial period, the ABL can adjust the amount of collateral he demands from a borrower. The ABL can demand a higher amount of collateral from the high risk borrowers in comparison to the low risk borrowers. Suppose that interest rates are dictated by the market (exogenous), but the ABL's can set collateral requirements (endogenous). If collateral is endogenous and the interest rate exogenous, the fair collateral rates would be equal to

$$\begin{aligned} H(-1+c^H)+(1-H)\,t &= 0 \\ c^H &= 1-\frac{(1-H)t}{H} \\ L(-1+c^L)+(1-L)\,t &= 0 \\ c^L &= 1-\frac{(1-L)t}{L} \end{aligned}$$

where c^H is the fair amount of collateral an ABL would demand from a high risk borrower and c^L is the fair amount of collateral an ABL would demand from a low risk borrower, where $c^L < c^H$.

Adverse selection is still present in the market with endogenous collateral and exogenous interest rates. The adverse selection of high risk borrowers prevents the application of a pure collateral setting strategy for the low risk borrowers and the borrowers on the market of opposite ABL. The inside asset based lender applies the following mixed collateral setting strategy to his low risk borrowers

$$B_1\,(c) = 1 + \frac{K\,[H(-1+c)+(1-H)\,t]}{M\,[L(-1+c)+(1-L)\,t]}. \tag{4.17}$$

At the upperboundary of the collateral distribution, $\overline{c}$, the cumulative probability function $B_1(\overline{c}) = 1$, which is the case when

$$\overline{c} = 1 - \frac{(1-H)t}{H} \tag{4.18}$$

At the lower end of the support of c, $\underline{c}$, the cumulative probability $B_1(\underline{c}) = 0$. Solving equation (4.17) for $\underline{c}$

$$\underline{c} = 1 - \frac{[K(1-H) + M(1-L)]\,t}{[KH + ML]} \tag{4.19}$$

The mixed collateral setting strategy for the outside asset based lender is

$$U_2(c) = 1 - \frac{K(L-H)(-1+c)}{[K(1-H) + M(1-L)]\,[L(-1+c) + (1-L)t]} \tag{4.20}$$

It follows[9] that with probability

$$\frac{K(1-H)}{K(1-H) + M(1-L)}$$

ABL demands collateral $\overline{c} = 1 - \dfrac{(1-H)t}{H}$ at the upperboundary of his mixed strategy. This is exactly the same masspoint in comparison to the model with an endogenous interest rate and an exogenous collateral rate. The bargaining power of asset based lenders after one period does not change the outcome of the mixed strategy equilibria of both asset based lenders.

In a theoretical model where both collateral and the interest rate are endogenous, the mixed strategies for the inside asset based lender $(B_1(t,c))$ and the outside asset based lender $(U_2(t,c))$ are

$$\begin{aligned}
B_1(t,c) &= 1 + \frac{K\,[H(-1+c) + (1-H)\,t]}{M\,[L(-1+c) + (1-L)\,t]} \\
\text{on } t &\in [\underline{t}, \overline{t}] \text{ and } c \in [\underline{c}, \overline{c}] \text{ for the low risk borrowers} \\
U_2(t,c) &= 1 - \frac{K(L-H)(-1+c)}{[K(1-H) + M(1-L)]\,[L(-1+c) + (1-L)t]} \\
\text{on } t &\in [\underline{t}, \overline{t}) \text{ and } c \in [\underline{c}, \overline{c}) \text{ for competing ABL's borrowers}
\end{aligned}$$

[9] The collateral setting strategy of the outside asset based lender at the upperboundary is $U_2(\overline{c}) = \frac{M(1-L)}{K(1-H)+M(1-L)}$.

In a theoretical model where both collateral and interest rates are endogenous, the mixed strategies remain identical for both asset based lenders. The forces that drive these mixed strategies remain unchanged (the price and quantity effect). The asset based lender wants to demand an interest rate or collateral amount that is as high as possible to his low risk borrowers (price effect). But on the other hand the ABL wants to demand an interest rate or collateral amount that is as low as possible, in order to gain as much borrowers as possible (quantity effect). These incentives are already described in literature. Farrell & Klemperer (2007) and Dubė et al. (2009) describe these incentives and refer to these incentives as the harvesting incentive[10] and the investing incentive[11]. Rajan's (1992) bargaining power for banks does not diminish the influence of these two opposing forces on the mixed strategies in our model.

4.9 Conclusion

We analyze interest setting strategies of asset based lenders in a dynamic market (with in- and outflow of borrowers) with an inelastic demand for loans. In this dynamic market there are borrowers with a high risk profile and borrowers with a low risk profile and two asset based lenders. The market is characterized by adverse selection of high risk borrowers and the lack of a pure strategy equilibrium. We use a theoretical model with infinite periods, where each period the high risk and low risk borrowers determine at which asset based lender they wish to borrow one unit. After one period the asset based lender learns the risk profile of the borrower, this information is lost if the borrower switches asset based lender. We find that the division of borrowers in each subsequent period can be modelled according to a series. The information asymmetry between the asset based lenders creates separate borrowers' markets. There is a borrowers' market in which neither of the asset based lenders has an informational advantage (new borrowers' market). And there are borrower's markets in which one of the asset based lenders has an informational advantage (the inside asset based lender). The inside asset based lender gains positive informational gains on the low risk borrowers in the market in which he has an

[10] The switching costs increase the costprice for asset based lenders and therefor increase the charged interest rate.

[11] If the asset based lenders would like to increase market share, they will have to decrease the interest rate.

informational advantage. The mixed strategy of the outside asset based lender has stochastic dominance over the mixed strategy of the inside asset based lender. The average interest rate the inside asset based lender offers is of lower value than the average interest rate the outside based lender offers over the distribution of interest rates of the mixed strategies. The mixed strategy equilibria for each new phase depend on the number of borrowers in the market, their risk profile and the probability of default of these borrowers. An increase in the amount of high risk borrowers on the market, increases adverse selection. As a consequence of the increased adverse selection the informational gains for the inside asset based lender increase (the value of information concerning the risk profile of the borrowers becomes more valuable). We find that the probability of switching for low risk borrowers depends on the relative size and riskiness of the low risk borrowers in comparison to the total market. We also find that the interest rate offered to low risk borrowers increases, when the probability of default for the high risk borrowers increases.

Asset based lending is not a research subject that is very frequently used in the literature, resulting in multiple future research opportunities. Theoretical research could be extended by adding a third or fourth asset based lender to the theoretical model or by inserting the possibility of 'regular' bank financing into the model. Empirical research is to be done to determine the influence of asset based lending on the funding opportunities of small and medium sized businesses. Also the influence of specific insolvency law determinants on the loss given default and the interest setting by asset based lenders would contribute to the analysis of the influence of country-based laws on banking, more specific asset based lending. In the Netherlands asset based lenders are primarily legally attached to wholesale banks and finance the high risk clients of those specific banks. The relationship between the asset based lender and the wholesale bank in combination with interest setting and profitable gains is still theoretically and empirically underexposed. Asset based lenders also use close monitoring and ex-ante selection instruments (performing a bank audit at the client for example) to observe and rate their (future) borrowers, this could also be implemented in the theoretical model.

4.A Appendix - Proof division of borrowers

The division of borrowers depends on the mixed strategy of both asset based lenders and the amount of borrowers that will accept the offered interest rate. After the initial phase the borrowers are equally divided amongst both asset based lenders. From the second phase onwards the division of borrowers is less obvious. But there are only three possible combinations of relative interest rates, that follow from the mixed strategies of the asset based lenders. These possible combinations of relative interest rates from the perspective of the borrowers are $t_c \geq t_h$, $t_l < t_c < t_h$ or $t_c \leq t_l$. The first combination of relative interest rates, $t_c \geq t_h$, states that the interest rate offered by the outside ABL is higher than the interest rate the high risk borrower receives from it's inside ABL. Even though we do not know the exact interest rate the ABL is offering, the limited amount of combinations of *relative* interest rates determines the division of borrowers.

At the start of the second phase the division of cohorts of borrowers is

	B_1	B_2
High risk borrowers (H)	$(1-H)$	$(1-H)$
Low risk borrowers (L)	$(1-L)$	$(1-L)$
New borrowers (N)	$H+L$	$H+L$

The new borrowers are assumed to always divide equally over the asset based lenders, due to the unique pure strategy equilibrium in which both asset based lenders offer the same marginal interest rate. Every period the total number of borrowers that fail ($2H$ high risk borrowers and $2L$ low risk borrowers) is equal to the total number of borrowers that enter the market. Hence the total number of borrowers aggregated across all markets, is constant (due to the law of large numbers assumption).

We will first focus on the high risk borrowers. We claim that ABL1 has an amount of high risk borrowers, $\#HR_1$, that is equal to

$$\#HR_1 \in \{1, 1 + (1-H)^n\} \tag{4.21}$$

In that case ABL has an amount of high risk borrowers, $\#HR_2$, that is equal to

$$\#HR_2 \in \{1, 1 - (1-H)^n\}$$

We assume that the high risk borrowers switch asset based lender, based on the relative interest rates the different asset based lenders offer. Assumption 1 is:

$$\begin{aligned} \text{if } t_c &< t_h \text{ the high risk borrowers switch} \\ \text{if } t_c &\geq t_h \text{ the high risk borrowers stay at their current asset based lender} \end{aligned} \tag{4.22}$$

There are three different markets that might consist of high risk borrowers. The new borrowers' market always consists of $2H$ high risk borrowers. The borrowers' market for ABL1 can consist of high risk borrowers in between 0 and $2-2H$. The borrowers' market for the ABL2 consists of high risk borrowers in between 0 and $2-2H$. The high risk borrowers on the new borrowers' market always divide equally amongst both ABL's[12]. There are three situations possible:

1. $t_c < t_h$ for the borrowers' market of ABL1 and ABL2. This implies that the high risk borrowers of ABL1 (that is K) switch to ABL2. And the high risk borrowers of ABL2 (that is Q) switch to ABL1. If $t_c < t_h$ every period, the amount of high risk borrowers at ABL1 ($K+k$) is equal to the amount of high risk borrowers at ABL2 ($Q+q$) every period, that is $K+k = Q+q = (1-H)+H = 1$. Because every period $(1-H)$ borrowers survive and H $(= k = q)$ new borrowers are captured by both asset based lenders on the new borrowers' market. After n periods the division of borrowers is still equal for both asset based lenders and remains $K+k = Q+q = (1-H)+H = 1$.
2. $t_c \geq t_h$ for the borrowers' market of ABL1 and ABL2. This implies that every period the high risk borrowers (K and Q) remain at their current ABL (they do not switch). If $t_c \geq t_h$ every period, the amount of high risk borrowers at ABL1 ($K+k$) is equal to the amount of high risk borrowers at ABL2 ($Q+q$) every period, that is $K+k = Q+q = (1-H)+H = 1$. Because every period $(1-H)$ borrowers survive and H $(= k = q)$ new borrowers are captured by both asset based lenders on the new borrowers' market. After n periods the division of borrowers is still equal for both asset based lenders and remains $K+k = Q+q = (1-H)+H = 1$.
3. combination of $t_c < t_h$ and $t_c \geq t_h$ over time and over the different borrowers

[12] So both ABL's receive H high risk borrowers from the new borrowers market. The high risk borrowers that are captured by ABL1 are named k. The high risk borrowers that are captured by ABL2 are named q, where $k = q = H$ every period.

markets.

A. *First combination:* ABL1 offers an interest rate $t_c < t_h$ to the borrowers of ABL2, while ABL2 offers an interest rate of $t_c \geq t_h$ to the borrowers of ABL1. This implies that the high risk borrowers of ABL2 switch to ABL1, while the borrowers of ABL1 stay at their current asset based lender. The amount of high risk borrowers as a consequence is for ABL1 $K+k = 2(1-H)+H = 1+(1-H)$ and for ABL2 $Q+q = H = 1-(1-H)$. Assume the next period ABL1 again offers an interest rate $t_c < t_h$ to the borrowers of ABL2, while ABL2 offers an interest rate of $t_c \geq t_h$ to the borrowers of ABL1. The amount of high risk borrowers for ABL1 then becomes $K+k = [1+(1-H)](1-H)+H(1-H)+H = 1+(1-H)$ and for ABL2 $Q+q = H = 1-(1-H)$. If both assets based lenders ask the same relative interest rates the following n periods, the division of high risk borrowers will not change. The amount of high risk borrowers for ABL1 will remain $K+k = 1+(1-H)$ and for ABL2 $Q+q = 1-(1-H)$ for ABL2. But if the relative interest rates change, the division of borrowers will change. Assume the second period ABL1 offers a relative interest rate of $t_c < t_h$ to the borrowers of ABL2, while ABL2 offers a relative interest rate of $t_c \geq t_h$ to the borrowers of ABL1 (same assumption as before resulting in $K+k = 1+(1-H)$ high risk borrowers for ABL1 and $Q+q = 1-(1-H)$ high risk borrowers for ABL2). Now assume that following this period ABL1 and ABL2 both offer an interest rate of $t_c \geq t_h$ to the borrowers of respectively ABL2 and ABL1. The number of high risk borrowers ABL1 will have after this period is then equal to $K+k = [1+(1-H)](1-H)+H = 1+(1-H)^2$ and for ABL2 $Q+q = [1-(1-H)](1-H)+H = 1-(1-H)^2$. Assume that the following n periods ABL1 and ABL2 still offer the high risk borrowers a relative interest rate equal to $t_c \geq t_h$. After n periods ABL1 has an amount of $K+k = 1+(1-H)^{n-1}$ high risk borrowers and ABL2 has an amount of $Q+q = 1-(1-H)^{n-1}$ high risk borrowers.

B. *Second combination:* Assume the second period ABL1 offers a relative interest rate of $t_c < t_h$ to the borrowers of ABL2, while ABL2 offers a relative interest rate of $t_c \geq t_h$ to the borrowers of ABL1 (same assumption as before) resulting in $K + k = 1 + (1 - H)$ high risk borrowers for ABL1 and $Q+q = 1-(1-H)$ high risk borrowers for ABL2. Now assume that following this period both asset based lenders offer a relative interest rate of $t_c \geq t_h$ to the high risk borrowers of ABL1 and ABL2. The number of high risk borrowers ABL1 will have after this period is then equal to $K+k = [1+(1-H)](1-H)+H = 1+(1-H)^2$ and for ABL2 $Q+q = [1-(1-H)](1-H)+H = 1-(1-H)^2$. Assume the following n periods the relative interest rates for the high risk borrowers of ABL1 is equal to $t_c \geq t_h$ and for the high risk borrowers of ABL2 is equal to $t_c < t_h$. After n periods the amount of high risk borrowers for ABL1 is equal to $K + k = 1 + (1 - H)$ and the amount of high risk borrowers for ABL2 is equal to $Q + q = 1 - (1 - H)$.

C. *Third combination:* Assume for x periods ABL1 offers a relative interest rate of $t_c < t_h$ to the borrowers of ABL2, while ABL2 offers a relative interest rate of $t_c \geq t_h$ to the borrowers of ABL1 (same assumption as before). The amount of high risk borrowers of ABL1 after x periods is equal to $K + k = 1 + (1 - H)$, while the amount of high risk borrowers of ABL2 is equal to $Q + q = 1 - (1 - H)$. Now assume that after x periods both ABL1 and ABL2 start offering the relative interest rate of $t_c \geq t_h$ for n periods to both the borrowers of ABL1 and ABL2 (neither the borrowers of ABL1 nor those of ABL2 will switch). In the period $x + 1$ a change in the division of high risk borrowers is visible. In period $x + 1$ ABL1 has $K + k = 1 + (1 - H)^2$ high risk borrowers, where ABL2 has $Q+q = 1-(1-H)^2$ high risk borrowers. After n periods the division of high risk borrowers is equal to $K + k = 1 + (1 - H)^{n-x+1}$ high risk borrowers for ABL1 and $Q + q = 1 - (1 - H)^{n-x+1}$ high risk borrowers for ABL2.

