MASTER THESIS

Managing corporate loan losses

A quantitative and qualitative research on Loss Given Defaults of corporate loans in emerging markets and developing countries: A FMO case study.

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Summary

This study is particularly focused on realized 'loss given defaults' (LGDs) of FMO's loan portfolio. FMO is a public-private development bank based in The Hague and supports the development of the private sector in Asia, Africa, Latin America and Central and Eastern Europe through the provision of equity and/or debt financing. Because FMO did not have insight into historical loan losses and is interested in them to improve capital adequacy and to learn from best practices and mistakes, the research question is stated as: What are realized LGDs of FMO's loan portfolio and what are their determinants?

While credit risk mainly consists of the parameters probability of default (PD), exposure at default (EAD) and loss given default (LGD); much attention in credit risk was initially given to PD only since LGD and EAD were seen as static factors and independent of PD. But, especially in the last decade, more studies dedicated attention on LGD and demonstrated that LGD ought to be seen as a systemic risk component as well.

LGD is simply determined by loss divided by EAD. But, in the study on LGD used methods and definition of default, EAD, recovery or loss are critical, because these directly affect LGDs. In this study LGD is determined by ultimate recoveries (workout LGD). This means that loss is determined by discounting all loan specific cash flows during the recovery process. As discount factor the contractual interest rate is used. Next, EAD is defined as the enumeration of outstanding amount, interest and fees at the exact moment of default and, lastly, a borrower is considered to have defaulted on a loan if (1) a scheduled interest or principal payment related to any instrument of the counterpart becomes 90 days past due; (2) a restructuring is employed as a means of preventing an instrument of the obligor from becoming delinquent; (3) FMO has filed for the obligor's bankruptcy or (4) FMO takes an account-specific provision.

Possible determinants of LGD are identified by a literature review and are divided by six groups, which subsequently can be divided by being manageable or unmanageable. These are presented in the table below. To structure the study two templates are developed, called *loss file* and *highlights*. The loss file is designed and used for the determination of LGD and measurement of determinants on loan level, while the highlights is used for case studies on client level.

Manageable determinants of LGD	Unmanageable determinants of LGD
Recovery process characteristics	Macroeconomic factors
Business connection	Industry conditions
	Borrower characteristics
	Loan characteristics

After months of data gathering with the use of the two templates, 73 loans of 52 clients are investigated on realized LGDs. The average LGD of the sample is 22%, which is bimodal distributed with a magnitude of loans with a very low LGD (< 10%) and a little magnitude of loans with a very high LGD (> 90%). With univariate and multivariate analyzes based on linear regression with the least-squares method the measured determinants are analyzed in their relation with LGD.

We found relevant results for loan characteristics, borrower characteristics, recovery process characteristics, business connection and the probability of default in relation to LGD with univariate analyzes. Especially the seniority and collateral of the loan, clients' solvency and liquidity prior default, support from other organizations, default type, multiple defaults, liquidations and incorrect judgments are strongly related to LGD following the single linear regressions. Next, with a multiple linear regression we found that the seniority of the loan, the default type and whether a loan experiences multiple defaults, liquidation or an incorrect judgment are strongly related to LGD.

With the case studies by the use of the highlights-template, specific key causes of default and key determinants of loss are identified and grouped. As a result, we see that borrower characteristics and macroeconomic or environment issues play an important role in the cause of default. Finally, as key determinants of loss we see that borrower characteristics, macroeconomic or environment issues and the recovery process play an important roll.

Following our result from the quantitative (regressions) and qualitative (case studies) analyzes we conclude that the manageable and unmanageable factors during the recovery process affect LGD. Especially in the case studies we see that specific decisions or action by the bank affect LGD. Therefore, we recommend FMO to continue to increase the LGD-sample in order to strengthen quantitative analyzes. This can be easily done due to the standardization via the two templates. Thereafter, in the long term, the LGD-scorecard can be improved by incorporating relevant determinants such as borrower characteristics. At last, the highlights per client should be studied within the bank to learn from best practices and mistakes.

With this research we tried to emphasize that determining and studying corporate loan losses is not straightforward. As a result, two templates are designed to standardize and structure the determination and monitoring of default cases for FMO, which will be embedded in the organization. This is necessary for managing corporate loan losses. Since LGD-studies are often based on limited data or on data of one institution, further research is needed on combining default and LGD-data in order to strengthen quantitative results. Secondly, we recommend further research on different methods of quantitative analyses when the sample size is significantly increased. Lastly, recovery process characteristics and the business connection between borrower and lender are underexposed in current LGD-studies. With this research we tried to indicate that the management of the bank matters in terms of realized LGDs. Therefore, we encourage further research on the management of recovery processes.

Preface

In 2006, directly after high school graduation, I went to the University of Twente and moved from a small village at the coast to the city Enschede. After getting my Bachelor of Science in Industrial Engineering and Management, I continued my student life in Enschede by getting my master degree in Financial Engineering and Management. Now, exactly seven years later, I am writing my last words of my master thesis, living again in the small village at the coast.

Since this master thesis also means that this is the end of my student life, I am very grateful that I could have an intensive, active and of course joyful life in the past seven years as a student in Enschede. Therefore, I really would like to thank my parents Dick en Bets for their never-ending support. Because of you I was able to have such a nice and educational time.

Furthermore, I would like to thank specific persons that supported me during my master assignment. First, I want to thank the colleagues of Risk Service Center at FMO for their support and giving me a very instructive and nice 6 months as intern. Especially Dietske Simons for her support and giving me the opportunity to conduct this research within FMO, and Walter van der Wees for his support in the completion of my thesis. It was a real pleasure to do this research for and within FMO and I am really looking forward to the 1st of September to start with my first job as Risk Management Officer at FMO.

Lastly, I want to thank Drs.ir. A.C.M. de Bakker and Dr. B. Roorda for their support and supervision. I always received positive feedback and you were really thinking along. This made the whole process of writing my master thesis easier and more fun.

Laurens Eijking

Castricum, June 25, 2013

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CHAPTER 1

Introduction

Insight in historic defaults and losses is key to financial institutions. Historic information may explain causes and consequences and therefore can be used to learn about and predict future happenings. In case of providing loans to organizations the likelihood that the provided loan will be repaid is very important. The involved risk is called credit risk and the likelihood is determined by the probability of default (PD). A default occurs when the counterparty is not able to meet its financial obligations (i.e. repay loan or pay interest). However, this does not mean that all the outstanding money (exposure) is lost when the counterparty is in default. Probably, the counterparty is able to repay a certain percentage of the exposure at default (EAD). The percentage of the EAD that is lost is called the loss given default (LGD).

The PD, EAD and LGD are main indicators of possible losses due to client defaults and thus are very important for the incurred credit risk. Therefore, when for example a bank provides a new loan the PD, EAD and LGD need to be determined in advance. For the continuity of a bank it is necessary to have sufficient capital available to absorb unexpected losses or shocks. The global financial crisis that started in 2008 and, inter alia, led to the fall of Lehman Brothers in September 2008 emphasized the importance for banks to have sufficient capital available. Consequently, it is important to determine accurate PDs, EADs and LGDs and monitor them in order to control a sound economic capital (EC). However, the predictions of the PD, EAD and LGD are not straightforward and involve thorough analyzes. This research is particularly focused on realized LGDs of the loan portfolio of FMO.