There are multiple combinations of relative interest rates over time and the different borrowers markets to consider. We have analyzed multiple combinations of relative interest rates and the consequence of these interest rates for the division of high risk borrowers in the different markets. We conclude from this analysis that the amount of high risk borrowers (and vice versa for low risk borrowers) for one asset based lender is always an element of the set $\#HR \in \{1, 1 + (1 - H)^n\}$ and for the other asset based lender an element of the set $\#HR \in \{1, 1 - (1 - H)^n\}$. So if the amount of high risk borrowers for ABL1 is an element of $K + k \in \{1, 1 + (1 - H)^n\}$, than the amount of high risk borrowers of ABL2 is an element of $Q + q \in \{1, 1 - (1 - H)^n\}$ or vice versa. The amount of high risk borrowers of ABL2 is always mirrored relatively to the high risk borrowers of ABL1. For example if ABL1 has $1 - (1 - H)^3$ borrowers, ABL2 has $1 + (1 - H)^3$ borrowers, this is because the total amount of borrowers on the market always remains 2. The same induction can be applied to the division of low risk borrowers. We state that the division of borrowers amongst the two asset based lenders, after the new borrowers are added, in phases $[2, \infty)$ in this banking game can be represented as follows:

	B_1	B_2
High risk borrowers (H)	$K + k = 1 + \omega$	$Q + q = 1 - \omega$
Low risk borrowers (L)	$M + m = 1 + \gamma$	$W + w = 1 - \gamma$

where $\omega = \{0, (1 - H)^n\}$ and $\gamma = \{0, (1 - L)^n\}$. If $\omega = 0$ and $\gamma = 0$, you have an equal division of the borrowers and a symmetric equilibrium. If $n = 1$ (that is $(1 - H)^1 = 1 - H$ and $(1 - L)^1 = 1 - L$), you will have a winner division of the borrowers and an asymmetric equilibrium. All the other division possibilities of borrowers in the subsequent stages are combinations of the above mentioned mathematical series where $n \in \mathbb{N}^*$ (all positive integers excluding zero) and they all give asymmetric equilibria. When we differentiate between the new borrowers and the existing borrowers, the division of existing borrowers can be represented as follows:

	B_1	B_2
High risk borrowers (H)	$K = (1 - H) + \omega$	$Q = (1 - H) - \omega$
Low risk borrowers (L)	$M = (1 - L) + \gamma$	$W = (1 - L) - \gamma$

This division of borrowers is used by the asset based lenders to determine their pricing strategy for existing borrowers. Because of the equal division of the new borrowers on the asset based lending market, the configuration where one asset based lender serves all low risk borrowers and the other asset based lender serves all high risk borrowers is not possible. The following phases of the game will always consist of one of the mentioned four configurations where $n \in \mathbb{N}^*$. The amount of borrowers one asset based lender has in the following phases is dependent on the outcome of the mixed strategy played in phase two and the following phases and the relative interest rates for that period.

4.B Appendix - Dynamics on the borrowers' market

Impact of market size on mixed strategies

	# LR borrowers M	# HR borrowers K
Masspoint $X = \frac{K(1-H)}{K(1-H)+M(1-L)}$	$\frac{dX}{dM} = \frac{-K(1-H)(1-L)}{[K(1-H)+M(1-L)]^2}$	$\frac{dX}{dK} = \frac{M(1-L)(1-H)}{[K(1-H)+M(1-L)]^2}$
Lower boundary $\underline{t} = -f\frac{HK+LM}{(1-H)K+(1-L)M}$	$\frac{d\underline{t}}{dM} = \frac{(H-L)fK}{[K(1-H)+M(1-L)]^2}$	$\frac{d\underline{t}}{dK} = \frac{(L-H)fM}{[K(1-H)+M(1-L)]^2}$
Upper boundary $\bar{t} = -f\frac{H}{(1-H)}$	-	-
Probability of switching $Y = \frac{1}{2}\frac{M(1-L)}{K(1-H)+M(1-L)}$	$\frac{dY}{dM} = \frac{K(1-L)(1-H)}{2[K(1-H)+M(1-L)]^2}$	$\frac{dY}{dK} = \frac{-M(1-L)(1-H)}{2[K(1-H)+M(1-L)]^2}$
Outside asset based lender $U_2(\bar{t}) = \frac{M(1-L)}{K(1-H)+M(1-L)}$	$\frac{dU(\bar{t})}{dM} = \frac{K(1-L)(1-H)}{[K(1-H)+M(1-L)]^2}$	$\frac{dU(\bar{t})}{dK} = \frac{-M(1-L)(1-H)}{[K(1-H)+M(1-L)]^2}$
Informational rents B1 $c = \frac{KM(L-H)f}{(1-H)K+(1-L)M}$	$\frac{dc}{dM} = \frac{(L-H)(1-H)K^2f}{[K(1-H)+M(1-L)]^2}$	$\frac{dc}{dK} = \frac{(L-H)(1-L)fM^2}{[K(1-H)+M(1-L)]^2}$

Impact of the probability of default on mixed strategies

	Prob default HR H	Prob default LR L
Masspoint $X = \frac{K(1-H)}{K(1-H)+M(1-L)}$	$\frac{dX}{dH} = \frac{-KM(1-L)}{[K(1-H)+M(1-L)]^2}$	$\frac{dX}{dL} = \frac{KM(1-H)}{[K(1-H)+M(1-L)]^2}$
Lower boundary $\underline{t} = -f\frac{HK+LM}{(1-H)K+(1-L)M}$	$\frac{d\underline{t}}{dH} = \frac{-(M+K)fK}{[K(1-H)+M(1-L)]^2}$	$\frac{d\underline{t}}{dL} = \frac{-(M+K)fM}{[K(1-H)+M(1-L)]^2}$
Upper boundary $\bar{t} = -f\frac{H}{(1-H)}$	$\frac{d\bar{t}}{dH} = \frac{-f}{(1-H)^2}$	-
Probability of switching $Y = \frac{1}{2}\frac{M(1-L)}{K(1-H)+M(1-L)}$	$\frac{dY}{dH} = \frac{\frac{1}{2}MK(1-L)}{[K(1-H)+M(1-L)]^2}$	$\frac{dY}{dL} = \frac{-\frac{1}{2}MK(1-H)}{[K(1-H)+M(1-L)]^2}$
Outside asset based lender $U_2(\bar{t}) = \frac{M(1-L)}{K(1-H)+M(1-L)}$	$\frac{dU(\bar{t})}{dH} = \frac{MK(1-L)}{[K(1-H)+M(1-L)]^2}$	$\frac{dU(\bar{t})}{dL} = \frac{-MK(1-H)}{[K(1-H)+M(1-L)]^2}$
Informational rents B1 $c = \frac{KM(L-H)f}{(1-H)K+(1-L)M}$	$\frac{dc}{dH} = \frac{-KMf(1-L)(K+M)}{[K(1-H)+M(1-L)]^2}$	$\frac{dc}{dL} = \frac{KMf(1-H)(K+M)}{[K(1-H)+M(1-L)]^2}$

Sign of impact on mixed strategies

	# LR borrowers M	# HR borrowers K	Prob default HR H	Prob default LR L
Masspoint $X = \frac{K(1-H)}{K(1-H)+M(1-L)}$	negative impact	positive impact	negative impact	positive impact
Lower boundary $\underline{t} = -f\frac{HK+LM}{(1-H)K+(1-L)M}$	negative impact	positive impact	positive impact	positive impact
Upper boundary $\bar{t} = -f\frac{H}{(1-H)}$	no impact	no impact	positive impact	no impact
Probability of switching $Y = \frac{1}{2}\frac{M(1-L)}{K(1-H)+M(1-L)}$	positive impact	negative impact	positive impact	negative impact
Outside asset based lender $U_2(\bar{t}) = \frac{M(1-L)}{K(1-H)+M(1-L)}$	positive impact	negative impact	positive impact	negative impact
Informational rents B1 $c = \frac{KM(L-H)f}{(1-H)K+(1-L)M}$	positive impact	positve impact	positive impact	negative impact

Chapter 5

The bounded distribution of bond recovery rates

Chapter is based on joint work with Casper G. de Vries[1]

5.1 Introduction

The current financial crisis shows the importance of risk management for financial institutions and the application of adequate risk models for their asset portfolios. One of the key items of measuring the expected loss is the modelling of the loss given default by financial institutions. The probability of default has received a lot of attention in academic literature[2], whereas the loss given default has received remarkably less attention. Even though the loss given default is as much of influence on the expected loss of a loan portfolio for financial institutions as is the probability of default and the exposure at default. Recent academic literature expands the traditional focus on the probability of default to include the analysis of the loss given default. The loss given default is equal to one minus the recovery rate of a defaulted loan.

In this chapter we analyze which bond characteristics influence the distribution of recovery rates. We model the different subsamples, according to these charac-

[1] We would like to thank Alex Koning, Rex Wang, André Lucas and other participants of the Marie Curie Workshop on Financial Risk and EVT for their valuable comments on an earlier version of this chapter.

[2] Literature concerning the probability of default (PD) dates back to Wilcox (1971) with a failure framework and Scott (1981), who analyzes the probability of bankruptcy based on cashflows.

teristics separately. We use the bond prices of all publicly available bond data of defaulted companies in the period 1981-2011 as proxies for the recovery rates of these bonds. We analyze whether the empirical subsamples are best modelled through a theoretical Beta distribution, a truncated normal or a truncated Weibull distribution. We test the goodness of fit of the theoretical distributions to the empirical data with the Kolmogorov-Smirnov test statistic and Cramer-von Mises test statistic. In accordance with Schuermann (2004) we find that a bond with a default date in a NBER recession period has a significant different recovery rate than a bond with a default date in a NBER non-recession period. Contrary to the analysis of Schuermann (2004) our analysis shows that collateral does not appear to be of significant influence on the bond recovery rate. We also analyze the percentage lifetime of the bond, this characteristic gives an indication of the timeperiod of the bond between issue date and default date in comparison to the duration of the bond (the numerator of this variable corresponds to the time to default). The percentage lifetime of a bond is always in between 0 and 1. A defaulted bond with a very low percentage lifetime is a bond that defaulted quite soon after it was issued in comparison to it's duration. The percentage lifetime is of significant influence on the bond recovery rate. We subsample the recovery rates according to their bond characteristics (NBER recession default date, percentage lifetime and collateral). We use the different subsamples to determine the goodness of fit of the theoretical distributions. We find that the different subsamples of the distribution of recovery rates of defaulted bonds are best modelled as a truncated Weibull distribution. The goodness of fit of the empirical data to the Weibull distribution increases, if the empirical data is separated according to the significant bond characteristics[3].

Our analysis contributes to current literature in two aspects. The first aspect concerns the percentage lifetime characteristic of a defaulted bond that is included in our analysis. This characteristic is of significant influence on the distribution of recovery rates. This result implies a (significant) correlation between the time to default in comparison to duration and the loss given default of bonds. To our knowledge this correlation is not yet been analyzed in literature. The second aspect of our analysis that contributes to current literature is the result that the recovery

[3]Prof.dr. Lucas brought to our attention that the other option would be to have regressors in the mean parameter of the theoretical distributions to deal with the different bond characteristics. This option is not exploited in this chapter, but could be a better alternative than the alternative presented in this chapter.

rates of defaulted bonds are best modelled through a truncated Weibull distribution.

The outline of this chapter is as follows. After this introduction we discuss related literature. In section three we give a description of the empirical data and in section four we describe the theoretical framework. In section five the results of the simulations of random draws of the theoretical distributions are analyzed and section six concludes.

5.2 Related literature

The related literature concerning this chapter can be divided into two strands: general default literature and recovery rate literature.

The first strand of related literature regarding defaults of bonds and loans can be divided into two categories: structural form models and reduced form models. Structural form models are based on the work of Merton (1974). Merton (1974) regards a default as an event that occurs when the market or book value of the assets of a company fall below the threshold of the face value of the debt. The first generation structural models (amongst others Black and Cox (1976), Geske (1977) and Vasicek (1984)) consider this threshold to be applicable when debt reaches maturity date, this would imply that companies would only default at the maturity date of debt. Second generation structural models relax this empirical difficult condition and assume default can occur between the issue date and the maturity date of debt (amongst others Kim et al. (1993), Hull & White (1995)). In structural form models the recovery rate is endogenously based on the value of the firm's assets at the time of default. Reduced form models consider a default to be exogenous to the specific features of a company or the market it is active in. In these models default is considered to behave as a stochastic variable, that is driven by an exogenous non-observable random variable (p.e. Litterman & Iben (1991), Madan & Unal (1998), Jarrow & Turnbull (1995), Chiang & Tsai (2010)). Default and default probabilities behave as unpredictable Brownian motions in reduced form models. Covitz & Han (2004) analyze theoretically and empirically the reduced form models for recovery rates and they find empirical evidence of non-linearities (jumps) in recovery rates, supporting the use of reduced form models to model recovery rates.

The second strand of related literature covers the topic of recovery rates. A clear distinction should be made between the recovery rates of defaulted bank loans or the recovery rates of defaulted bonds. Banks have informational advantages and incentives and means to screen and monitor their loans, whereas bondholders usually have no other information than is present in the public domain. Another distinction in this matter is that bank loans usually have a higher seniority than commercial bonds. Altman et al. (2006) find that the price behavior in secondary markets of bank loans also differs from the price behavior in de secondary markets of defaulted bonds. In this chapter we use the price of publicly traded defaulted bonds as a proxy for the recovery rate of these bonds in order to model the distribution of recovery rates. Current literature does not only take into account the correlation between the probabilities of default of different companies (Zhou (1997)), but also the correlation between the probability of default of a specific portfolio of assets and the loss given default of these assets ((Altman et al. (2003), Hillebrand (2006) and Bade et al. (2011)). The correlation between the loss given default on loans and borrower specific characteristics has been studied by Gupton et al. (2000) for bank loans and by Gupton & Stein (2002) concerning loan specific characteristics and macroeconomic conditions. Schonbucher (2003)[4] and Gupton & Stein (2002) use a Beta distribution to approximate the defaulted debt prices, recovery rates, of defaulted bonds. Schuermann (2004) shows that recovery rate distributions (without distinction in characteristics) are bimodal. Partly in contrast to our analysis, Schuermann (2004) also finds that seniority and the business cycle are of significant influence on the recovery rate distribution. To model dependency and systemic risk in loss given default distributions, generalized beta regression models (Huang & Oosterlee (2011), Bruche & Gonzalez-Aguado (2008)), single-factor models (for the dependency between default and loss given default, we refer to Witzany (2009)) or Bernouilli mixture models (Frey & McNeil (2002) and Frey & McNeil (2003)) are used.

5.3 Empirical data description

We do not have any data on the actual recovery rates of defaulted commercial bonds. Accordingly we use the quoted prices of defaulted bonds as a proxy for the recovery

[4] On page 147 Schonbucher (2003) refers to beta distributions being used for modelling recovery rates in credit risk models.

rates of these bonds[5]. We use the quoted prices of defaulted bonds 112 days after the default date. We use the prices of the defaulted bonds several months after the default date in order to get a more reliable proxy. The prices still show variance after the default date, but the variance declines as time elapses. If we choose our proxy to distant from the default date, data are lost. We balance the variance of the proxy and the loss of data and choose the quoted prices 112 days after default[6]. The empirical data originate from Datastream, Bloomberg[7] and the NBER website[8]. We use the quoted prices of straight bonds with fixed interest coupons, that defaulted between 1981 and 2011 from Datastream. We combine the Datastream data with the data from the Bloomberg database to obtain more characteristics of the defaulted bonds. We do not include the defaulted bonds of governments and municipalities in our analysis. The defaulted commercial bond data we use primarily concern developed countries[9].

Bruche and González-Aguado (2008) also use the post-default prices divided by the face value of the loan as the historical recovery rate. But in contrast to Bruche and González-Aguado (2008), we use a different approach concerning the recovery rates that are present in the data that have a value that is larger than one.

A recovery rate is more than hundred percent, if debtholders claim a larger amount than the face value of the specific bond (Calabrese and Zenga (2008)). The reason for the height of this claim can be found in the externalities concerning the default of debt. The legal representation after default is costly for the bondholder and he demands a larger amount of interest, because of the delayed payment. Bruche and González-Aguado (2008) scale the recovery rates with a factor .9 in order to get the recovery rate between zero and one.

[5] Schuermann (2004) refers to this method of measuring the loss given default (LGD) as the market LGD.

[6] Because only weekdays contain quoted prices of bonds, we use 112 days after default. This is exactly 16 weeks after the default date (also a weekday) and balances the variance and the loss of data best.

[7] We use the name of the company, the ISIN code, the issue date, the bond type, the coupon type and coupon interest and the quoted prices from the Datastream database. The ISIN code, the maturity and default date, the country code, currency and the collateral type originates from the Bloomberg database.

[8] Website of NBER: http://www.nber.org/cycles/cyclesmain.html.

[9] Of the defaulted bonds that could be matched between Datastream and Bloomberg (N=659 excluding Lehman), 457 bonds originate from the US, 63 from Europe, 38 of Canada, 29 of Iceland and 27 of Britain.

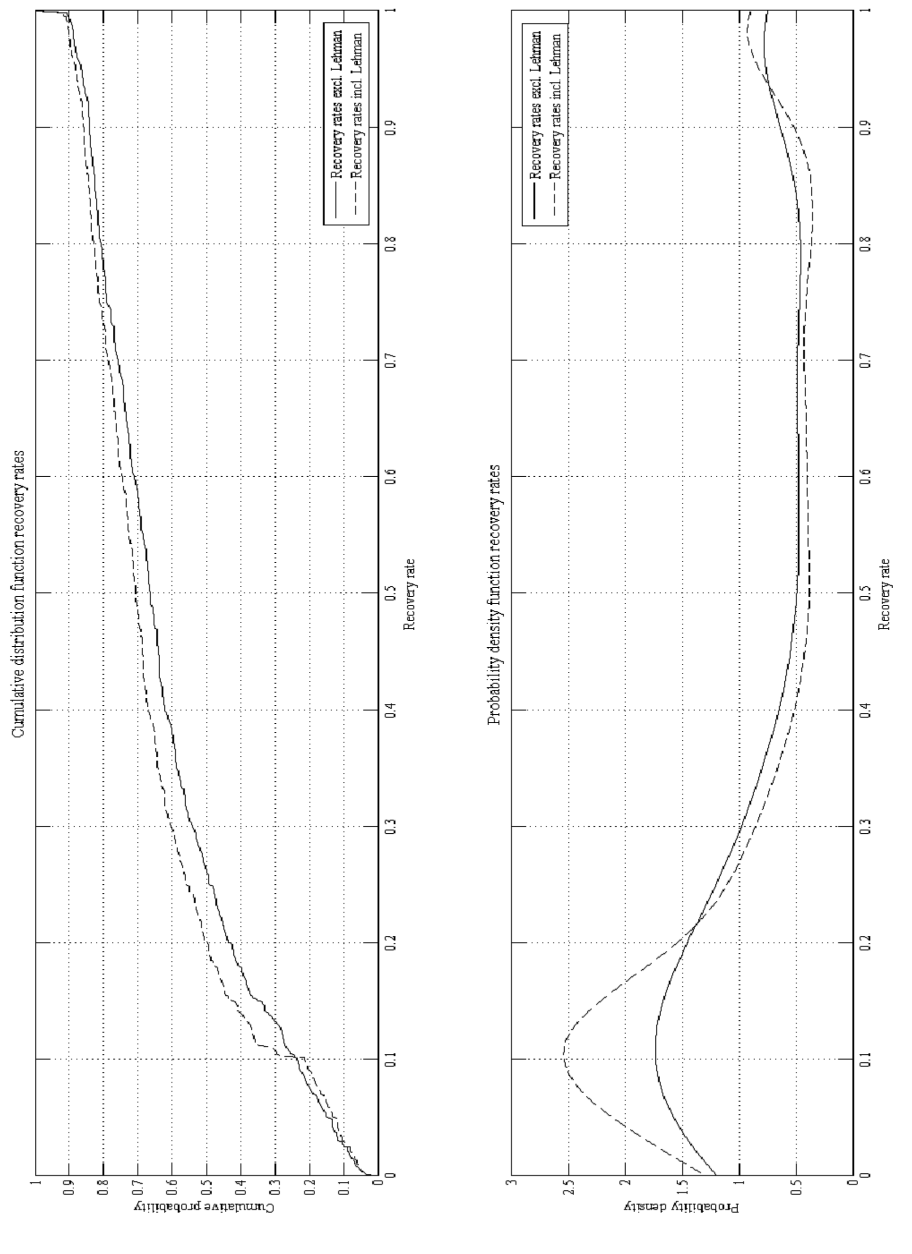


Figure 5.1 The empirical cumulative distribution function and probability density function for the samples including and excluding Lehman

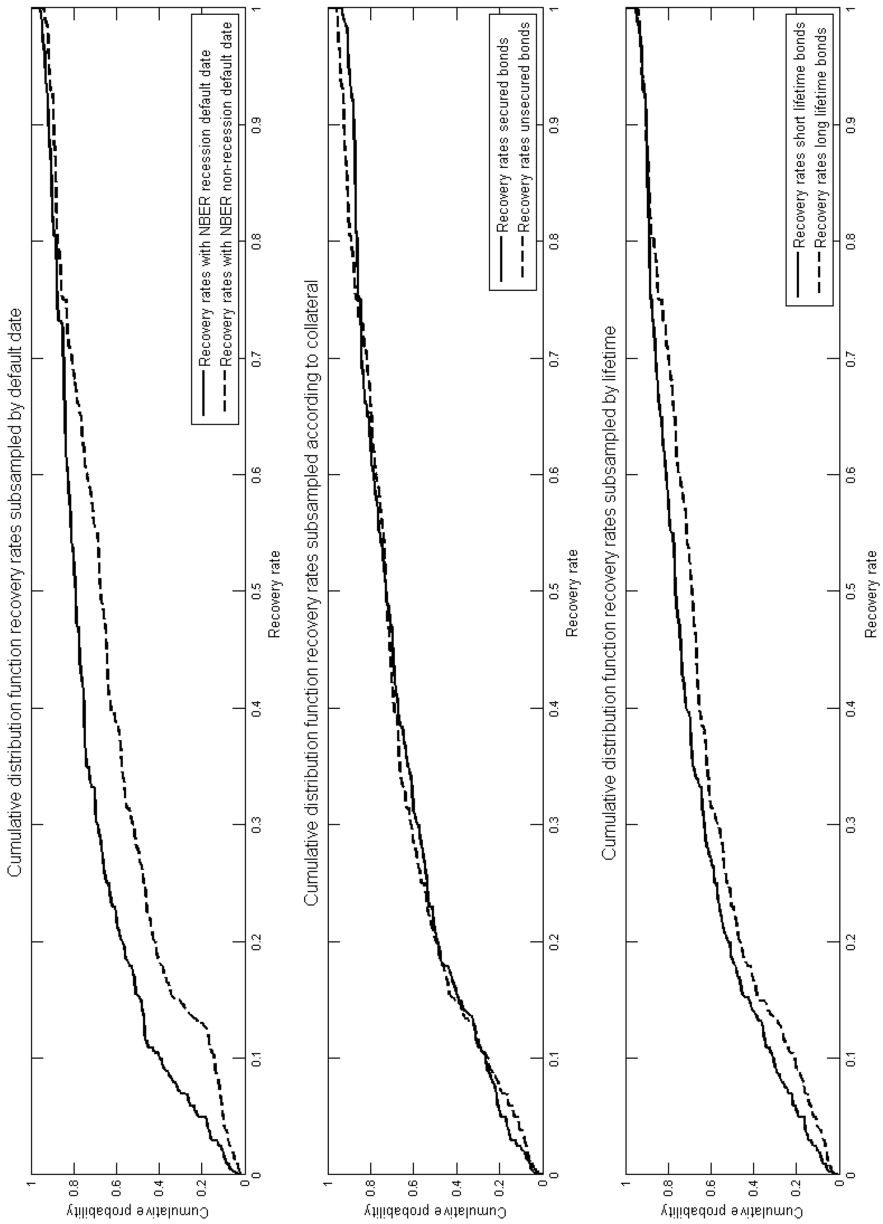


Figure 5.2 The cumulative distribution functions of the different subsamples.

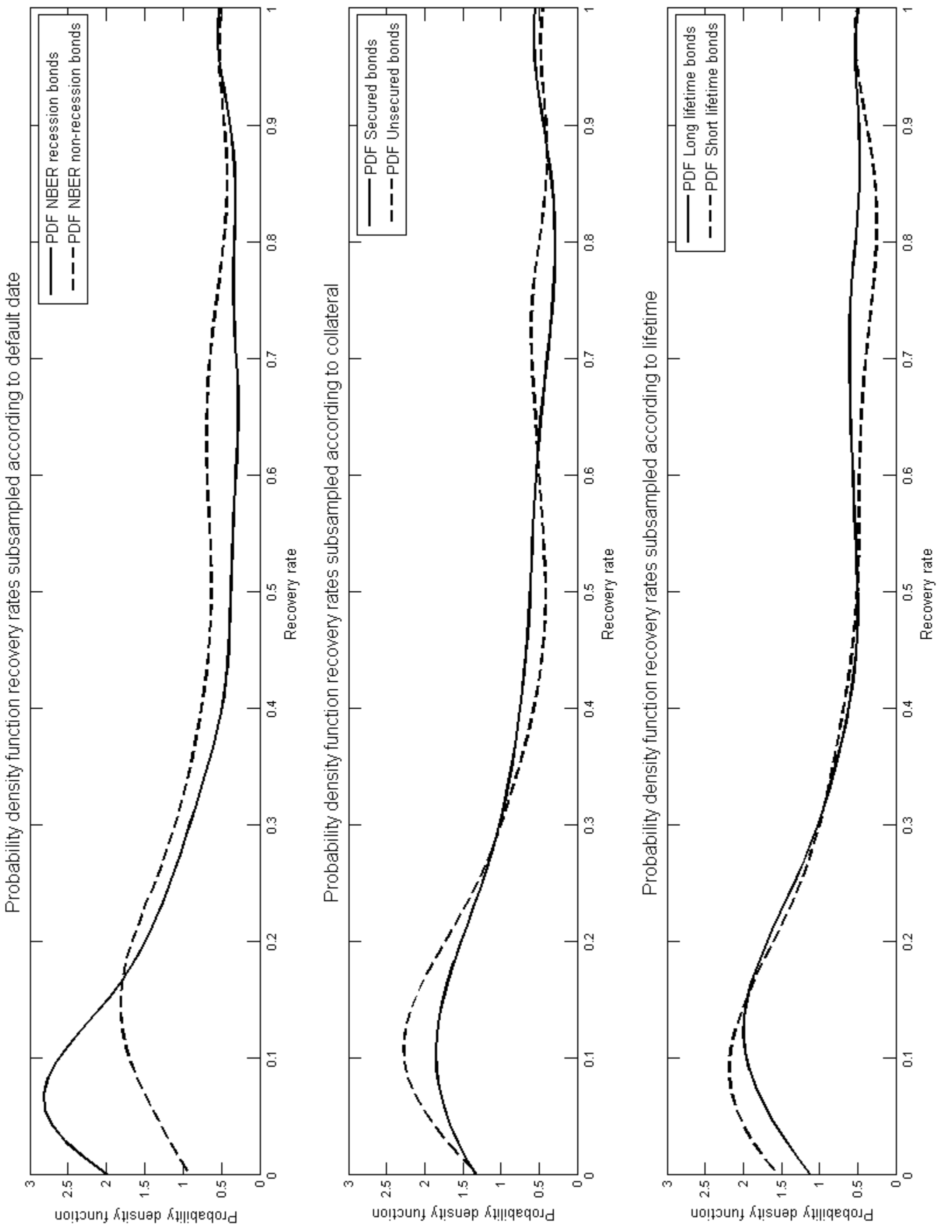


Figure 5.3 Probability density functions of the different subsamples.

We use the technique Calabrese and Zenga (2010) also use, to ensure that the recovery rate is in between zero and one. If the quoted price of a defaulted bond, p_x, divided by the face value of the bond (equal to 100) is above one, we consider the recovery rate, x, to be equal to one

$$\begin{aligned} \text{if } \frac{p_x}{100} &\in [0,1]\,, \text{ then } x \in [0,1]\,. \\ \text{if } \frac{p_x}{100} &> 1, \text{ then } x = 1. \end{aligned}$$

We use the same approach as Calabrese and Zenga (2010), because we analyze the recovery rate and not the loss given default. The loss given default gives an indication of the loss the bondholders make, this loss should include the costs for legal representation and delayed payment. The recovery rate is the return bondholders have on their defaulted bonds, costs for externalities caused by the default are not part of the recovery rate[10].

Recovery rate distribution full sample

The full sample of recovery rates of defaulted, straight bonds with a fixed interest coupon, that defaulted between 1981-2011 consists of 1135 observations. The full sample shows the impact the default of Lehman Brothers in September 2008 had on the bond market. Of the 1135 bonds that defaulted between 1981-2011, 185 bonds originate from Lehman Brothers. Figure 5.1 shows the cumulative distribution function for the sample including Lehman and excluding Lehman. The recovery rates including Lehman have first order stochastic dominance over the recovery rates excluding Lehman, but not for the full distribution. The average recovery rate including Lehman bonds is of lower value than the average recovery rate excluding Lehman for the bonds with a recovery rate larger than 0.1. In order to avoid bias we do not include the Lehman observations ($N = 185$) in our simulations and analysis. The sample of recovery rates used in our analysis excluding Lehman consists of $N = 950$ observations and the descriptive statistics of this sample are in Table 5.3. The average recovery rate is 39%. The standard deviation is quite large (34%). The large standard deviation is caused by clustering of the probability mass at 0.1

[10] This means that the recovery rate is not always one minus the loss given default, because of externalities. The loss given default with costs for legal representation can for example be 1.2 minus the recovery rate. So the externalities increase the loss given default, but not the recovery rate.

and 0.9, as can be seen in Figure 5.1 and is also in accordance with research of Schuermann (2004).

Of the 950 defaulted bonds in Datastream, only 659 (excl. Lehman, 823 incl Lehman) could be linked to Bloomberg through the ISIN number. The defaulted bonds that could not be linked to Bloomberg do not show the default date. We analyze which characteristics of the defaulted bonds are of influence on the recovery rate distribution. We test the following hypotheses concerning our bond characteristics:

Table 5.1
Hypothetical effect of bond characteristics

The table presents the expected theoretical effect, prior to the regressions of the different explanatory variables on our dependent variable, the recovery rate of the defaulted bonds.