1.1 Background

FMO is a public-private development bank founded in 1970 that is based in The Hague. The Dutch government holds 51% stake and therefore is the major shareholder. Other shareholders include large Dutch banks, employers' associations, trade unions and individual investors (FMO, 2013). FMO supports sustainable private sector growth in developing countries and emerging markets by investing in ambitious companies. FMO believes a strong private sector leads to economic and social development, empowering people to employ their skills and improve their quality of life. Therefore, FMO's higher goal is:

"We empower entrepreneurs to build a better world."

FMO does this by supporting the development of the private sector in Asia, Africa, Latin America and Central and Eastern Europe through the provision of equity and/or debt financing. FMO's relationship with clients is long-term and therefore FMO is seen as a partner in financial development. FMO complies with internationally accepted banking standards, is supervised by the Dutch Central Bank and holds an AAA rating from Standard & Poor's (FMO, 2013). The investments of FMO come from two sources, i) for its own account (called FMO A) and ii) through the management of government funds. The government funds include MASSIF, Infrastructure Development Fund (IDF), Access to Energy Fund (AEF), and Facility Emerging Markets (FOM) and are all dedicated to specific sectors in poorer or least-developed countries.

The committed portfolio of FMO in 2012 amounted to EUR 6.3 billion of which EUR 1 billion equity investments and EUR 0.8 billion government funds, while FMO's own share capital was EUR 1.8 billion. In 2008, the committed portfolio and share capital amounted to EUR 3.6 and EUR 1.2 billion respectively, and so FMO is a growing institution. Historical figures of FMO's financials and committed portfolio per product group, sector, region and currency can be found in Appendix A.

1.2 Research purposes

Before this research, FMO did not have historical information about LGDs of its loans. However, FMO is interested in historical LGDs because it wants to improve the capital adequacy and wants to learn from best practices and mistakes. Improving the capital adequacy improves the monitoring of the financial health and therefore the continuity of the bank, while learning from best practices and mistakes from the past is helpful when doing new business. So, the reasons for FMO to understand historical LGDs are:

- Capital adequacy
- Learning from best practices and mistakes

The capital adequacy can be improved by improving the predictions of LGDs per loan. At this moment, FMO uses a simple scorecard-method to determine the LGDs for new loans. This scorecard is only based on the seniority and security of the corresponding loan. But, since FMO does not monitor realized LGDs, FMO does not know in detail if the LGD-scorecard is representative of incurred losses. The first identified problem is therefore what realized LGDs are. Identifying the LGDs and comparing them involves quantitative analyzes.

In addition to the performance, FMO does not know how the LGD-scorecard could then be improved. This problem encompasses the 'learning from best practices and mistakes' and involves why realized LGDs are for example high or low or deviate much from set expectations. This may lead to factors that influence the LGDs, called determinants, and therefore should be monitored to predict new ones. Furthermore, the question why clients went into default in the first place is very meaningful for the learning experience.

1.3 Research question and variables

Following the problem definition the research question is twofold. The first part involves the determination of historical LGDs and the second part involves the study on possible determinants of LGD, which can be useful to predict new ones. And so, the research question is stated as:

What are realized LGDs of FMO's loan portfolio and what are their determinants?

In order to answer this question, six sub questions are specified that divide the research question into manageable parts. These are presented in Table 1. The first two sub questions are part of the starting phase (set up) of this research and involve how LGD should be calculated and which determinants should be monitored. By means of a literature research on LGD-studies relevant factors and major constraints in LGD-research are identified, which subsequently are used to set up the methodology of this research. The third sub question involves the identification of the units of analysis in this research. These are the loans in FMO's loan portfolio that went into default. The fourth sub question is part of the execution of the research. Here, the dependent variable (LGD) and independent variables (possible determinants) are determined and scored. Next, sub question five involves analyzes on the dependent and independent variables. We want to know how the possible determinants relate to realized LGDs. Finally, when the LGDs and important factors are known, we ask ourselves how FMO can learn from this research and the investigated cases. This is covered in the last question, sub question six, which is a reflective and concluding question.

Research Question	**What are realized LGDs of FMO's loan portfolio and what are their determinants?**
Set up	1. How should we calculate LGDs and how can these be determined in a structured way? 2. What are possible factors (determinants) that affect LGD and how can these be measured?
Execution	3. Which loans of FMO are useful for this research? 4. What are the LGDs of these loans and how do the identified determinants score?
Analyzes	5. How do the identified determinants relate to the determined LGDs?
Reflection	6. How can FMO learn from this research and the investigated cases?

Table 1 – Research question and sub questions

1.4 Outline

The remaining of this thesis is structured as follows. In Chapter 2, existing studies on credit risk and in particular on LGD are discussed. This chapter provides an overview of current findings and challenges in the field of LGD. Subsequently, the used methodology in this research and possible determinants of LGD are presented in Chapter 3. In Chapter 4 the sample of the defaulted loans of FMO is set out and analyzed by means of size, industry and region. Successively, the findings of the analysis of the possible determinants of LGD are discussed in Chapter 5. Chapter 6 concludes and the thesis ends with a discussion and recommendations for further research in Chapter 7.

CHAPTER 2

Literature review

Determining and monitoring LGDs is not straightforward. While LGD received little attention before, it has received much more attention in the last two decades. Especially in the field of what factors have a significant effect on realized LGDs.

This chapter sets out the literature research that is conducted to identify relevant definitions, methods and results of studies in the field of credit risk and in particular studies on LGD. To identify relevant articles a structured literature research is conducted which is thoroughly explained in Appendix B. This chapter first describes general findings in the field of credit risk. Thereafter, we elaborate on important definitions in the determination of LGD and discuss different findings of LGD-determinants. The chapter ends with a conclusion and overview of the literature review.

2.1 Credit Risk

In the last decades, credit risk has received much attention in the financial world, as well from financial economists, bank supervisors as from practitioners whose interest lies in accurate pricing purposes of financial products (Altman, et al., 2001). Discussions about minimal capital requirements resulted in the first capital accord in 1988, known as Basel I. While this original accord focused mainly on credit risk, it is since been amended to address other risks as well, such as market risk, operational risk, and to a lesser extent interest rate, liquidity, legal and reputational risks (BIS, 1999, 2001, 2006). However, as Altman et al. (2004) describes, studies within the field of credit risk developed the understanding of credit risk what led to changes in the way of monitoring and modeling it. While credit risk mainly consists of three parameters: (i) the probability of default (PD), (ii) the exposure of default (EAD), and (iii) the loss given default (LGD); much attention was initially given to PD only (Frye, 2000b, 2000a; Altman, et al., 2001; Frye, 2003; Grunert & Weber, 2009).

Altman et al. (2001) argue that the focus on PD was because of the tendency of credit pricing models and risk management applications to focus on systematic risk components of credit risk only where LGD and EAD were seen as static factors and independent of PD. However, in the last two decades and especially the last decade, more studies dedicated attention on LGD and demonstrated that LGD ought to be seen as a systemic risk component too and correlates with the PD component (Frye, 2000b, 2000a; Altman, et al., 2001; Hu & Perraudin, 2002; Altman, et al., 2004; Düllmann & Trapp, 2004; Emery, et al., 2004; Miu & Ozdemir, 2006; Acharya, et al., 2007; Chalupka & Kopecsni, 2008; Bade, et al., 2011; Khieu, et al., 2012).