Bond characteristic	Hypothetical effect
NBER recession dummy (1 = default date in recession)	negative
Percentage lifetime bond	positive
Secured dummy (1 = secured bond)	positive
Seniority variable (1 = secured bond - 3 = junior bond)	negative
Interest rate bond coupon	negative

The NBER recession dummy denotes whether or not a bond defaults in a NBER recession period or a NBER non-recession period[11]. If a bond defaults in a NBER recession period, the recovery rate is most likely of lower value. In a NBER recession period the (fire-)sale of assets results in a lower return in comparison to a non-recession period, thus resulting in lower recovery rates. This hypothesis is conformity with research by Pulvino (1998) and Schuermann (2004). The percentage lifetime of a bond gives an indication of the timeperiod of the bond between issue date and default date in comparison to the duration of the bond. We use the data concerning the issue date ($= I$), default date ($= D$) and the maturity date ($= M$) of the defaulted bond to calculate the percentage lifetime: $(D - I)/(M - I)$. The percentage lifetime (the numerator of this variable is known as the time to default) is always in between 0 and 1. A defaulted bond with a very low percentage lifetime is a bond that defaulted quite soon after it was issued in comparison to it's duration. We would expect short lifetimebonds to have a lower recovery rate: the companies that issue bonds with a short lifetime do so in a period when they already have going-concern problems and a high credit risk profile. They issue bonds to gain liquidity on the short term, but that does not solve their going-concern problems

[11] National Bureau of Economic Research website, http://www.nber.org/cycles/cyclesmain.html;

and they default shortly after the issue date of the bonds. The secured dummy and the seniority dummy show some overlap, they both give an indication of collateral and the seniority of a bond. We expect the secured dummy to have a positive effect on the recovery rate, for collateral should have a positive influence on the return after default. We expect the seniority dummy to have a negative influence on the recovery rate, because a junior bond is lower in ranking when the returns after a default are distributed amongst the creditors. A high coupon interest rate should correspond to a company with a high credit risk profile, resulting in a lower recovery rate at default.

We run OLS regressions of these characteristics on the recovery rate. The results of the OLS regressions are in appendix 5A. Because we only have some characteristics of the bonds, but no characteristics of (for example) the company that issued the bonds, the adjusted R squared is very low. The adjusted R squared is however of minor interest, since we only use the regressions to determine which subsamples might have differently shaped recovery rate distributions.

In conformity with Schuermann (2004) the variable NBER recession at default is of significant influence on the distribution of the recovery rate. The coefficient is negative, in conformity with our hypothesis. Another characteristic of the defaulted bonds that is of significant influence on the recovery rate distribution is the percentage lifetime of a bond. The positive sign of the coefficient is in conformity with our hypothesis. But if short lifetime bonds indeed have a higher credit risk profile at issue date, because of going concern problems, we should be able to find this in the data. Bondholders that invest in bonds of companies with a higher (credit) risk profile, demand a higher coupon interest rate and / or a lower issue price to compensate for the higher risk profile. Table 5.2 presents the regression results on the lifetime of bonds with the bondprice at issue date and the coupon interest rate as explanatory variables. Both explanatory variables are significant on a 1% level and confirm our hypothesis that bonds with a shorter lifetime indeed seem to have a higher risk profile at issue date.

Table 5.2
Lifetime of defaulted bonds at default date

The table presents the regression results of the bond price at issue date + 28 days and the coupon interestrate on the lifetime of defaulted bonds at default date. The standard errors are show n in parentheses in the table.

(1) We divided the bond price 28 days after the issue date by it's face value (F = 100)

***, **, * denote statistically significant effects at a 1%, 5% and 10% level respectively.

Dependent variable: lifetime of defaulted bond at default date		
	(1)	(2)
Bondprice at issue date +28 days (1)	0.461 ***	0.440 ***
	(0.10)	(0.09)
Coupon interest rate	-1.400 ***	-2.200 ***
	(0.44)	(0.47)
Constant	0.054	0.171
	(0.11)	(0.10)
Summary statistics		
Regression	Incl. Lehman	Excl. Lehman
Number of observations	439	366
Adjusted R-squared	0.078	0.122
Standard error of regression	0.238	0.223
Durbin Watson statistic	1.388	1.623

As already mentioned before, the regressions in appendix 5A also show that whether or not a bond originates from Lehman is significant for the recovery rate. A result that is in contrast with the analysis of Schuermann (2004) is, that secured and senior bonds do not have a significant higher recovery rate than unsecured or more junior bonds. Schuermann (2004) uses data from the Moody's Default Risk Service Database. This database includes information on all defaulted corporate debt instruments of corporations primarily domiciled in the US. Our data only concerns defaulted bonds, our limited scope might be of influence on the significance of seniority. Apparently collateral or a senior position in default does not result in a significant higher recovery rate for a defaulted bond.

We use the results of the regressions to analyze and model the distribution of recovery rates. The different subsamples of secured and unsecured bonds, bonds with a default date in a NBER recession or non-recession period and bonds with a short or long lifetime period are analyzed separately[12]. The descriptive statistics of

[12] We will use the data without Lehman to analyze these subsamples to minimize bias. The first three regressions in Appendix 5A show the impact of Lehman on for example the current crisis dummy and seniority. We do not analyze subsamples with recovery rates with different industry codes separately (eventhough they have some significance in the regression), because of limited

the full sample and the subsamples are in Table 5.3.

Table 5.3
Descriptive statistics

The table presents the descriptive statistics of the full sample of recovery rates of defaulted bonds and the different subsamples. The number of observations for the full sample of defaulted bonds differs from the aggregated number of observations of the subsamples, because some bonds in Datastream could not be linked to the data in Bloomberg. The defaulted bonds could then not be separated according to the characteristics of the different subsamples.

(Sub) sample	Number of observations	Mean	Median	Standard deviation
Full sample	950	0.391	0.264	0.343
Secured bonds	273	0.343	0.210	0.319
Unsecured bonds	386	0.333	0.203	0.304
NBER recession	304	0.282	0.154	0.305
NBER non-recession	355	0.384	0.280	0.308
Short % lifetime	316	0.312	0.186	0.305
Long % lifetime	339	0.363	0.230	0.314

Recovery rate distribution subsampled by collateral type

We divide our empirical data in a subsample with secured bonds (with collateral) and a subsample with unsecured bonds (without collateral). The descriptive statistics of these subsamples are shown in Table 5.3. In accordance with the regressions in appendix 5A, the mean of the different subsamples with or without collateral does not differ much. This implies that collateral on average does not generate a higher revenue in default (higher recovery rate) for bondholders. The distribution of recovery rates of secured bonds is not very different from the distribution of recovery rates of unsecured bonds. The probability density functions of the recovery rate subsamples of Figure 5.3 support this result. We do not have an explanation for this result. One hypothesis might be that the collateral of bondholders is of inferior quality in comparison to, for example, the collateral of bank loans. We have no information on the characteristics of the collateral of bondholders to further analyze this hypothesis.

Recovery rate distribution subsampled by default date

We split the dataset of recovery rates into a subsample with a default date in a NBER recession period and a subsample with a default date in a NBER non-recession period. The descriptive statistics of the subsamples are shown in Table 5.3. These subsamples do not include data concerning the Lehman bonds to prevent bias. The

amount of data.

mean of the recovery rates of a bond that defaulted in a NBER non-recession period (38%) is substantially higher than the mean of a bond that defaulted in a NBER recession period (28%). Figure 5.2 shows that the subsampled distributions of NBER non-recession defaulted bonds have first order stochastic dominance over the NBER recession defaulted bonds.

Recovery rate distribution subsampled by percentage lifetime at default

We use the median lifetime of our observations to divide the full sample of recovery rates into two subsamples with a short percentage of lifetime at default and a long percentage of lifetime at default. We define a short lifetime as a percentage smaller or equal to 40% and a long lifetime as a percentage larger than 40%. The descriptive statistics of these subsamples are shown in Table 5.3[13]. The mean recovery rate of a long lifetime bond is substantially higher (36%) than the mean recovery rate of a short lifetime bond (31%). Figure 5.2 and (5.3) show first order stochastic dominance of the long lifetime bonds over the short lifetime bonds.

5.4 Theoretical framework

This section describes the theoretical framework we use to analyze the distribution of recovery rates. Subsection one gives a specification of the theoretical distributions and the truncation form we use to model the recovery rates. The next subsection describes the maximum likelihood estimates of the theoretical distributions. The goodness of fit tests to compare the theoretical distributions and the empirical data are introduced in the last subsection.

5.4.1 Theoretical distributions

Beta distribution

Schonbucher (2003)[14] mentions that the standard choices to model recovery rates would be the Beta distribution or transformations of the "standard" normal distribution. Other academic literature also suggests the Beta distribution (Gupton &

[13] Four observations are left out in comparison to the other subsamples, because these bonds did not have a maturity date, but were perpetual bonds.

[14] Chapter 6.1.6, page 147.

Stein (2002) and Credit Metrics^{TM}) or transformed normal distributions[15]. The Beta distribution has probability mass between zero and one and therefore fits the range of the empirical recovery rates. The probability density function of the Beta distribution reads

$$\widetilde{f(x)} = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1} \qquad \text{if } x \in [0,1]$$

where α ($\alpha > 0$) is referred to as the "center" parameter and β ($\beta > 0$) is referred to as the "shape" parameter while x is the recovery rate. Outside the interval $[0,1]$ the Beta distribution has zero mass. We use maximum likelihood estimation to determine the shape and scale parameters of the Beta distribution, α and β.

Normal distribution

The normal distribution is an unbounded distribution, while the recovery rate distribution is bounded between zero and one. Truncation of the theoretical normal distribution is necessary in order to determine the goodness of fit to the empirical distribution. One form of truncation is Mood et al. (1974) truncation, where the probability density function is divided by the difference in the cumulative probability function at truncation points (for recovery rates that is zero and one). If x is the recovery rate with a probability density function $f(x)$ and a cumulative distribution function of $F(x)$, the truncated density of this variable truncated on the left at a and truncated on the right at b is given by Mood et al. (1974):

$$\widetilde{b(x)_M} = \frac{b(x)}{B(b) - B(a)} \qquad \text{where } x \in [a,b]. \tag{5.1}$$

Truncation in this form shifts the entire distribution upwards and divides the probability mass of the distribution $f(x)$ that is beyond the truncation points equally over the distribution of $\widetilde{f(x)}$ in between $[a,b]$. Applying the truncation form of Mood et al. (1974), depicted by using the subscript M, to the density function of the normal distribution reads

$$\widetilde{g(x)_M} = \frac{\frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}}{G(1) - G(0)} \qquad \text{where } x \in [0,1]. \tag{5.2}$$

Our empirical distribution of recovery rates has primarily mass at or close to the

[15] Probit or logit distributions are suggested.

truncation points, as can be seen in figures (5.1) and (5.3). Because of the mass close to or at the truncation points, we use a different form of truncation to truncate the theoretical normal (and Weibull) distribution. Another form of truncation is to place the probability mass beyond the truncation points, as mass points on the truncation points a and b. This form of truncation creates the mixed distribution:

$$\widetilde{b(x)_N} = \left\{ \begin{array}{ll} B(a) & \text{if } x = a \\ b(x) & \text{if } x \in (a,b) \\ 1 - B(b) & \text{if } x = b \end{array} \right\}. \tag{5.3}$$

The truncation points have masspoints and the distribution is not continuous at these truncation points. This form of truncation takes into consideration the possibility of more probability mass at the endpoints of the distribution. We transform the normal distribution to this new form of truncation, depicted by the subscript N. This form of truncation results in the following mixed density function:

$$\widetilde{g(x)_N} = \left\{ \begin{array}{ll} G(0) & \text{if } x = 0 \\ \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2} & \text{if } x \in (0,1) \\ 1 - G(1) & \text{if } x = 1 \end{array} \right\}. \tag{5.4}$$

Weibull distribution

In medicine, information technology and biology[16] the Weibull distribution is used for modelling recovery rates of survival rates. The Weibull distribution is also one of the three extreme value distributions to model the behavior of the maxima of a sample from a distribution with an endpoint.

We analyze whether the empirical data of recovery rates fits a truncated Weibull distribution. The Weibull distribution is a partly bounded distribution, that only exists on $[0, \infty)$. In order to compare this theoretical distribution to our bounded recovery rate data, it has to be truncated at one. Applying the Mood et al. (1974) truncation form to the Weibull distribution gives the following density function

$$\widetilde{h(x)_M} = \frac{\frac{k}{s}\left(\frac{x}{s}\right)^{a-1} e^{-(x/s)^a}}{e^{-(1/s)^a}} \qquad \text{where } x \in [0,1]. \tag{5.5}$$

[16] A Weibull distribution is commonly used to model the failure and recovery data of software and hardware (Matz et al (2002)), recovery rates in medicine (Reid (1997)) and survival distributions in nature (Pyke and Thompson (1986)).

where s $(s > 0)$ is the shape parameter, a $(a > 0)$ is the scale parameter and x is the recovery rate. We determine the parameters of the Weibull distribution through a maximum likelihood estimation on the empirical data. Applying our new form of truncation as in equation (5.4), to the Weibull distribution leads to the mixed density function:

$$\widetilde{h(x)_N} = \left\{ \begin{array}{ll} \frac{a}{s}(\frac{x}{s})^{a-1} e^{-(x/s)^a} & \text{if } \ x \in [0,1) \\ e^{-(1/s)^a} & \text{if } x = 1 \end{array} \right\}. \tag{5.6}$$

5.4.2 Maximum likelihood estimates

We use maximum likelihood to determine the parameters of the theoretical distributions. We estimate the parameters of the truncated normal, Beta and truncated Weibull distribution for the different (sub)samples according to this estimation method.

5.4.3 Goodness of fit tests

The chi-square test of Pearson (1900) is probably the best known goodness of fit measure[17]. One of the disadvantages of the chi-square test is that it uses arbitrary classes to subdivide the data. Each class of the chi-square test has to have at least five observations. Because we have only samples with relatively small amounts of observations (the subsamples consist of approximately 300 observations) and the data cluster around $0.0 - 0.2$ and 1, the chi-square test will aggregate the data in very few classes, losing a good deal of the information. The chi-square test statistic will become unreliable with few observations and few classes. To counter this disadvantage we use the Kolmogorov-Smirnov and the Cramer - von Mises goodness of fit measures.

The Kolmogorov-Smirnov test for goodness of fit

[17] The chi-square test statistic is given by:

$$T_c = \sum_{k=1}^{k=k\max} \frac{(\widehat{n}_k - n_k)^2}{n_k};$$

where $\widehat{n}_k$ is the empirical number of observations at class k and n_k is the theoretical number of observations at class k.

The Kolmogorov-Smirnov (1933) test measures the maximum vertical distance between the empirical distribution function $F(x)$ and the theoretical distribution function $F^*(x)$, in order to determine if the theoretical distribution is a reasonable approximation of the unknown true distribution function. The two sided test statistic for Kolmogorov-Smirnov test reads

$$T_K = \max |F^*(x) - F(x)|$$

where T_K is the Kolmogorov-Smirnov test statistic, $F(x)$ is the empirical distribution function and $F^*(x)$ is the theoretical distribution function. The Kolmogorov-Smirnov test statistic is used to test the null hypothesis that the empirical distribution function originates from the theoretical distribution function

$$\begin{aligned} H_0 &: F(x) = F^*(x) \qquad \text{for all } x \text{ from } -\infty \text{ to } +\infty \\ H_1 &: F(x) \neq F^*(x) \qquad \text{for at least one value of } x \end{aligned}$$

if the T test statistic $T_K > T_s$ we reject the null hypothesis, if $T_K \leq T_s$ we accept the null hypothesis. The threshold T_s (decision rule) is determined according to

$$T_s = \frac{x_p}{\left(n + \sqrt{n/10}\right)^{\frac{1}{2}}} \tag{5.7}$$

where n is the number of observations present in the data and x_p is the value from the standardized normal distribution[18].