The majority of studies on LGD is based on default data of bonds (Carey, 1998; van de Castle & Keisman, 1999; Fridson, et al., 2000; Frye, 2000b; Altman, et al., 2001; Carey & Gordy, 2001; Hu & Perraudin, 2002; Frye, 2003; Düllmann & Trapp, 2004; Acharya, et al., 2007; Guo, et al., 2008; Guo, et al., 2009; Bade, et al., 2011; Mora, 2012), while studies on LGDs of bank loans are available to a lesser extent since bank loans are private instruments and so information is hardly available (Dermine & Carvalho, 2006; Chalupka & Kopecsni, 2008). Consequently, studies on loan LGDs rely mostly on data of a single financial institution. However, it seems that in the very recent years LGD of bank loans is given much more attention, probably due to the financial crisis that started in 2008. Furthermore, studies on LGD are mainly based on data of American or West-European markets. Data of emerging or developing markets is to our understanding, very scarce. In total, only two studies on LGDs in emerging markets are found (Felsovalyi & Hurt, 1998; Koŝak & Poljŝak, 2010).

The remaining of this chapter discusses findings of studies on LGD and sets out relevant strengths and weaknesses in the field of LGD-research. Overall, three issues in LGD-studies come forward, i) many LGD-studies rely on default data of corporate bonds rather than on bank loans, ii) there exist differences in used definitions in the determinations of LGD, and iii) there are generalization issues of loan LGD-studies due to specific institutional or limited data.

2.2 LGD-determination: definitions and measurements

The most relevant weakness in LGD-research is the diversity in the definition and determination of LGD, such that studies are hardly comparable. Subsequently, when presenting a study one should be clear about which definitions are used (Chalupka & Kopecsni, 2008). In order to identify relevant definitions we deconstruct loss given default. First, the LGD is the inverse of the recovery rate (LGD = 1 - RR), and so studies on RR investigate the same as studies on LGD. Second, LGD is calculated by dividing the incurred loss by the exposure at default (EAD), and so LGD is dependent on the definition of the two factors loss and EAD. However, the LGD can only be determined when the counterparty is in default. Consequently, a third factor is involved in LGD, which is the definition of default. The remaining of this section discusses definitions of default, EAD, recovery and loss.

2.2.1 Definitions of default

The Bank for International Settlements (BIS) gives clarity about the definition of default. In the Basel Accords multiple conditions are provided on which ground a specific counterparty should be seen as in default (BIS, 2006). The complete definition is given in Appendix C. However, while the regulatory definition of default is clear, the used definitions in studies still diversify mostly because of limited available information of the used samples, like in the studies of Carty & Lieberman (1996), Gupton, et al. (2000), Emery, et al. (2004), and Dermine and de Carvalho (2006).

A second problem with Basel's definition of default is that the conditions are based on two sets of conditions: one, "the bank considers that the obligor is unlikely to pay [in full]", and two "the obligor is past due more than 90 days on any material credit obligation" (Bennett, et al., 2005; BIS, 2006). Consequently, the first set of conditions is subjective, while the second set of conditions is objective. Because the first set of conditions is subjective, studies that use exactly the same definition of default but use different samples of different financial institutions are still difficult to compare because the financial institutions may differ in their considerations of when a client is in default. Therefore, the different studies are representative for the respective financial institution, but not for others, which makes the generalization of findings limited.

Therefore, to make reliable comparisons between LGD studies, the definitions of default must be clear since it directly influences LGD and direct benchmarking exercises make little sense if the definitions of default differ. Furthermore, LGD estimates must be consistent with the regulatory definition of default of Basel II and should be consistent with the definition used when estimating PDs (Bennett, et al., 2005). As

Bennett, et al. (2005) argues, this is needed to obtain useful and sensible values for economic capital and expected loss.

2.2.2 Definitions of EAD

The second important definition in determining LGDs is the exposure at default (EAD). Unfortunately, studies on LGD often provide the definition of default and method of determining the loss or recovery, but do not provide the exact definition of EAD. It must, however, be noted that differences in interpretation of EAD are possible. Some may interpret exposure as the current outstanding amount (principal) of the loan, while others may add the outstanding interest and outstanding fees that the client still needs to pay.

In the standardized approach of Basel II that FMO uses, the EAD is determined differently. It is defined as the current principal amount plus 50% of the committed but not disbursed amount. If, for example, a bank provided a client a loan of EUR 10 million and the client only used EUR 5 million of it, the EAD amounts EUR 7.5 million following the standardized approach. If only EUR 2.5 million is finally recovered, the LGD results in 67%. But, we obtain a LGD of 50% if only the principal is used as EAD, which is significantly different.

The central question in defining the EAD is, to our understanding, what the bank can actually lose from a client directly when it defaults. So, when the bank does nothing, what amount will the bank lose at the exact moment of default? This is, however, not in compliance with the definition of EAD following the standardized approach of Basel II.

2.2.3 Definitions of Recovery or Loss

The third relevant factor in the determination of LGD is the incurred recovery or loss. Recovery is simply defined as the income that is generated on a loan specific account after the occurrence of default. The incurred loss is then the EAD minus the recovery.

Overall, two different methods are used in studies on LGD. The first method is called 'market LGD', where the loss is determined by the market price of the financial product after the event of default, mostly the price 30 days after default (van de Castle & Keisman, 1999; Gupton, et al., 2000; Hu & Perraudin, 2002; Frye, 2003; Emery, et al., 2004; Acharya, et al., 2007; Mora, 2012). The second method is called 'workout LGD', which is based on ultimate recoveries (Asarnow & Edwards, 1995; Carty & Lieberman, 1996; Felsovalyi & Hurt, 1998; Dermine & Carvalho, 2006; Chalupka & Kopecsni, 2008; Grunert & Weber, 2009; Bastos, 2010; Koŝak & Poljŝak, 2010; Khieu, et al., 2012). This means that actual generated cash flow in the post-default period is used to determine the actual realized loss on the financial product. Consequently, the generated cash flows need to be discounted by a proper discount factor.

Currently, there is no general accepted method and so the debate about which method is the best is still going on. Both methods have some advantages and some disadvantages. The major advantage of the market LGD is that bid and ask prices shortly after the event of default represent the involved risk in a proper way. However, macroeconomic factors may have too much impact on the bid and ask prices, which eventually cause biased losses. But the major drawback of market prices is that it is based on the prices of the secondary market and many financial institutions are not active in this market, which for example applies to FMO as well. Therefore, this approach is common in studies on recoveries on corporate bonds defaults, but less common in studies of loan recoveries (e.g. Gupton, et al., 2000), since prices may not be available (Grunert & Weber, 2009; Bastos, 2010; Koŝak & Poljŝak, 2010).

The major benefit of the workout LGD is that it represents the actual incurred loss of the specific financial product. The major drawback is that there are different ways in determining workout LGD, mostly concerning the appropriate discount factor, and there still is an important debate about how to choose one (Bennett, et al., 2005). Following Bennett et al. (2005), the appropriate discount rate is theoretically the risk-appropriate rate. Some researchers use historical rates, while others use current rates mainly because historical rates were not accessible (Asarnow & Edwards, 1995; Carty & Lieberman, 1996; Koŝak & Poljŝak, 2010). Historical rates are based on original contractual rates or risk-free rates plus a certain spread to cover the involved risk. Current rates, on the other sides, are fixed rates that are often determined by averages of risk-similar rates during that same period. By following the motivations of using which discount factor in existing literature, discounting with the contractual interest rate seems to dominate (Asarnow & Edwards, 1995; Carty & Lieberman, 1996; Koŝak & Poljŝak, 2010; Khieu, et al., 2012).

2.2.4 Conclusion on LGD-determinations

Determining LGDs of defaulted financial instruments requires specific attention to used definitions and methods, since these can highly influence the results of the study. Unfortunately, available studies on LGD in the literature are not all that clear about used definitions, especially on the definition of default and definition of EAD. Used methods to calculate LGDs are well provided, as we will see in the next section when specific studies are discussed.

2.3 Determinants of LGD

This section describes findings of studies on LGD and factors that affect the loss of financial products in the event of default, called LGD-determinants. These determinants can be categorized into different groups of factors, such as industry characteristics, macroeconomic characteristics, loan characteristics, borrower characteristics, the recovery process and business connection between the lender and borrower. In the next subsections we elaborate on these group factors by providing findings of existing literature. Furthermore, these group characteristics can be divided by external factors and internal factors. Industry characteristics and macroeconomic characteristics cannot (easily) be influenced by a single bank and therefore are seen as external factors. Loan characteristics, borrower characteristics, the business connection and recovery process can be influenced by means of loan agreements and intensive management, and therefore are seen as internal factors. An overview of identified relevant studies is presented in Appendix D.

2.3.1 First studies on bank loan LGD

As already discussed, studies on LGD relied mostly on bonds than on defaulted loans. The first identified LGD studies on loans are the studies of Asarnow & Edwards (1995), Carty & Lieberman (1996), and Felsovalyi & Hurt (1998). The study of Asarnow & Edwards (1995) is based on 831 defaulted loans at Citibank over the period 1970-1993. They found that the recovery rate is bimodal, with a concentration of recovery rates on either low or high recovery. They reported an average LGD of 35% and used ultimate recoveries to determine the LGDs. Asarnow & Edwards (1995) concluded that the LGDs over the period of 24 years were relative stable, while they argued that the PD is a more volatile and cyclical component. Furthermore, they concluded that loan-LGDs are significantly lower than bond-LGDs due to a combination of the presence of loan security and the active management of problem loans.

The study of Carty and Lieberman (1996) confirms the difference between loan recoveries and bond recoveries. Their analysis is based on 58 borrowers with one loan per borrower over the period 1989-1996 in the U.S., which was provided by Moody's. They found an average LGD of 29%, while the LGDs are determined by secondary market prices. The median LGD of their sample is 23%, and so there is a magnitude of loans with lower losses, just like Asarnow & Edwards (1995) shows. Because of the development in secondary markets for loans in the nineties, Moody's began assigning credit ratings to bank loans in 1995. In assigning credit ratings, the seniority and involved security of the loan were important inputs where the more senior and the higher the security coverage, the better the credit rating. By comparing the loan recoveries with bond recoveries, Carty & Lieberman (1996) concluded that these inputs matter. Furthermore, Carty & Lieberman (1996) performed an analysis on 24 loans by using ultimate recoveries instead of market prices and found an average LGD of 21%, with a median of 8%. By dividing the loans by size, they showed that larger loans have a higher LGD than smaller loans, combined with a higher standard deviation. However, because of the small difference and low sample size over a short workout period, these are not significant results. They argue that the difference in LGD between market LGD and workout LGD is caused by the different used methodologies and samples.

In 1998, Felsovalyi & Hurt (1998) completed a research on 1,149 commercial and industrial bank loans of Citibank that defaulted from 1970 to 1996 in 27 countries in Latin America. To our understanding, this is the first research on LGD based on non-U.S. data. Felsovalyi and Hurt (1998) found an average LGD of 31.8% with a large number of loans with small losses and a small number of loans with losses approaching or exceeding 100%. In their research, LGD is defined as "the present value of all costs of credit incurred on a loan through the full workout process, expressed as a percentage of the initial default amount" (Felsovalyi and Hurt, 1998, p. 2). Because loan-specific contractual lending rates were not available, they used yearly average interest rates on non-U.S. commercial and industrial loans as discount factor. Unfortunately, the definition of default and EAD is not provided. The factor that seems to affect the LGDs is the size of the loans. Typically, smaller loans tend to have a higher recovery, and so a lower LGD than larger loans, just as the study of Carty & Lieberman (1996) suggested. Furthermore, while Felsovalyi and Hurt (1998) did see increases and decreases in the number of defaults during economic cycles, the LGD seemed not to reveal any changes. At last, LGDs of loans that defaulted during sovereign events, like strong devaluations, were not different of other loans that defaulted during other periods.

However, around the turn of the millennium, multiple studies appeared that specifically investigated the relation between default rate and recoveries. Mainly because of the noticed parallel increase of default rates and decrease of recovery rates in the 1999-2001 period (Altman, et al., 2001). Altman, et al. (2001) provides a good overview of the studies of Fridson, et al. (2000), Gupton, et al. (2000), Jokivuolle & Peura (2000), Frye (2000a, 2000b), Carey & Gordy (2001), and Jarrow (2001) and provides extra evidence for the positive relation between default rates and LGDs, and so the supply of defaults seems to affect recovery rates. While the majority of these studies rely, however, on data of public debts, Gupton, et al. (2000) and Jokivuolle & Peura (2000) particularly focused on bank loans. Jokivuolle & Peura (2000) suggest a model where collateral value is correlated with the PD and therefore correlates with the LGD. However, they found the counterintuitive results that expected LGD decreases when PD increases. The reasons for this might be that collateral tends to be uncorrelated with the clients assets and the collateral coverage in their sample differed (i.e. not all loans were fully collateralized).

The first published study on LGDs of European bank loans is conducted by Dermine & Carvalho (2006). Their study is based on 374 loans granted to SMEs, provided by Banco Comercial Português, which became nonperforming between June 1995 and December 2000. Among other things, their data show a bimodal distribution with many observations with a very high or very low recovery and an average LGD of 29%, which are quite similar as the results of Asarnow & Edwards (1995), Carty & Lieberman (1996) and Felsovalyi & Hurt (1998). In their analysis, Dermine & Carvalho (2006) determined recoveries based on ultimate recoveries including direct and indirect costs, discounted by the interest rate charged. Because of data availability, only clients that were past due more than 90 days on any credit obligation were included in the sample. With a log-log model, Dermine & Carvalho (2006) determined that the size of the loan (negatively related), the types of collateral/guarantees, the year of recovery and the industry sector are explanatory variables of loan recoveries. Interesting to note is the low established recovery in 1999 due to internal reorganization of Banco Comercial Português. Furthermore, economy factors, lengths of relationships and interest rates were non-significant and therefore seem not to be explanatory variables of loan recoveries. In the following sections we elaborate on the specific group of factors.