Cramer - von Mises test for goodness of fit

The Cramer-von Mises (1928) test measures the sum of the vertical distance between the empirical distribution function $F(x)$ and the theoretical distribution function $F^*(x)$, in order to determine if the theoretical distribution is a reasonable approximation of the unknown true distribution function. The two sided test statistic for Cramer - von Mises test reads

$$W^2 = \int_0^1 \left[F^*(x) - F(x)\right]^2 dF(x)$$

where W^2 is the Cramer - von Mises test statistic, $F(x)$ is the empirical distribution

[18] For $p = .90$ this value is 1.22, for $p = .95$ this value is 1.36 and for $p = .99$ this value is 1.63.

function and $F^*(x)$ is the theoretical distribution function. If the sample values are arranged in increasing order, the Cramer-von Mises test statistic reads

$$W^2 = \frac{1}{12n^2} + \frac{1}{n}\sum_{1}^{n}\left[F^*(x_v) - \frac{2v-1}{2n}\right]^2$$

where W^2 is the Cramer - von Mises test statistic, $F^*(x)$ is the theoretical cumulative distribution function, n the number of observations and v is the number of sample values $\leq x$. The Cramer - von Mises test statistic is used to test the null hypothesis that the empirical distribution function originates from the theoretical distribution function

$$\begin{aligned} H_0 &: \; F(x) = F^*(x) \qquad \text{for all } x \text{ from } -\infty \text{ to } +\infty \\ H_1 &: \; F(x) \neq F^*(x) \qquad \text{for at least one value of } x \end{aligned}$$

if the test statistic $W^2 > W_s$ we reject the null hypothesis, if $W^2 \leq W_s$ we accept the null hypothesis. The threshold W_s (decision rule) is determined according to

$$E(W_s) = \frac{1}{6n} \tag{5.8}$$

where n is the number of observations present in the data.

We determine the Kolmogorov-Smirnov and Cramer-von Mises test statistic for our empirical data in comparison with the (truncated) theoretical distributions. We use the new truncation forms for the theoretical normal and Weibull distribution. We simulate 10,000 random draws from the theoretical distributions and compare these draws to the theoretical cumulative distribution functions. We determine the goodness of fit test statistics (Kolmogorov-Smirnov and Cramer-von Mises) for each random draw. We determine the 95% confidence interval for the distribution of the test statistics (10,000 observations). And use this 95% confidence interval to determine whether the empirical data originate from a Beta, truncated normal or truncated Weibull distribution.

5.5 Empirical analysis

5.5.1 Maximum likelihood estimates

The maximum likelihood estimates of the truncated normal, the Beta and the truncated Weibull distribution of the full sample and the different subsamples are in Table 5.4.

Table 5.4
Maximum likelihood parameter estimation

The table shows the maximum likelihood estimations of the parameters of the beta, normal and Weibull distribution of the different subsamples and the full sample of the recovery rates of bonds. The maximum likelihood estimations were computed using the sample data in Matlab.

		Subsamples						
Distribution	Parameter	Full sample	Secured bonds	Unsecured bonds	NBER recession	NBER non-recession	Short % lifetime	Long % lifetime
Beta distribution	Alpha	0.246	0.266	0.305	0.268	0.313	0.282	0.294
	Beta	0.145	0.187	0.269	0.264	0.206	0.249	0.210
Normal distribution	Mean	0.391	0.343	0.333	0.282	0.384	0.312	0.363
	St Dev	0.343	0.319	0.304	0.304	0.308	0.305	0.313
Weibull distribution	s	0.378	0.333	0.324	0.253	0.398	0.295	0.363
	a	0.916	0.934	0.935	0.805	1.115	0.881	1.002

The NBER non-recession and the long lifetime subsample of bonds in contrast to all other estimations, have a scale parameter a of the Weibull distribution that is larger than one. A scale parameter $a > 1$ has a large impact on the theoretical Weibull distribution close to zero. If the scale parameter of the Weibull $a < 1$, the Weibull density tends to go to infinity, close to zero. If the scale parameter of the Weibull $a > 1$, the Weibull density tends to go to zero, close to a recovery rate of zero.

5.5.2 Analysis of the test statistics

We use the maximum likelihood parameters to construct the theoretical normal, Beta and Weibull distributions for the full sample and different subsamples. We randomly draw n observations from these theoretical distributions, where n is equal to the observations in the empirical distribution. We simulate these random draws 10,000 times, compare the observations from the draws from the theoretical distributions to the empirical observations and calculate the goodness of fit test statistics. Each simulation gives a new value of the goodness of fit test statistic (Kolmogorov-Smirnov and Cramer - von Mises) and the distribution of test statistics ($n = 10,000$) can be analyzed.

Full distribution of recovery rates

The results of the simulations for the full distribution of recovery rates ($n =$ 950 observations) are shown in Table 5.5. The average value of the Kolmogorov-Smirnov test statistic is highest for the theoretical Beta distribution and least for the truncated Weibull distribution. If we compare the empirical value of the test statistic with the 95% confidence interval of the critical value, all of the null hypotheses that the empirical data originate from the specified theoretical distributions are rejected.

Recovery rate subsampled by default date

The results of the simulations for the subsamples with a default date in a NBER recession period or a default date in a NBER non-recession period are shown in Table 5.5. The null hypothesis that the empirical data of bond recovery rates with a default date in a NBER recession period originate from a truncated Weibull distribution is accepted for both the Kolmogorov-Smirnov test statistic and the Cramer-von Mises test statistic. The null hypothesis that the empirical data of bond recovery rates with a default date in a NBER non-recession period originate from a truncated Weibull distribution is accepted only for the Kolmogorov-Smirnov test statistic. If we compare the lowest value of the Cramer-von Mises test statistic of Table 5.5, 0.006, to the lowest Cramer-von Mises test statistic of the full sample data of Table 5.5 (of which the Cramer-von Mises test statistic of the truncated Weibull, 0.0013, is the lowest), an improvement of the test statistics is visible. Modelling the recovery rates of bonds that defaulted in a NBER recession period separately from the bonds that defaulted in a non-NBER recession period improves the goodness of fit of the distribution of recovery rates. The recovery rates of these subsamples, according to our analysis of the test statistics, are best modelled using a Weibull distribution.

Table 5.5

Simulation results of the Kolmogorov-Smirnov and Cramér-von Mises test statistics

These tables present the simulation results of the Kolmogorov-Smirnov and Cramér-von Mises test statistics. We simulate 10,000 random draw s from the theoretical distributions and calculate the test statistics of these random draw s in comparison to their theoretical cumulative distribution function to determine the 95% confidence interval of the test statistics. The critical value of the test statistic is determined on a 5% significance level according to the formulas show n in equation (5.7) and (5.8).

	Full sample of recovery rates of defaulted bonds (N = 950)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.345	0.040	0.151	0.008	0.086	0.001
Critical value test statistic	0.044	0.000	0.044	0.000	0.044	0.000
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.039	0.000	0.039	0.000	0.039	0.000
Standard deviation critival value	0.012	0.000	0.012	0.000	0.012	0.000
95% confidence interval critical value	0.015-0.063	0.000-0.001	0.016-0.062	0.000-0.001	0.015-0.062	0.000-0.001
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Rejected	Rejected

	Recovery rates of defaulted bonds with default date in NBER recession period (N = 304)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.305	0.031	0.190	0.013	0.056	0.001
Critical value test statistic	0.077	0.001	0.077	0.001	0.077	0.001
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.067	0.001	0.067	0.001	0.067	0.001
Standard deviation critival value	0.021	0.001	0.021	0.001	0.021	0.001
95% confidence interval critical value	0.026-0.108	0.000-0.002	0.026-0.108	0.000-0.002	0.025-0.109	0.000-0.002
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Accepted	Accepted

	Recovery rates of defaulted bonds with default date in NBER non-recession period (N = 355)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.357	0.040	0.151	0.006	0.075	0.001
Critical value test statistic	0.072	0.000	0.072	0.000	0.072	0.000
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.063	0.001	0.062	0.001	0.063	0.001
Standard deviation critival value	0.020	0.000	0.020	0.000	0.020	0.000
95% confidence interval critical value	0.0243-0.1011	0.0000-0.0013	0.0241-0.1005	0.0000-0.0013	0.0243-0.1007	0.0000-0.0013
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Accepted	Rejected

	Recovery rates of defaulted secured bonds (N = 273)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.361	0.040	0.166	0.008	0.058	0.001
Critical value test statistic	0.082	0.001	0.082	0.001	0.082	0.001
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.071	0.001	0.071	0.001	0.071	0.001
Standard deviation critival value	0.022	0.001	0.022	0.001	0.022	0.001
95% confidence interval critical value	0.028-0.114	0.000-0.002	0.028-0.114	0.000-0.002	0.027-0.114	0.000-0.002
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Accepted	Accepted

Table 5.5 - *Continued*

	Recovery rates of defaulted unsecured bonds (N = 386)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.288	0.031	0.175	0.010	0.068	0.001
Critical value test statistic	0.069	0.000	0.069	0.000	0.069	0.000
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.060	0.000	0.060	0.000	0.060	0.000
Standard deviation critival value	0.019	0.000	0.019	0.000	0.019	0.000
95% confidence interval critical value	0.024-0.097	0.000-0.001	0.0232-0.097	0.000-0.001	0.023-0.097	0.000-0.001
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Accepted	Accepted

	Recovery rates of defaulted bonds with a short lifetime (N = 316)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.312	0.033	0.170	0.009	0.050	0.000
Critical value test statistic	0.076	0.001	0.076	0.001	0.076	0.001
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.066	0.001	0.066	0.001	0.066	0.001
Standard deviation critival value	0.021	0.001	0.021	0.001	0.021	0.001
95% confidence interval critical value	0.025-0.106	0.000-0.002	0.025-0.106	0.000-0.002	0.025-0.108	0.000-0.002
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Accepted	Accepted

	Recovery rates of defaulted bonds with a long lifetime (N = 339)					
	Beta distribution		Normal distribution		Weibull distribution	
	KS	CvM	KS	CvM	KS	CvM
Value test statistic	0.340	0.038	0.168	0.008	0.075	0.001
Critical value test statistic	0.073	0.000	0.073	0.000	0.073	0.000
Number of simulations critical value	10,000	10,000	10,000	10,000	10,000	10,000
Mean critical value test statistic	0.064	0.001	0.064	0.001	0.064	0.001
Standard deviation critival value	0.020	0.000	0.020	0.000	0.020	0.001
95% confidence interval critical value	0.025-0.102	0.000-0.001	0.025-0.103	0.000-0.001	0.025-0.102	0.000-0.001
Null hypothesis	Rejected	Rejected	Rejected	Rejected	Accepted	Accepted

Recovery rates subsampled by collateral type

The characteristics of the simulation of the critical value for the Kolmogorov-Smirnov and Cramer-von Mises test statistic of the subsamples of secured and unsecured bonds are shown in Table 5.5. These test statistics show the same results as for the subsamples according the default date: the goodness of fit between the theoretical distributions and the empirical data improves, if not the full sample of recovery rates is modelled, but the sample of secured bonds and unsecured bonds separately. The null hypothesis that the empirical data originate from a truncated Weibull distribution is accepted for both the Kolmogorov-Smirnov test statistic and the Cramer-von Mises test statistic. Because both test statistics are in the 95% confidence interval of the critical value.

Recovery rates subsampled by lifetime

The specifications of the critical value of the Kolmogorov-Smirnov and Cramer-von Mises test statistics for the 10,000 simulations can be found in Table 5.5. These test statistics show the same results as for the subsamples according the default date: the goodness of fit between the theoretical distributions and the empirical data improves, if not the full sample of recovery rates is modelled, but the sample of short lifetime bonds and long lifetime bonds separately. The null hypothesis that the empirical data originate from a truncated Weibull distribution is accepted for both the Kolmogorov-Smirnov test statistic and the Cramer-von Mises test statistic. Both test statistics are in the 95% confidence interval of the critical value.

Appendix 5B shows the QQ-plots[19] of the empirical data and the theoretical distributions. Both the QQ-plots of the full data sample and the QQ-plots of the subsamples show that using a Beta distribution to model empirical recovery rates tends to overestimate the probability of having a recovery rate close to 100% and underestimate the probability of having a recovery rate close to 0%. Modelling recovery rates of defaulted bonds as a Beta distribution according to our analysis overestimates the expected recovery rate and might result in unexpected losses. The use of a truncated Weibull gives a better representation of the distribution of recovery rates of defaulted bonds.

[19] A QQ-plot compares the empirical quantiles with the quantiles of the theoretical distributions.

5.6 Conclusion

The distribution of recovery rates of defaulted bonds, according to our analysis, can best be modelled using a truncated Weibull distribution and taking into account the bond characteristics. The bond characteristics concerning a default date in a NBER recession period and the bond lifetime at default are of significant influence on the distribution of recovery rates. We find that in contrast to Schuermann (2004) the impact of collateral on the recovery rate of defaulted bonds is not significant. Whereas there seems to be correlation between the time to default in comparison to duration of a bond and the recovery rate.

5.A Appendix - Regressions on the recovery rate

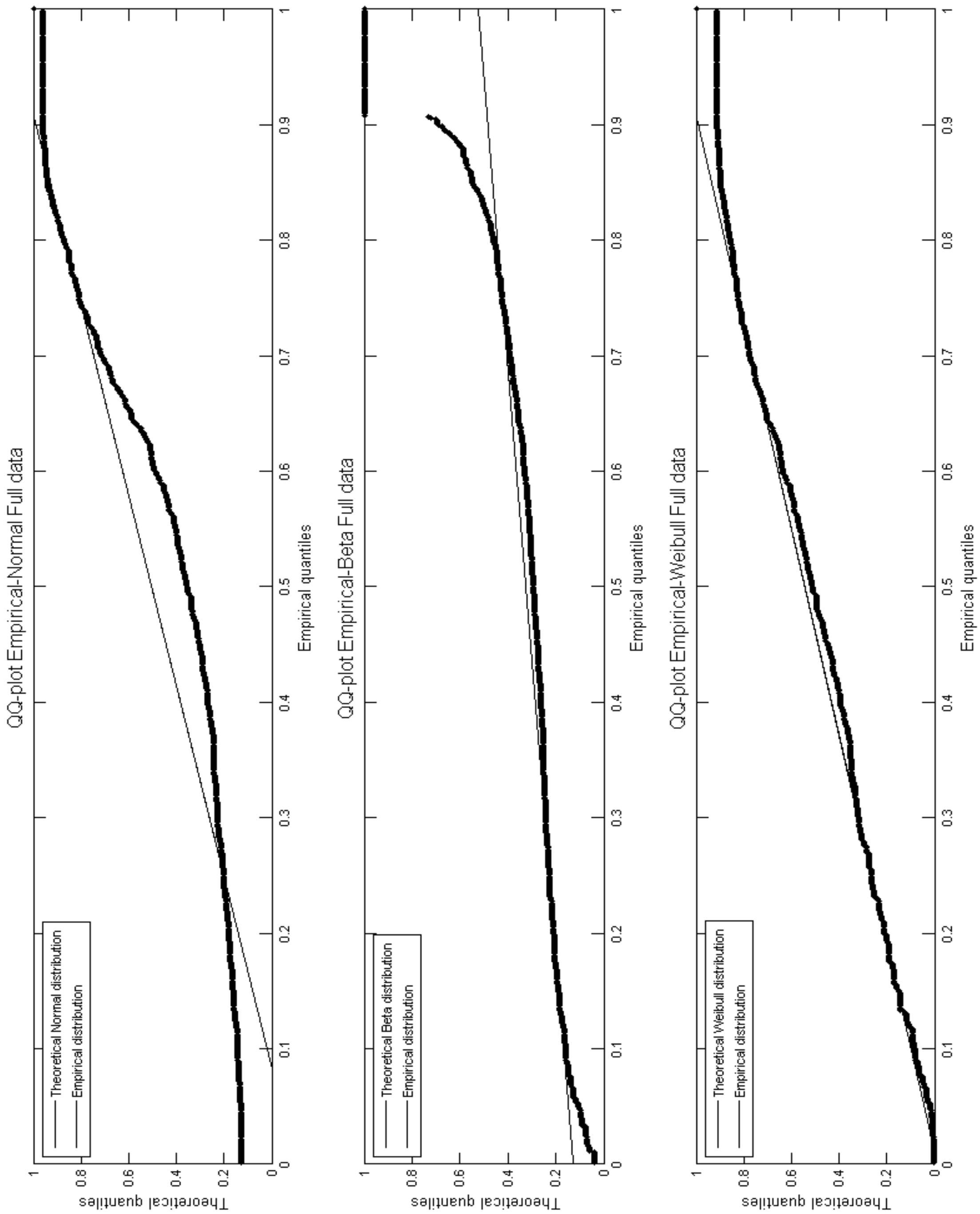
Appendix 5A

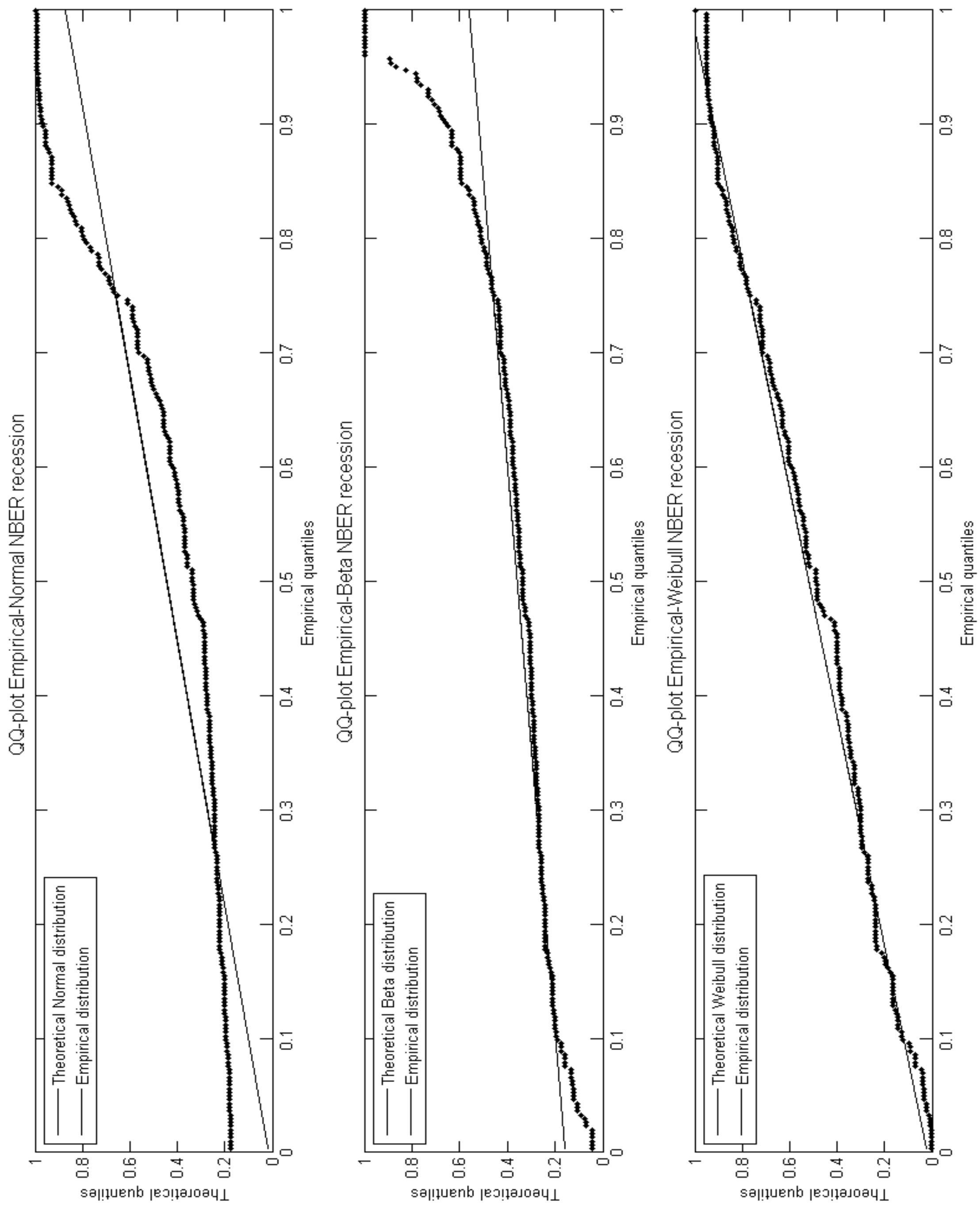
Recovery rates and market & bond characteristics

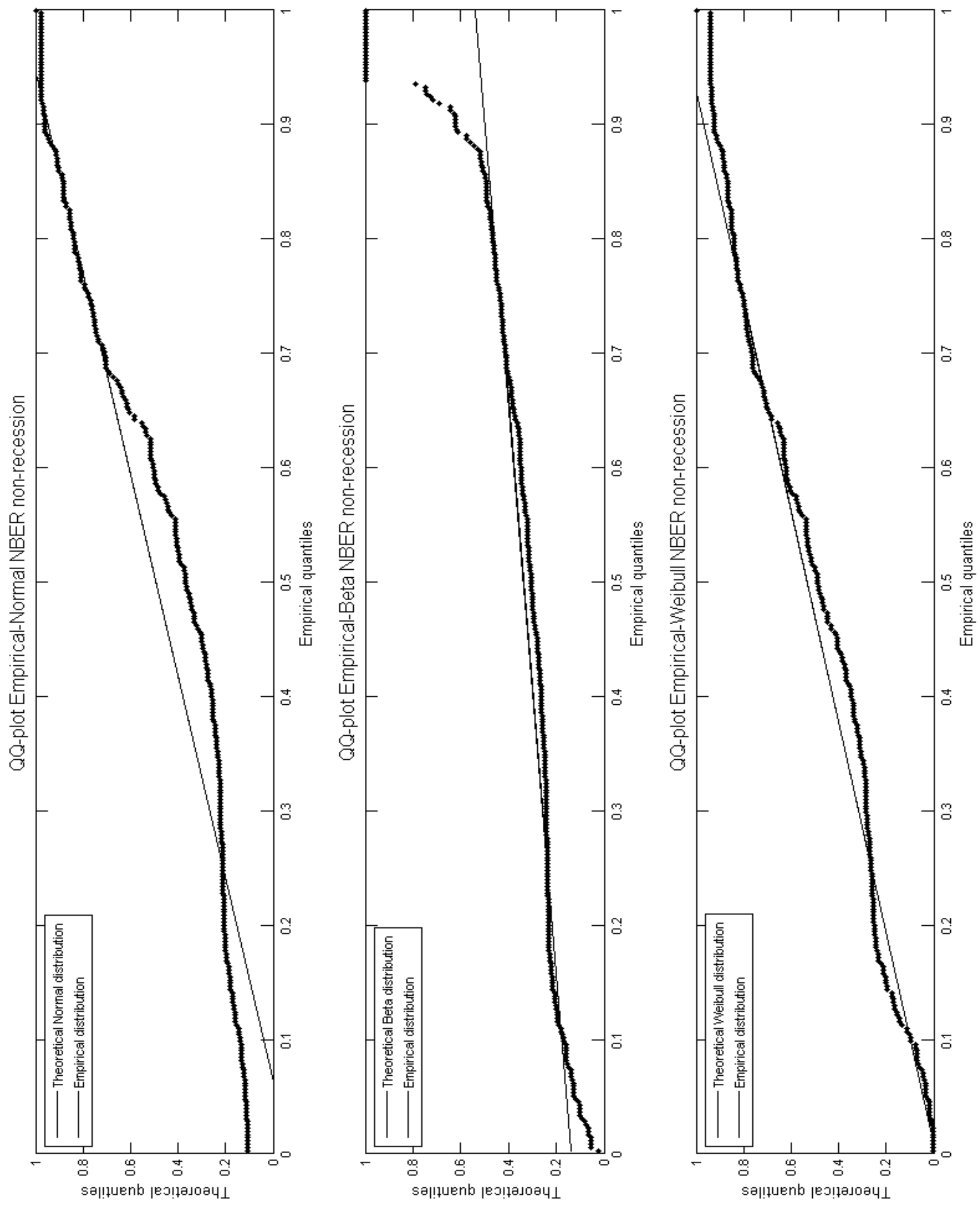
The table presents the results of regressions of bond and market characteristics on the recovery rates of defaulted bonds. The explanatory variables bond seniority and secured bond dummy are correlated, so only one of these explanatory variabes can be used in each regression. The explanatory variables US market dummy & US dollar dummy, NBER recession dummy & current crisis dummy are also correlated and only one of these variables is used in each regression. The standard errors are shown in parentheses in the table. ***, **, * denote statistically significant effects at a 1%, 5% and 10% level respectively.

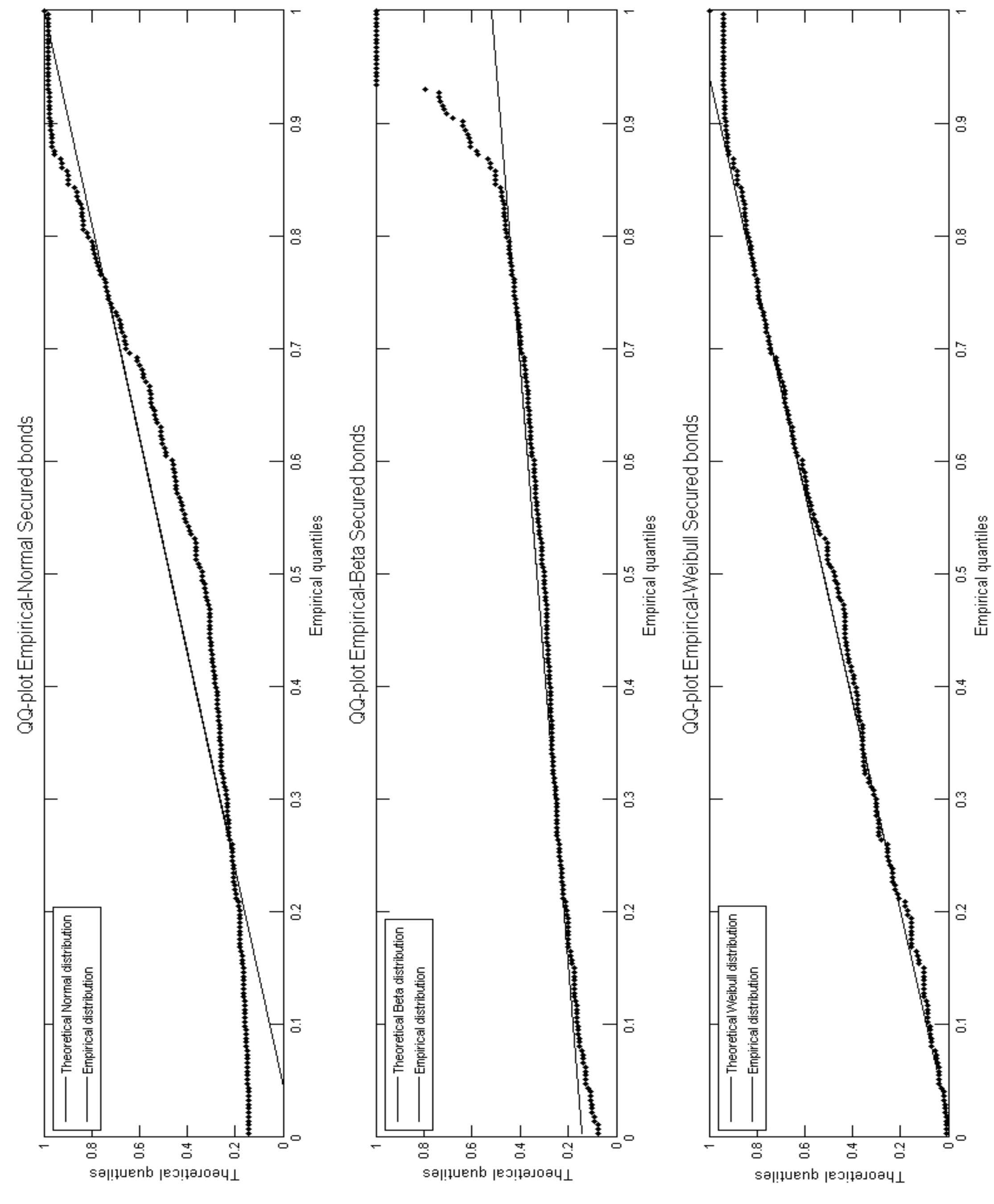
Dependent variable: recovery rate of defaulted bond						
	(1)	(2)	(3)	(4)	(5)	(6)
Interest rate coupon	-0.256	-0.092	0.045	0.463	0.332	0.261
	(0.47)	(0.46)	(0.45)	(0.50)	(0.51)	(0.51)
Industry	-0.001 **	-0.000 *	-0.000 *	-0.001 *	-0.000 *	-0.000 *
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lehman dummy	-0.094 ***	-0.077 **	-0.077 **			
	(0.03)	(0.03)	(0.03)			
Percentage lifetime at default	0.252 ***	0.243 ***	0.245 ***	0.200 ***	0.198 ***	0.195 ***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Current crisis dummy	-0.074 ***					
	(0.02)					
NBER recession at default dummy		-0.096 ***	-0.095 ***	-0.096 ***	-0.098 ***	-0.100 ***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Secured bond dummy			0.013	0.009		
			(0.02)	(0.02)		
Bond seniority	-0.033 **	-0.029 *			-0.024	-0.023
	(0.02)	(0.02)			(0.02)	(0.02)
US Market dummy	0.021	0.020	0.019	0.008	0.009	
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
US Dollar dummy						0.034
						(0.03)
Constant	0.374 ***	0.354 ***	0.287 ***	0.282 ***	0.337 ***	0.322 ***
	(0.07)	(0.06)	(0.05)	(0.06)	(0.07)	(0.07)
Summary statistics						
Regression	Incl. Lehman	Incl. Lehman	Incl. Lehman	Excl. Lehman	Excl. Lehman	Excl. Lehman
Number of observations	818	818	818	655	655	655
Adjusted R-squared	0.107	0.116	0.113	0.051	0.053	0.054
Standard error of regression	0.286	0.284	0.285	0.303	0.302	0.302
Durbin Watson statistic	1.248	1.258	1.256	1.249	1.249	1.253