2.3.2 Industry characteristics & Macroeconomic factors

Industry characteristics and macroeconomic factors are closely related, since they either can strengthen or weaken each other. Industry characteristics that seem to affect LGDs are the type of industry sector and industry distress. Identified economic factors are the rate of default, GDP (growth), and differences in legal systems.

Following the studies of Hu & Perraudin (2002), Dermine & Carvalho (2006), Koŝak & Poljŝak (2010), and Mora (2012) the LGD differs between different types of industry sectors and so the type of industry sector might affect the LGD. The differences are mainly explained by the differences in types of assets between companies of different sectors. For example, recovery rates of defaulted debt in the utilities sector are relatively high, because utilities are natural monopolies and often have many tangible assets that can be easily sold (Mora, 2012). On the other hand, recoveries on defaulted debt in the financial sector are relatively low, but this is mainly because of high contagion risk and so is associated with higher default rates. While differences between industry sectors are clear, not all studies found significant differences in recoveries between industry sectors. Gupton, et al. (2000) did, for example, not find significant differences between broad industry groups in their study, while they argue that differences indeed seem logic. Reasons for the insignificance might be the strong focus on bank loans and relatively small sample size of 121 clients in the study of Gupton, et al. (2000). Consequently, they conclude that industry sectors are important and need more investigation.

Acharya, et al. (2007) analyzed the effect of industry-wide distress on creditor recoveries on more than 300 defaulted loans and bonds of non-financial, public and private companies in the United States over the period 1982-1999, which were provided by S&P's Credit Pro database. For bank loans they report an average LGD of 19%, while senior secured bonds have an average LGD of 41%, senior unsecured 44%, senior subordinated 66%, subordinated 73% and junior subordinated 82%. Acharya, et al. (2007) found that creditors recover less if the industry is in distress and non-defaulted firms in the industry are illiquid. They defined an industry to be distressed if the median stock return for this industry in the year of default was less than or equal to -30%. Their evidence suggests that the recoveries fall due to a downward revision in company's assets and the financial constraints that industry related companies face. The magnitude of the industry distress factor is about half the relative effect of seniority of the instrument (i.e. senior versus subordinated debt). In their OLS-regression Acharya et al. (2007) used contract characteristics, firm characteristics, and multiple industry characteristics. Seniority and collateral, firm and industry profitability seem to affect creditor recoveries as well. Furthermore, Acharya, et al. (2007) indicated that defaulted companies in distressed industries are more likely to emerge as restructured companies than to be acquired or liquidated, and spend longer time in bankruptcy. They concluded that the determinants of risk of default and the risk of recovery are positively, but not perfectly, correlated. In their study, the recoveries are based on prices at emergence, and so are based on market LGD. Unfortunately, the definition of default and EAD are not well provided and thus unclear, which causes difficulties for generalizing their findings. The negative effect of industry distress on recovery is also recognized by Carey (1998) cited in (Chalupka & Kopecsni, 2008), Frye (2000b), Hu & Perraudin (2002), Emery, et al. (2004), Khieu, et al. (2012) and Mora (2012).

Jon Frye, a senior economist at Federal Reserve Bank of Chicago, performed multiple studies on the relation between default and recovery (Frye, 2000b, 2000a, 2003), which were all published in Risk Magazine. In Frye's early articles (2000a, 2000b) he particularly criticized used credit risk models (such as CreditManager or CreditRisk+), since these focused on default probability and so simple recovery assumptions were made. Frye (2000b) argues that if banks depend on such models, they might enter a severe downturn holding too little capital because if economic downturn is severe the rate of default will go up while the recovery rate of defaulted loans will be lower. Eight years later Lehman Brothers fell due to high losses (mainly because of the continuing subprime mortgage crisis) and capital shortage. In the studies, Frye used the Moody's Default Risk Service database, which contained information about debt issues rated by Moody's since 1970. The recovery rates were based on market prices one month after the first occurrence of a default event. Frye (2000b) showed that there is significant synchrony between default and LGD. Furthermore, Frye (2003) found that low LGD debt types are more sensitive to economic downturn than higher LGD debt types, because there is more downward risk. Consequently, this has implications for stress testing, capital models and pricing of credit risky assets (Frye, 2003).

The study of Hu and Perraudin (2002) also concludes that there is a relation between defaults and recoveries. They conducted a research on quarterly default rates in relation to average recovery rates, and recoveries tend to be lower when default rates are higher. Hu and Perraudin (2002) used date of 1,422 default observations of Moody's-rated, long-term bond defaults from financial institutions, industrials, transportations, utilities and sovereigns between 1971 and 2000, which were provided by Moody's. To analyze the correlation between default and recovery rate, Hu and Perraudin (2002) filtered the recoveries by estimating standardized recovery rates with the help of four variables. They filtered the data by industry, region (domicile), seniority and presence of support from other organizations, since these variables seemed to affect the recovery rates as well.

The very recent study of Mora (2012) on defaulted U.S. corporate debt securities over the period 1978-2010 (provided by Moody's) also confirmed the dependency of macroeconomic factors on recovery rates. However, Mora (2012) provides a more complete picture by arguing that macroeconomic and industry factors are related and can cause distressed scenarios for typical industry sectors. For example, a drop in GDP can cause problems for furniture and luxurious sectors, since consumers are expected to cut back more on these purchases. Khieu, et al. (2012) also recognizes GDP growth as an explanatory variable of LGD. Secondly, an increase of default rates causes an increase of illiquidity in the market, which can affect the fundamental economic worth of company's assets and therefore can affect recovery rates. A third factor that may affect recoveries is specific country legal systems. Just as the study of Franks et al. (2004), cited in (Grunert & Weber, 2009), recoveries differ between France (56%), Germany (67%) and UK (92%) because legal systems across countries give banks different legal power to influence outcomes (Mora, 2012).

2.3.3 Loan characteristics

Loan characteristics come forward in several studies as relevant determinants of LGD. Specifically, the size of the loan or EAD, collateral coverage, type of collateral, seniority and year of origination are found as significant determinants of LGD (Felsovalyi & Hurt, 1998; Gupton, et al., 2000; Emery, et al., 2004; Dermine & Carvalho, 2006; Acharya, et al., 2007; Chalupka & Kopecsni, 2008; Bastos, 2010; Khieu, et al., 2012). The study of Chalupka & Kopecsni (2008) focused on counterparty related, contract related and collateral related factors and furthermore used several model techniques in order to find a good fit. Their study is based on historical closed files of an anonymous European commercial bank over the period 1989-2007. Higher proportion of collateral and specific collateral classes, like land, cash and real estate, seemed to have a strong positive relationship on loan recovery, while the year of origination and the length of the business connection have a negative relation. Secondly, the correlation of EAD and loan recovery seemed to be negative, which is also indicated by Felsovalyi & Hurt (1998), Emery (2004), Dermine & Carvalho (2006), Bastos (2010) and Khieu et al. (2012). However, Asarnow & Edwards (1995), Carty & Lieberman (1996) and Franks et al. (2004) did not find a significant relation between EAD or the size of the loan and recovery and Koŝak & Poljŝak (2010) even found a positive relation between the size of the loan exposure and recovery, but the reason for this can be found in the differences of collateralization between the small and large loans.