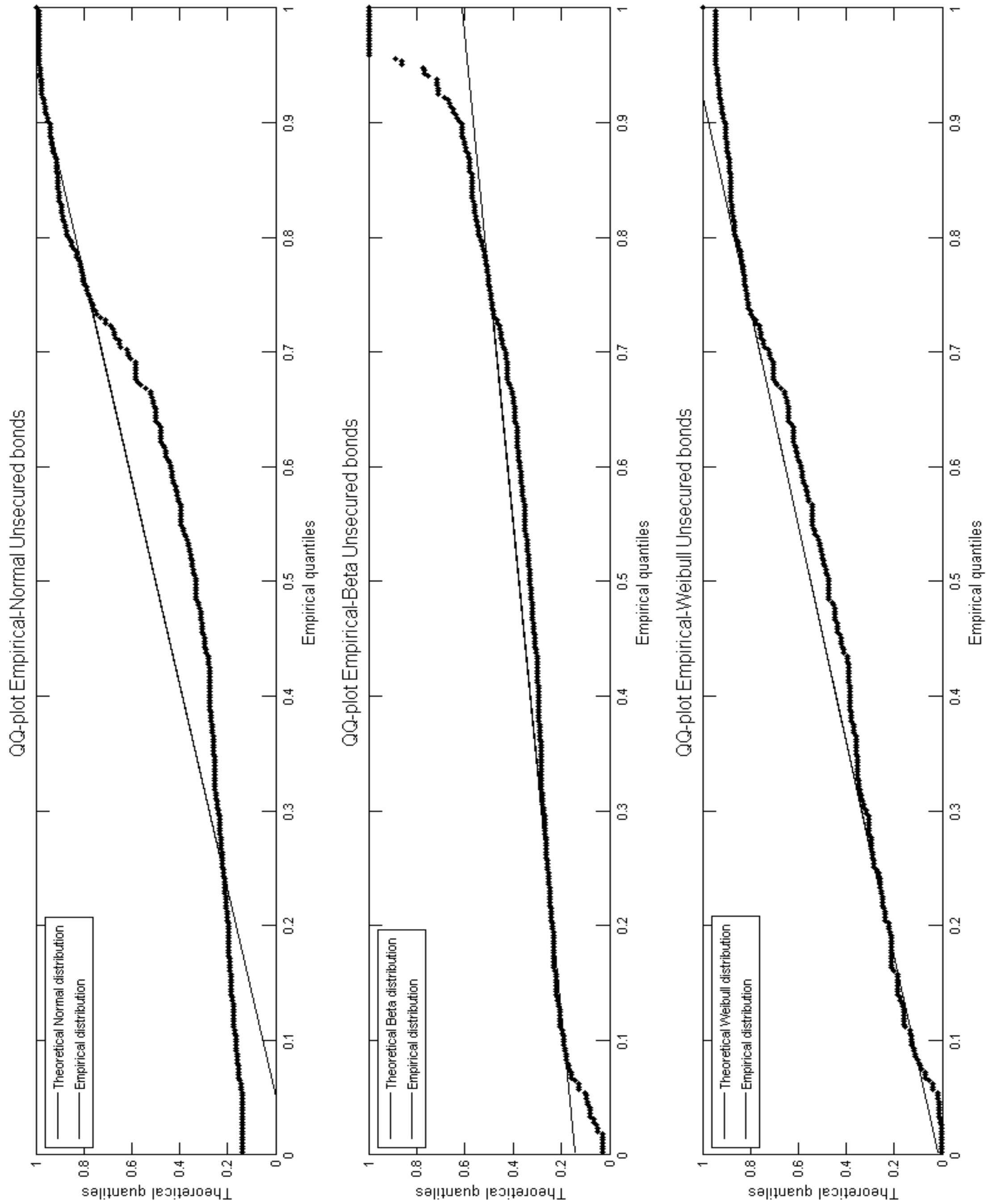
5.B Appendix - Empirical quantile and theoretical quantile plots (QQ-plots)

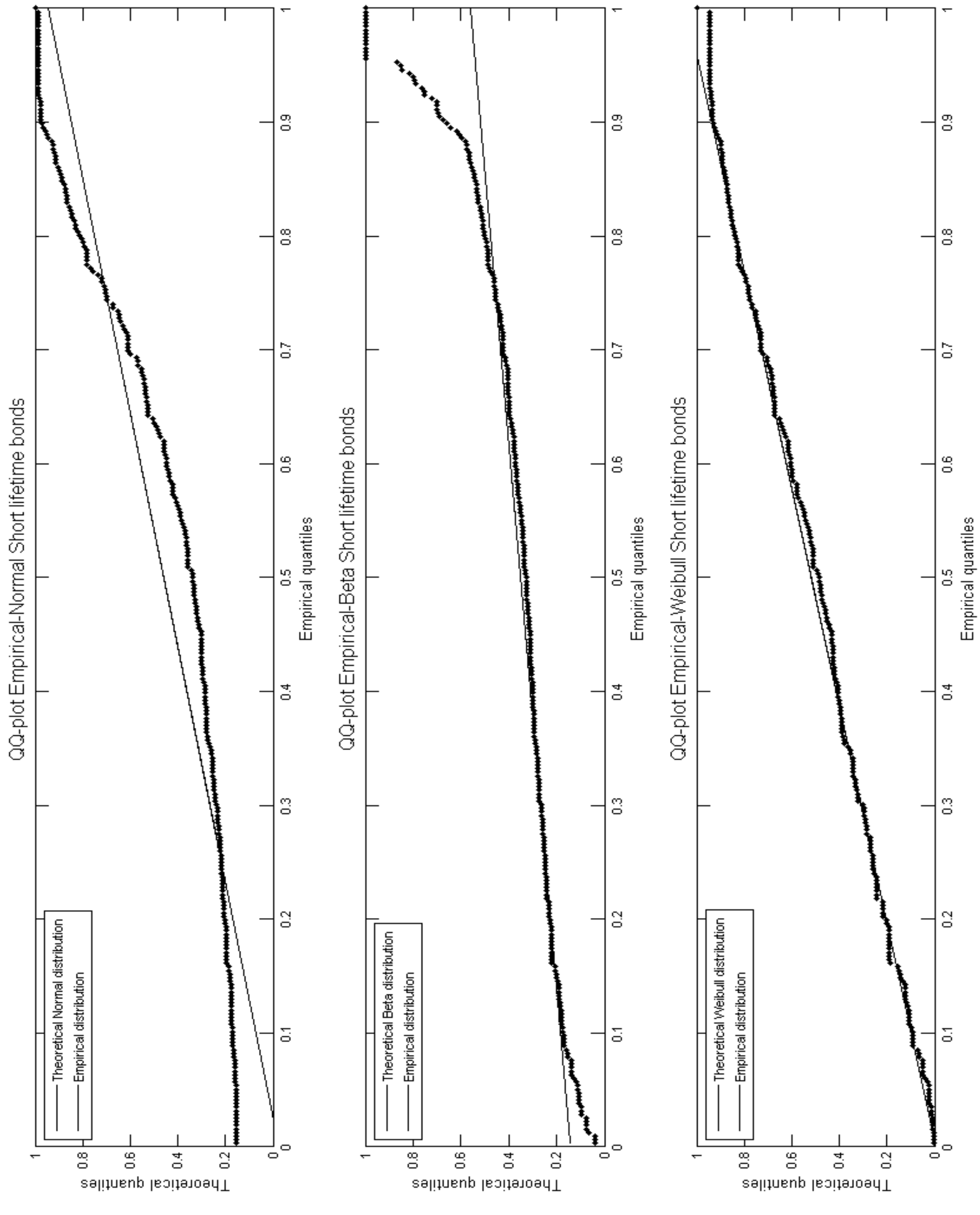


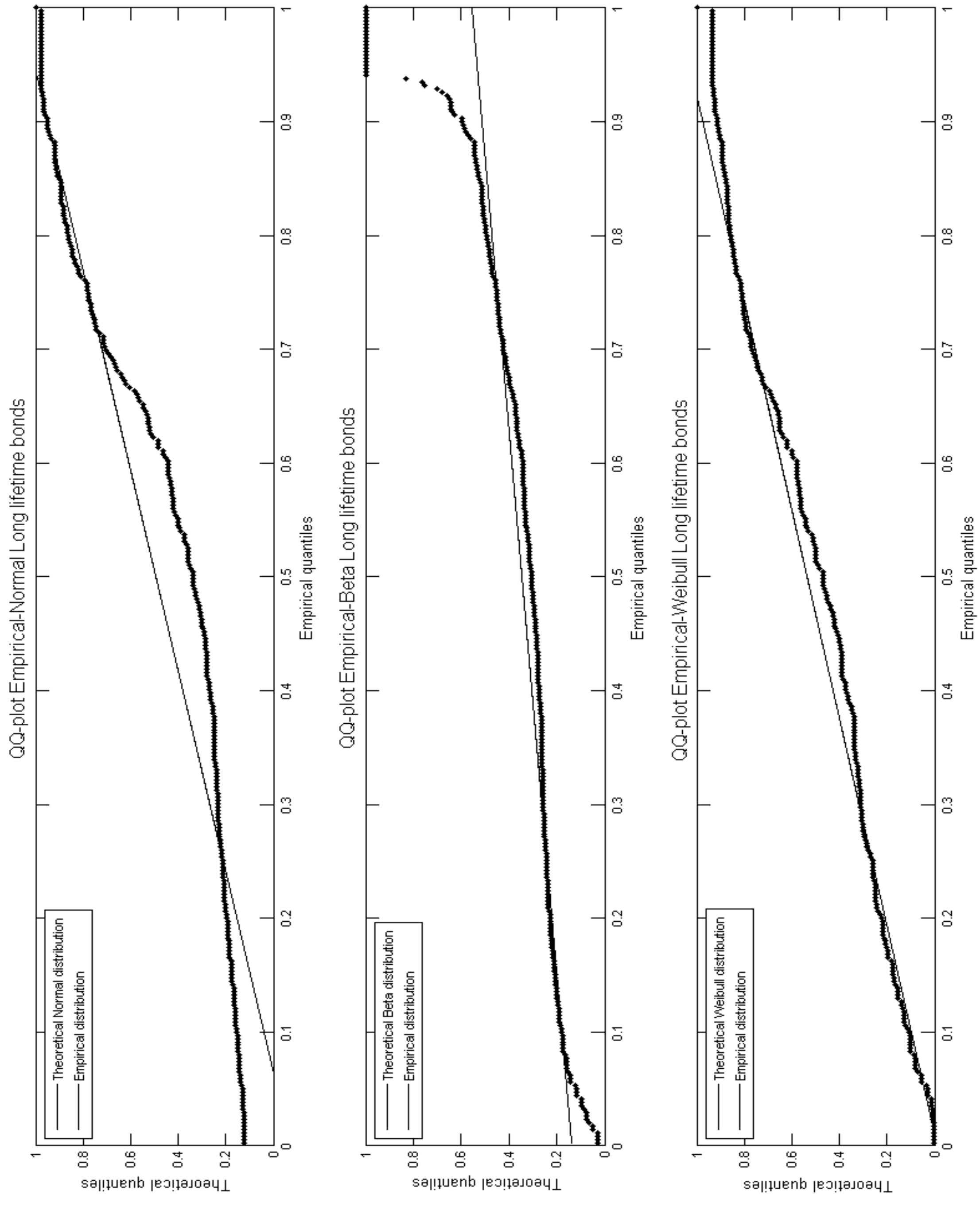

QQ-plot Empirical-Normal NBER recession
Theoretical Normal distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Beta NBER recession
Theoretical Beta distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Weibull NBER recession
Theoretical Weibull distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles


QQ-plot Empirical-Normal NBER non-recession
Theoretical Normal distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Beta NBER non-recession
Theoretical Beta distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Weibull NBER non-recession
Theoretical Weibull distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles


QQ-plot Empirical-Normal Secured bonds
Theoretical Normal distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Beta Secured bonds
Theoretical Beta distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Weibull Secured bonds
Theoretical Weibull distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles


QQ-plot Empirical-Normal Unsecured bonds
Theoretical Normal distribution
Empirical distribution
Empirical quantiles
Theoretical quantiles
QQ-plot Empirical-Beta Unsecured bonds
Theoretical Beta distribution
Empirical distribution
Empirical quantiles
Theoretical quantiles
QQ-plot Empirical-Weibull Unsecured bonds
Theoretical Weibull distribution
Empirical distribution
Empirical quantiles
Theoretical quantiles


QQ-plot Empirical-Normal Short lifetime bonds
Theoretical Normal distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Beta Short lifetime bonds
Theoretical Beta distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles
QQ-plot Empirical-Weibull Short lifetime bonds
Theoretical Weibull distribution
Empirical distribution
Theoretical quantiles
Empirical quantiles


QQ-plot Empirical-Normal Long lifetime bonds
Theoretical Normal distribution
Empirical distribution
Empirical quantiles
Theoretical quantiles
QQ-plot Empirical-Beta Long lifetime bonds
Theoretical Beta distribution
Empirical distribution
Empirical quantiles
Theoretical quantiles
QQ-plot Empirical-Weibull Long lifetime bonds
Theoretical Weibull distribution
Empirical distribution
Empirical quantiles
Theoretical quantiles

Samenvatting (Summary in Dutch)

Introductie

Kredietrisico is het risico van een financieel verlies als gevolg van het in gebreke blijven van een tegenpartij inzake de nakoming van contractuele verplichtingen[20]. Deze definitie legt de nadruk op een aantal afzonderlijke aspecten van kredietrisico. Een afzonderlijk aspect van kredietrisico is het risico dat de tegenpartij in gebreke blijft. Dit risico wordt ook wel counterpartyrisk of defaultrisk genoemd en wordt uitgedrukt in een percentage dat de waarschijnlijkheid van ingebrekestelling weergeeft (ook wel de probability of default genoemd). Het tweede afzonderlijke aspect van kredietrisico betreft de regresmogelijkheid van de schuldeiser om voldoening van de contractuele verplichting te eisen bij het in gebreke blijven van de schuldenaar. Dit risico wordt ook wel recovery risk genoemd en wordt gekwantificeerd door middel van een percentage dat het verlies of de uitkering in vergelijking met het geïnvesteerde bedrag na ingebrekestelling weergeeft. Het percentage verlies na ingebrekestelling wordt ook de loss given default genoemd. De tegenhanger van de loss given default wordt de recovery rate genoemd[21]. Het risico ten aanzien van de hoogte van de vordering op het moment van ingebrekestelling, ook wel credit exposure risk genoemd, vormt het laatste aspect van kredietrisico. Dit laatste risico wordt gekwantificeerd aan de hand van een geldbedrag, waarbij de kredietlimiet het openstaand bedrag begrensd. Financiële (kredietverlenende) instellingen nemen maatregelen om het kredietrisico te mitigeren. Eén van de maatregelen betreft het contractueel

[20] Dit is een Nederlandse vertaling van de definitie van kredietrisico zoals deze door Jorion (2007) wordt gehanteerd.

[21] Waarbij de recovery rate één minus de loss given default is.

vastleggen van onder andere het interestpercentage, informatieverplichtingen van de schuldenaar, onderpand en de kredietlimiet. Het volledig afwenden van kredietrisico door financiële instellingen is niet mogelijk vanwege de asymmetrische informatie tussen de schuldeiser en de schuldenaar en de onvolledigheid van convenanten. De asymmetrische informatie tussen schuldeiser en schuldenaar veroorzaakt hiaten in de informatieverstrekking (adverse selection) en aangepast keuzegedrag bij de schuldenaar (moral hazard). Het toepassen van een selectieprocedure voorafgaand aan het verstrekken van de lening (screening) draagt zorg voor het verstrekken van een lening op basis van een grotere informatieset. De convenanten tussen financiële instellingen en kredietnemers worden door de financiële instelling op naleving gecontroleerd door toezicht uit te oefenen (monitoring). Op deze wijze proberen financiële instellingen het zicht op en de beperking van kredietrisico te waarborgen. De doelstelling van dit proefschrift is te onderzoeken op welke wijze financiële instellingen omgaan met kredietrisico in drie specifieke situaties. In hoofdstuk twee en drie onderzoeken we de mogelijkheid voor financiële instellingen om tegengesteld aan de macro-economische cyclus verlies voorzieningen te vormen voor de leningenportefeuille. De perceptie van kredietrisico door financiële instellingen kent een verloop dat meebeweegt met de macro-economische cyclus[22]. De gevolgen van deze perceptie zijn direct merkbaar in de kredietverlening en versterken de macro-economische cyclus. In hoofdstuk vier analyseren we op welke wijze asset based lenders de interest bepalen in een dynamische markt met asymmetrische informatie aangaande het risicoprofiel van de kredietnemers. In hoofdstuk vijf voeren we een empirisch onderzoek uit naar de distributie van recovery rates van in gebreke zijnde commerciële obligaties.

Accounting perspectief op kredietrisico

Hoofdstuk twee introduceert een nieuwe methode van verlies voorzieningen vormen voor financiële instellingen waarbij rekening wordt gehouden met de macro-economische cyclus. Op basis van de perceptie van het kredietrisico in de leningenportefeuille van financiële instellingen, wordt door een financiële instelling een inschatting gemaakt van de te verwachten verliezen welke nog in de portefeuille aanwezig zijn. Deze inschatting wordt gemaakt op basis van historische gegevens, macro

[22] Wanneer de macroeconomische omstandigheden gunstig zijn, is de perceptie van kredietrisico laag. Echter wanneer een recessie waarneembaar wordt, verhoogt dit de perceptie van kredietrisico.

economische data en recente marktkennis[23]. Voor de te verwachten verliezen in de leningenportefeuille wordt een verliesvoorziening getroffen. De door ons voorgestelde methode van een verliesvoorziening vormen, zorgt voor een directe link tussen de liquiditeitspositie van een financiële instelling en de hoogte van de verliesvoorziening. Indirect wordt op deze wijze het risicoprofiel van de activa van de financiële instelling gekoppeld aan de liquiditeitspositie van deze financiële instelling. De literatuur kent reeds methoden om verliesvoorzieningen te vormen waarbij rekening wordt gehouden met de macro-economische cycli, waaronder de methoden van de Lis et al. (2000) en Burroni et al. (2003). De (Spaanse) methode van de Lis et al. (2000) stelt de cyclische invloed van verliesvoorzieningen vormen naar beneden bij. De methode van Burroni et al. (2003) werkt acyclisch, waarbij ongeacht de macro-economische cyclus een zelfde percentage worden gedoteerd aan de verliesvoorziening. De door ons voorgestelde methode van verliesvoorzieningen vormen, beweegt tegen de macro economische cyclus in. De voorgestelde methode hanteert een multiplier bij het vaststellen van de verliesvoorziening om optimaal gebruik te maken van de kennis binnen financiële instellingen ten aanzien van het risicoprofiel van hun leningenportefeuille. De multiplier is gestoeld op macro-economische variabelen (hoofdstuk 3) en wordt vastgesteld door de toezichthouder. Op deze wijze wordt de subjectiviteit van de vorming van verliesvoorzieningen verkleind. Dit komt de verifieerbaarheid van de hoogte van de verliesvoorziening ten goede en beperkt de invloed van de cyclische perceptie van kredietrisico. De in dit hoofdstuk voorgestelde methode van verlies voorzieningen treffen, stelt de hoogte van de verliesvoorziening naar beneden bij in een recessie[24] en naar boven in een voorspoedige periode. De multiplier die wordt voorgesteld in dit hoofdstuk wijkt af van de multiplier die Repullo et al. (2010) voorstellen. Repullo et al. (2010) stellen een multiplier voor ten behoeve van de kapitaalvereisten van Basel III, waarbij de multiplier dient te worden gebaseerd op de afwijking tussen de stand van het bruto nationaal product en de lange termijn trend van deze variabele. De methode, die in dit hoofdstuk wordt geïntroduceerd, stelt voor een gedeelte van de verliesvoorziening van de specifieke financiële instelling af te storten bij een Financiële Markten Stabiliteitsfonds (FMSF). Het beheer van het FMSF wordt verricht door de financiële toezichthouder (centrale bank). Op deze

[23] In sommige gevallen wordt deze inschatting ook gemaakt op basis van forecasts.

[24] Om op deze wijze de kredietverlening te verruimen. Op deze wijze wordt de invloed van een creditcrunch verkleind.

wijze wordt de correlatie tussen de solvabiliteit en de liquiditeit van een financiële instelling, welke in de literatuur onderkend wordt door bijv. Diamond & Rajan (2005), ook daadwerkelijk toegepast in de praktijk. Het gebruik van een FMSF is een beleidsmaatregel om er zorg voor te dragen dat de financiële toezichthouder invloed kan uitoefenen op de omvang van de kredietverlening, de omvang van verliesvoorzieningen en de geldhoeveelheid. Zowel Basel III als ook IFRS laten de ruimte voor aanvullende maatregelen door financiële toezichthouders. Wanneer de financiële toezichthouder het gebruik van een multiplier en een FMSF bestendigt via wetgeving, is opname op de balans van de voorgenoemde methode van verliesvoorzieningen vormen naar onze mening wel mogelijk volgens de voorwaarden van IFRS.

Macro-economisch perspectief op kredietrisico

De vorming van verliesvoorzieningen door financiële instellingen tegen de macroeconomische cyclus in, behoeft een indicator die aangeeft of dat de perceptie van kredietrisico door de financiële instellingen wordt overgewaardeerd of ondergewaardeerd. Kredietrisico is altijd aanwezig in een leningenportefeuille van financiële instellingen, echter de perceptie van het risico verschilt. Wanneer de economische omstandigheden voor een financiële instelling gunstig zijn, wordt het kredietrisico onderschat. Wanneer de economische omstandigheden voor een financiële instelling negatief zijn, wordt het kredietrisico overschat. Deze subjectiviteit in de perceptie van kredietrisico is één van de oorzaken van het cyclisch gedrag van financiële instellingen. Ondanks dat de perceptie van kredietrisico subjectief is, is het uiteindelijke resultaat van een hoge mate van kredietrisico dat niet: een hoge mate van ingebrekestellingen van kredietnemers. Het verlies dat financiële instellingen maken als gevolg van ingebrekestellingen van kredietnemers is niet zichtbaar in de macro-economische data. Maar de hoeveelheid ingebrekestellingen van kredietnemers die gevolgd worden door een faillissement zijn wel zichtbaar op landniveau. Voorafgaand aan een faillissement van een kredietnemer, is er een periode waarin de financiële instelling probeert de kredietnemer naar een veilige haven te loodsen. Het kredietrisico op de lening is gedurende deze periode reeds hoog. Het aantal faillissementen is dan ook een vertraagde indicator van de hoeveelheid kredietrisico in de financiële sector. We analyseren in dit hoofdstuk in hoeverre de business cycle indicators, uit de bestaande literatuur, onze vertraagde indicator van kredietrisico kunnen voorspellen voor de financiële sector in Nederland en de Verenigde Staten van Amerika. We gebruiken vertraagde, autoregressieve OLS regressions om de correlatie tussen de business cycle indicators en onze proxy voor kredietrisico vast te stellen. Vervolgens analyseren we via een out-of-sample forecast welke indicatoren geschikt zijn om het aantal faillissementen als percentage van het uitgezette krediet te voorspellen. Ondanks het kleine aantal observaties van de analyse, zijn de resultaten van regressies significant. De out-of-sample forecasts tonen dat een combinatie van de indicatoren credit-to-gdp gap en de stand van de aandelenbeurs met een vertraging van één en twee perioden voor Nederland de beste voorspelling van onze proxy weergeeft. De voorspellingen van onze proxy voor de Verenigde Staten zijn minder nauwkeurig en de beste voorspelling is gebaseerd op GDP growth, domestic credit growth, credit-to-gdp gap en de stand van de aandelenbeurs met twee perioden vertraging. Wij denken dat de mogelijke verklaring van de slechtere voorspelling voor de Verenigde Staten is gelegen in de navolgende reden. In Europa worden veel niet-financiële ondernemingen gefinancierd door bankleningen[25], echter in de Verenigde Staten is dit niet het geval. Hackethal & Schmidt (1999) geven aan dat dit onderscheid is gelegen in het verschil tussen een bank-based en een capital-market based financiëel systeem. Dit zou tot gevolg hebben dat de door ons gekozen proxy van het aantal faillissementen als percentage van domestic credit, niet een correcte indicator is voor de hoeveelheid kredietrisico in de financiële sector van de Verenigde Staten.

Micro-economisch perspectief op kredietrisico

De asset based lending markt is niet een frequent onderwerp van academisch onderzoek. Asset based lending is een term die wordt gebruikt voor het verstrekken van krediet op basis van onderpand in de vorm van werkkapitaal. De asset based lending markt wijkt af van de reguliere bancaire markt ten aanzien van het verstrekken van bankleningen doordat voornamelijk leningen worden verstrekt aan hoog risico kredietnemers. De asset based lending markt kent ook een vrij inelastische vraag naar leningen. Wij analyseren in dit hoofdstuk de asset based lending markt waar

[25] Zie Hackethal & Schmidt (1999). De schulden van niet-financiële ondernemingen in Duitsland (in figuur 2 pagina 8) bestaan voor ongeveer 50% uit bankleningen, waar dit percentage voor the US ongeveer 15% betreft.

twee asset based lenders leningen aanbieden aan cohorten laag en hoog risico kredietnemers. De markt kent iedere periode een verloop waarbij zowel hoog als ook laag risico kredietnemers failliet gaan en nieuwe kredietnemers zich voor het eerst op de markt begeven. In deze dynamische markt verkrijgt een asset based lender na één periode inzicht in het risicoprofiel van de kredietnemer. Wij analyseren in hoofdstuk vier op welke wijze de asset based lenders de interest vaststellen voor de verschillende groepen kredietnemers en de wijze waarop kredietnemers zich verdelen over de twee asset based lenders. We geven de volledige set van Nash evenwichten weer in deze markt. De verdeling van de kredietnemers over de twee asset based lenders kan in iedere periode worden weergegeven door een wiskundige reeks. De markt wordt gekenmerkt door adverse selection van hoog risico kredietnemers. De asset based lenders onderscheiden separate markten met kredietnemers als gevolg van de asymmetrische informatie over het risicoprofiel van de kredietnemers. Ten aanzien van de kredietnemers die niet failliet zijn gegaan en welke de asset based lender reeds één periode in de portefeuille heeft, heeft de asset based lender informatie over het risicoprofiel van de kredietnemer. Ten aanzien van de nieuw toetredende kredietnemers en de kredietnemers van de concurrerende asset based lender heeft hij geen informatie over het risicoprofiel. De asset based lender verkrijgt een positieve marge op de interest over de leningen die hij verstrekt aan de laag risico kredietnemers in zijn eigen portefeuille. De gemengde strategie van de concurrent asset based lender heeft stochastische dominantie ten opzichte van de gemengde strategie van de asset based lender met het informatievoordeel. Dit heeft tot gevolg dat de gemiddelde interest die de asset based lender met het informatievoordeel aanbiedt lager is dan de gemiddelde interest die de concurrerende asset based lender (zonder informatievoordeel) aanbiedt over het volledige bereik van de interest. De gemengde strategie van de asset based lenders hangt af van de hoeveelheid hoog en laag risico kredietnemers in een specifieke markt en de waarschijnlijkheid van een faillissement van de kredietnemers. Een toename in de hoeveelheid hoog risico kredietnemers op een markt zorgt voor een toename in adverse selection. Als gevolg van de toename in adverse selection kan de asset based lender met het informatievoordeel een hoger positief resultaat op zijn laag risico kredietnemers verkrijgen, immers de waarde van informatie over het risicoprofiel van de kredietnemers is toegenomen. We stellen vast dat de kans dat een laag risico kredietnemer van asset based lender wisselt, afhangt van de relatieve omvang en de kans op faillissement van de laag risico kredietnemers ten opzichte van de totale markt. Tevens stellen wij vast dat de interest die wordt aangeboden aan de laag risico kredietnemers toeneemt, wanneer de kans op faillissement voor de hoog risico kredietnemers toeneemt.

Finance perspectief op kredietrisico

Hoofdstuk vijf analyseert de recovery rates van beursgenoteerde obligaties, welke in gebreke zijn gebleven in de periode 1981-2011. We analyseren welke obligatiekarakteristieken van invloed zijn op de distributie van recovery rates. We hanteren de prijzen van beursgenoteerde obligaties enkele maanden na ingebrekestelling als indicator voor de recovery rate. Een obligatie met een ingebrekestellingsdatum in een NBER recessie periode heeft significant andere recovery rate dan een obligatie met een ingebrekestellingsdatum in een NBER niet-recessie periode. Het resultaat dat onderpand geen significante invloed heeft op de distributie van recovery rates is niet alleen tegen onze verwachting in, het is eveneens in tegenstelling tot de uitkomsten van reeds aanwezig onderzoek van Schuermann (2004). Onderpand zou in geval van een ingebrekestelling voor meer comfort in de uitwinning van de schuld moeten zorgen (en dus een hogere recovery rate tot gevolg moeten hebben), echter blijkt dit niet uit onze analyse. Wij veronderstellen dat deze uitkomst wordt veroorzaakt door de kwaliteit van het onderpand van obligaties (echter hebben wij daar geen verder bewijs van). We bestuderen eveneens een obligatie karakteristiek die wij "percentage lifetime" noemen. Percentage lifetime geeft een indicatie van de tijdsperiode tussen de uitgave van de obligatie tot aan de ingebrekestellingsdatum in vergelijking met de beoogde looptijd van de obligatie. Een obligatie met een korte percentage lifetime is relatief gezien, kort na de uitgave van de obligatie in gebreke geraakt. We modelleren de empirische data van de gehele distributie van recovery rates, maar ook de distributie van obligaties met verschillende obligatiekarakteristieken volgens verschillende theoretische verdelingen. We gebruiken de Beta verdeling, de afgeknotte normale verdeling en de afgeknotte Weibull verdeling voor het modelleren van de recovery rate distributies. Om vast te stellen of dat de empirische recovery rate data afkomstig zijn van één van de theoretische verdelingen gebruiken we de Kolmogorov-Smirnov test statistic en de Cramer-von Mises test statistic. In de huidige literatuur wordt voorgesteld een Beta verdeling te gebruiken voor het modelleren van de recovery rate distributie. Echter uit onze analyse blijkt dat het onderverdelen van de distributie naar de verschillende obligatie karakteristieken en het gebruik van een afgeknotte Weibull distributie voor het modelleren van de recovery rates de beste weergave van de empirische data geeft.

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About the author

Suzanne H. Bijkerk (1979) received her propedeuse in 1998 with honors at the Erasmus University Rotterdam. She received her Master of Science title at the Erasmus University Rotterdam in 2001, where she majored in Accounting and Internal Control. During seven years (1998-2005) she worked in multiple positions at Deloitte & Touche (the current Deloitte Accountants B.V.), of which the last five years at the auditing department. In 2005 she received the Dutch Certified Public Auditor (Register Accountant) certificate at the Erasmus University Rotterdam (not registered). She worked as a senior auditor for ABN AMRO N.V. at their subsidiary IFN Finance B.V from 2007 onwards. In 2008 she completed the training Insolvency Law for Financial Institutions at the Centre for Postacademic Legal Education (part of the Radboud University Nijmegen). Suzanne received the opportunity as part of the Mature Talent project in 2009 at the Erasmus School of Economics to write a PhD thesis. Her research interests are in the field of risk management for financial and non-financial institutions, financial economics, micro economics of banking, internal control and management of organizations. As of January 2013, Suzanne will be working as an assistant professor at the Erasmus School of Economics.

The presence of risk enables financial institutions to gain a positive return, but risk can also cause large losses when it is not well managed. Jorion (2007) defines credit risk as the risk of financial loss owing to counterparty failure to perform its contractual obligations. This thesis analyzes different aspects of credit risk, the mitigation of credit risk by financial institutions and how interest setting is influenced by the presence of credit risk. Chapter two introduces a new method of forming loan loss provisions for financial institutions, that takes into consideration the influence of the macro economic cycle on the solvency and liquidity of financial institutions. An indicator for the amount of credit risk in the financial sector is essential to construct a countercyclical provision for loan losses. Chapter three determines which business cycle indicators are best fit to indicate the amount of credit risk within the financial sector in The Netherlands and The United States of America. Chapter four gives an analysis of the interest rate setting behavior of two asset based lenders in a dynamic market with borrowers with different risk profiles. This chapter characterizes the complete set of Nash equilibria in a duopoly with incomplete information, learning and a dynamic borrowers' market. In chapter five we determine the influence of bond characteristics on the distribution of recovery rates. We find that the empirical recovery rate data can best be modeled using a truncated Weibull distribution.

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