While the study of Bastos (2010) mainly focused on testing different models, some determinants were identified with a parametric regression of the recovery rate as a function of loan and firm characteristics. The analysis is based on the same data as Dermine & Carvalho (2006); 374 loans granted to SMEs, provided by Banco Comercial Português, which became nonperforming between June 1995 and December 2000. Their first remark is that the size of the loan has a negative effect on recovery rates, which means the higher the size of the loan, the lower the recovery. Other statistically significant results are the positive impact of collateral and the age of the company, and the negative impact of personal guarantees and a poor creditworthiness. Bastos (2010) describes that a possible explanation for the counterintuitive result of personal guarantees is that low risk clients may be exempt from providing personal guarantees.

The major finding of the study of Gupton et al. (2000) is the difference in the recovery of senior secured and senior unsecured bank loans. The secured loans had an average recovery rate of 70%, while the unsecured loans had an average of 52%. Furthermore, the volatility in recovery rates of the secured loans was lower than the volatility in recovery rates of the unsecured loans, but the range of valuation is broadly dispersed in both sub samples. The analysis of Gupton, et al. (2000) is based on 181 defaulted bank loans of 121 issuers in the U.S. between 1989-2000, which was provided by Moody's. Recoveries were based on market prices and most of the borrowers involved formal bankruptcies. Next to the securitization, Gupton et al. (2000) paid attention to the effect of borrowers having multiple loans, resolution time, and industry groups. They found that the recovery is lower only if borrowers have multiple loans regarding unsecured loans, and that defaults with average LGD are among the longest to resolve. Remarkably, they did not find significant influence of industry groupings on LGD.

In the very recent study of Khieu, et al. (2012) loan characteristics seemed to be more significant with recovery than borrower characteristics. Particularly, the loan type, the presence and type of collateral tend to be factors that affect recovery rates. The positive effect of collateral is confirmed by Castle & Keisman (1999), Dermine & Carvalho (2006), Acharya (2007), Chalupka & Kopecsni (2008), Grunert & Weber (2009), Bastos (2010), Koŝak & Poljŝak (2010) and Mora (2012). Especially collateral with a high liquidity factor tend to have a high impact on recovery, since these can be easily turned into cash flows. In their study, Khieu et al. (2012), incorporated diverse factors related to loan characteristics, borrower characteristics, recovery process characteristics, and macroeconomic and industry conditions. The study is based on 1,364 observations of North American commercial and industrial firms over the period 1987-2007, provided by Moody's Ultimate Recovery Database. While Khieu, et al. (2012) used ultimate recoveries for their analysis, they did compare recoveries based on market prices with ultimate recoveries and concluded that market prices are biased and inefficient predictors of ultimate recovery.

Besides the size of the loan exposure and the type of collateral, Koŝak & Poljŝak (2010) also indicated the maturity of a loan as an explanatory variable of recovery. The loan's maturity is already taken into account by almost all banks, since it is an important factor in calculating the price of a loan. Because short-term loans have lower uncertainty (less things can happen due to shorter time), the interest rates are lower than for long-term loans. However, Koŝak & Poljŝak (2010) found that short-term loans have higher average losses (30%) than long-term ones (23%) , no matter if they are secured or not. The reason for this is that short-term loans experience worse collateral types and therefore higher losses (Koŝak & Poljŝak, 2010). The analysis of Koŝak & Poljŝak (2010) is based on 124 loans of a commercial bank operating in Slovenia that defaulted in the period from 2001 to 2004. And so, after the study of Felsovalyi & Hurt (1998), this is the second study focused on loans of emerging markets, and to our understanding this is the only LGD-study on loans provided in the Eastern European banking markets. In their study, Koŝak & Poljŝak (2010) defined default only as clients that were 90 days past due any payment obligation, and used ultimate recoveries to calculate the LGDs. Since contractual rates were not available they took the average interest rate on Slovenian

Tolar denominated loans for the 2001-2005 period as an alternative. Other significant results were the type of industry of the client, the last available client rating before default and the method of recovery.

2.3.4 Borrower characteristics

Besides the correlation between LGD and the size of a loan, Felsovalyi & Hurt (1998) find a negative correlation between LGD and the presence of economic groups. Here, "economic groups can be either formal legal entities composed of more than one company or more informal groupings of companies that need not be wholly or even majority owned" (Felsovalyi & Hurt, 1998 p. 3). Especially family owned organizations often involve larger loans, while recovery may be more difficult because of an informal structure, lack of integrated management, and multiple banking relationships that they generally maintain. Furthermore, lending to economic groups was often not secured by specific assets in their sample.

The most important explanatory variable of recovery of the study of Emery, et al. (2004) is loan debt cushion, which is defined as "the amount of debt junior to the loans" (Emery, et al., 2004 p. 7) and is measured by loans divided by total debt, implying the larger the value the lower the debt cushion. They found that higher debt cushion of a borrower (i.e. lower value of loans divided by total debt) are associated with higher recoveries. The study of Emery, et al. (2004) is based on 202 issuers over 370 North American default syndicated loans over the period 1989-2003. Moody's Loan Default Database provided the data where the recoveries are based on average bid prices one month after default. Here, the definition of default includes three events: i) missed or delayed disbursement, ii) bankruptcy filing or iii) a distress exchange or distressed restructuring. The conducted analysis was based on a regression analysis with a number of firm, loan, macroeconomic and industry factors. Next to loan debt cushion, other significant findings reported by the study of Emery, et al. (2004) are issue amount, industry distress, and time from the loan's origination to default. Interestingly, macroeconomic factors seemed not to be statistically significant.

The importance of loans divided by total debt is confirmed by Castle & Keisman (1999) and Khieu, et al. (2012), however Khieu, et al. (2012) indicated it as the borrower's leverage. In the study of Castle & Keisman (1999), which is based on 829 debt instrument over the period 1987-1997 provided by Standard & Poor', borrower's leverage even outperformed the seniority and collateral as explanatory variables of recovery. The average recovery of their analysis is 84.5%, while loans with a borrower's leverage of 75% or more, 89% of the loans had recoveries of 90% or more.

Other borrower characteristics are studied by Grunert & Weber (2009). They found a negative relation between the size of the company and the recovery, because they argue that the work-out-process is more complicated for bigger companies. Furthermore, they found a positive relationship between the creditworthiness of the company and recovery. When the company is able to continue its business, the recovery will be higher. The dataset of Grunert & Weber (2009) contained information about 120 companies that defaulted in the period 1992-2003 of a single large bank located in Germany. Other relevant determinants in their study are the positive relation of high quota collateral, high EAD and intensity of relationship on the recovery. Macroeconomic factors were not related to recovery.

2.3.5 Recovery process and business connection

Studies have shown that recovery rates of bank loans are higher than of bonds. A clear reason is that loans are typically senior to other liabilities (Mora, 2012), but some other reasons are suggested as well, which relate the recovery process and business connection. Banks have more access to information, more intensive monitoring and management, enclosed covenants, higher exposures and therefore probably more bargaining power. The finding of Dermine & Carvalho (2006) that the average LGD over 1999 in their sample was relative high due to the internal reorganization of the bank suggests that the recovery process seems to be a determinant of loss indeed. However, in the current literature, these possible determinants of LGD are not well covered, perhaps, because it is difficult to quantify and measure the impact of a bank's actions on realized LGDs.

Some findings suggest that the recovery process and business connection should be taken into account in LGD-studies. The recent studies of Khieu, et al. (2012) and Mora (2012), for example, show that the type of bankruptcy affects the LGD. Usually, a default situation is resolved by a restructuring of the loan, or liquidation (Khieu, et al., 2012), where a restructuring probably leads to a lower LGD since the client is able to continue its business. In case of liquidation, the process debtors use to resolve the situation is likely to affect the LGD (Khieu, et al., 2012). Specifically, prepackaged bankruptcies arrangements, which is a hybrid form of financial reorganization where a debtor files a bankruptcy petition together with a reorganization plan, lead on average to a lower LGD than traditional bankruptcies (Khieu, et al., 2012; Mora, 2012).

Another process characteristic in an event of default is timing. Gupton, et al. (2000) find that the longer a client is in default the higher the LGD becomes. However, in spite of the bank's management that affects the duration of a default, many factors may influence the duration of a default as well. Khieu, et al. (2012) is more specific and describes it as the time to emergence. They define time to emergence as "the time it takes a defaulting borrower to emerge from bankruptcy or a restructuring" (Khieu, et al., 2012 p. 926). The longer the time to emergence the higher the LGD is expected to be, because of the more generated costs due to the longer period and lost revenue of interest payment in the workout period. Furthermore, Khieu, et al. (2012) argue that it is probably more likely that stakeholders do not agree with each other when the time to emergence is longer. Besides, the prepackaged bankruptcies and timing are close related, since prepackaged bankruptcies do shorten the time of emergence and the time of resolution.

Franks, et al. (2004) and Grunert & Weber (2009) both found a positive relation between the intensity of the client relationship and the recovery. The recovery rate tends to increase because a bank will experience more influence on the business policy and the workout process of the default when the client relation is more intense (Grunert & Weber, 2009). In the study of Grunert & Weber (2009) the variables 'multiple loan contracts' and the fraction of the loan of total assets are used as proxies for the intensity of the client relationship. However, the question is if these are indeed correct variables to measure the intensity of a client relationship. Dermine and Carvalho (2006) used the distance between the domicile of the company and the bank's headquarter as measure for the client relationship, and subsequently did not find a relation between the client relationship (distance) and LGD.

Concluding, recovery process characteristics and the business connection are both underexposed topics in the current literature on LGD. Especially in the field of bank loan LGD the process after default combined with bank's relationships between clients, shareholders and co-lenders might be interesting factors that significantly affect realized losses.

2.4 Conclusion

In the field of credit risk, the LGD component experienced much less attention than the PD component, since the LGD was seen as a static factor, rather than a systematic factor such as the PD. However, LGD received much more attention in the last two decades based on the fact that LGD ought to be seen as a systematic factor too. First studies on LGD mostly relied on default information of bonds, but, probably due to the financial distress in the first years of the 21st century and the financial crisis that started in 2008, bank loan LGD studies received more attention.

Critical in the study on LGD are the used definitions and methods in order to determine specific LGDs. The definitions of default, EAD and loss or recovery highly influence LGD results, and so these should be clearly explained in each LGD study in order to make reliable comparisons and generalizations. Unfortunately, used definitions in existing LGD studies are not always clearly provided, and so direct comparisons make little sense. However, there exist interesting LGD studies that particular investigated certain factors that are expected to be determinants of LGD. These have been discussed in this chapter. An overview of the important definitions and differences in definitions in determining LGD is presented in Table 2.

Definitions in determining LGD

Default	**EAD**	**Loss (or recovery)**
- Objective defaults	- Standardized approach	- Market LGD method
- Subjective defaults	- Principal at default	- Workout LGD method (ultimate recovery)
	- All outstanding amounts at default	

Table 2 - Overview of definitions for determining LGD

Investigated determinants of LGD can be categorized in macroeconomic factors, industry conditions, loan characteristics, borrower characteristics, recovery process characteristics and the business connection between the debtor and creditor. Macroeconomic factors and industry conditions are closely related and are seen as external factors. Relevant variables seem to be the type of industry sector, industry distress, default rate, GDP (growth) and country legal systems. Loan and borrower characteristics are common in LGD studies as well and are seen as internal factors since a bank manages this itself. Relevant loan characteristics are the size of the loan or EAD, collateral coverage, type of collateral, seniority and loan's maturity or year of origination. Relevant borrower characteristics are the client's corporate governance, loan debt cushion or leverage, size of the client, the creditworthiness, and the last credit rating prior default. Recovery process characteristics and the business connection are internal factors too but received much less attention in conducted LGD studies. The tendency is the post-default process influence the LGD, because bank loan recoveries are typically higher than bond recoveries. Investigated factors in LGD studies are the type of solution, duration of default, time to resolution and time to emergence. Furthermore, the intensity of the client relationship seems to have a positive effect on recoveries, but intensity is difficult to quantify. An overview of all identified relevant factors is per group presented in Table 3. Now that major issues and challenges in LGD studies are known, we elaborate on the used methodology and data of this study in the next chapter.

Explanatory factors of LGD					
External factors		Internal factors			
Macroeconomic	**Industry**	**Loan**	**Borrower**	**Process**	**Business connection**
- Default rate - GDP (growth) - Legal systems	- Distress - Sector	- Collateral (type) - Size / EAD - Seniority - Year of origination - Maturity	- Size - Age - Creditworthiness - Debt cushion - Corporate governance - Support - Last rating	- Resolution time - Time to emergence - Type of bankruptcy - Type of solution - Duration of default	- Intensity of client relation - Length of relationship

Table 3 - Overview of explanatory variables (determinants) of LGD

CHAPTER 3

Methodology

In determining LGDs used definitions and methods are critical. Therefore, the methodology in LGD studies must be clearly and carefully given. In recent literature this is however not always the case, which causes limitations in the generalization of findings.

This chapter describes and explains the methodology that is used in this research. First, we discuss how LGDs are determined. This involves used definitions of default, EAD, loss and LGD. Thereafter, the independent variables that are measured in this research are discussed. To complete the set up of the research, we discuss how the research is conducted. This involves the operationalization of the research and methods of analyzes. Important here are the two templates that are designed to gather and structure all the data for this research. Lastly, we provide some general hypotheses that were made prior the conducted analyzes.

3.1 LGD-determination

This section presents the used definition and methods to determine the ultimate recoveries of defaulted FMO loans. As is discussed in the previous chapter, the definition of default, EAD and incurred loss needs to be clear. This section discusses the used definition of default, EAD and loss, and elaborates on currency issues, LGD and recovery rate (RR).

3.1.1 Definition of default

The used definition of default by FMO and so in this research is in compliance with the used definition by Basel II[1]. The complete definition of default by Basel II is presented in Appendix C. The parts that specifically apply to FMO's loan portfolio are as follows: A borrower is considered to have defaulted on a loan if (1) a scheduled interest or principal payment related to any instrument of the counterpart becomes 90 days past due; (2) a restructuring is employed as a means of preventing an instrument of the obligor from becoming delinquent; (3) FMO has filed for the obligor's bankruptcy or (4) FMO takes an account-specific provision. The moment of default is the date on which at least one of the above conditions occurs. Furthermore, when a client defaults on a loan, all outstanding loans to that client (so all exposure) are considered as in default.

3.1.2 Definition of exposure at default (EAD)

The EAD is the exposure at the exact day of default. In this research the EAD is defined as the total exposure that is still owed at the exact moment of default. This is the enumeration of:

- Outstanding Amount (OA)
- Outstanding Interest (OI)
- Outstanding Fees (OF)

However, within FMO the expected EAD is determined differently. For FMO it is the total outstanding amounts plus 50% of the committed but not disbursed portfolio. This is the definition that complies with the standardized approach as Basel II prescribes.

3.1.3 Definition of loss

The definition and quantification of loss is a critical and therefore an important matter in this research, because the loss highly influences LGDs and second, as discussed, there are discrepancies in quantifying loss on loans in existing literature. Some studies use market prices of loans while others use ultimate recoveries, which are based on present values of generated cash flows. Because market prices of loans are neither used nor available within FMO, while all cash flows and interest rates are, the discounted cash flow approach (ultimate recoveries) is used to quantify the loss on the defaulted loans. In case of ultimate recovery the loss

[1] Basel II, June 2006: Paragraphs 452-453 on pages 100-101.

can be build up in two separate ways, since the lender has two options when a client goes into default. The two options are 1) cure or 2) foreclosure, and therefore we need to define loss in case of both options. However, the basis of the incurred loss is the same for both options and takes the form,

$$L = EAD + PV(D) + PV(C) - PV(R) \quad (1)$$

where L is the incurred loss on the loan at the moment of default, *EAD* is the exposure at default as defined in subsection 3.1.2; *D*, *C* and *R* respectively indicate post-default streams of disbursements, costs and generated revenue, and *PV* represents the present value of these streams.

In case of the cure-option the specific loan (or loans) is not changed or restructured in order to restore the position of the client. This means that the client, loan and so relationship will continue to exist. Generated revenue (*R*) therefore consists of principal repayments *(P),* interest payments *(I)* and paid fees *(F)*. A restructuring is identified when a change in the cash flow scheme is made. With the cure-option the expected income can be determined or the realized (re)payments of the client after default can simply be retrieved.

In case of foreclosure the specific loan (or loans) will be liquidated. Consequently, all exposure to the client will be removed and so the client will be removed from FMO books. With a foreclosure FMO has several possibilities for generating any revenue: FMO can receive client (pre-)payments (*P*, *I* and *F*), retrieve guarantees (*G)* from third parties or can receive earnings from collateral *(S)*.

Next, the costs in Equation 1 are any costs made for a specific client after default. These can be specific fees, break-hedging costs (like discontinue swaps), processing costs (internal budgets) and other external costs like legal costs. It is possible that some costs are declared and paid by the client, while some are not.

Finally, the income and the costs need to be discounted with a proper discount factor in order to make them comparable with the EAD. Because the EAD is the exact value of the exposure at the moment default, we are interested in the value of the disbursements, costs and revenue at the exact moment of default. As discount factor the actual charged interest rate to the client is used, because the pricing of the loan should be the most appropriate rate for the involved risk on the loan. Subsequently, the actual interest rate of FMO's loan portfolio is directly accessible within FMO. The charged interest rate by FMO consists of a costs-of-funds rate and a margin. The costs-of-funds rate often is floating (based on the LIBOR/EURIBOR rate), while the margin is fixed per loan. Theoretically, when no changes in the facility occur and the client (re)pays everything as originally agreed, the present value of all streams after default should equal the EAD. Practically, still minor differences occur due to payment periods on which no interest is charged and the use of the simple interest method instead of compounding interest to calculate interest obligations. But from a market perspective this should be seen as loss or profit too.

The present value calculations for the revenue (*R*) of a cured facility, for example, take the form,

$$PV(R) = \sum_{k=1}^{K} \frac{I_k}{1 + \left(r * \frac{T_k}{T_r}\right)} + \sum_{l=1}^{L} \frac{P_l}{1 + \left(r * \frac{T_l}{T_r}\right)} + \sum_{m=1}^{M} \frac{F_m}{1 + \left(r * \frac{T_m}{T_r}\right)} \tag{2}$$

where *k*, l and m are the number of interest payments (I), principal repayments (P) and fee payments (F) respectively, I_k, P_m and F_n represent the values of these payments, r is the relevant contractual interest rate, T_k, T_m and T_n indicate the number of days between the date of default and the date of receiving payment *k*, *m* or *n*, and T_r represents the number of days on which the interest rate is based. Note that the interest rate r is based on simple interest and therefore is not a compounding rate, since FMO uses this method to calculate owed interest.

Because the costs-funds-rate might change during the post-default period, the contractual interest rate r might change too. Therefore, post-default interest rate changes are monitored and incorporated in the present value calculations in order to embody the correct involved risk. Table 4 on the next page summarizes the determination of loss.

3.1.4 Currency

Because FMO operates in developing countries and emerging markets, loans are provided in more than one currency. As of 2012, a major part (72%) of FMO's committed portfolio is provided in USD, 16% in Euro and 12% in local currency. While LGD is expressed as a percentage of loss on EAD, a loan in another currency will result in the same LGD when no exchange differences are taken into account. However, it gets more complicated if multiple currencies are associated with a loan. Within FMO, fees are, for example, sometimes based in another currency than the principal. Furthermore, loan specific costs might be based in another currency as well. Therefore, in order to calculate incurred losses on defaulted loans and to compare LGDs, differences in currencies need to be managed.

FMO has defined currency risk as the risk of potential loss due to adverse movements in foreign exchange rates and has the policy to minimize losses as a result of open currency positions and therefore does not take active positions in any currency. Therefore, the foreign exchange position is monitored on a daily base and when an open position exceeds a certain barrier, it is mitigated. In the currencies with assets or liabilities beyond a value of EUR 100 million, the limit is set to EUR 5 million (plus and minus), while for all other currencies the limit is set to EUR 2 million.

Because the base currency of FMO is the Euro and so FMO-capital is in EUR, all amounts are converted to EUR to calculate the LGDs. In case the loan is based on another currency, the applicable exchange rate is accessible in the loan management system (ACBS) of FMO.

Determination of loss		
Loss	**=**	$\boldsymbol{EAD + PV(D) + PV(C) - PV(R)}$
EAD	=	$OA + OI + OF$
PV(D)	=	$\sum_{k=1}^{K} \frac{D_k}{1+\left(r * \frac{T_k}{T_r}\right)}$
PV(C)	=	$\sum_{k=1}^{K} \frac{C_k}{1+\left(r * \frac{T_k}{T_r}\right)}$
PV(R)	Cure =	$\sum_{k=1}^{K} \frac{I_k}{1+\left(r * \frac{T_k}{T_r}\right)} + \sum_{l=1}^{L} \frac{P_l}{1+\left(r * \frac{T_l}{T_r}\right)} + \sum_{m=1}^{M} \frac{F_m}{1+\left(r * \frac{T_m}{T_r}\right)}$
	Foreclosure =	$\cdots + \cdots + \cdots + \sum_{n=1}^{N} \frac{G_n}{1+\left(r * \frac{T_n}{T_r}\right)} + \sum_{q=1}^{Q} \frac{S_q}{1+\left(r * \frac{T_q}{T_r}\right)}$

Where	EAD = exposure at default	I_k = value of interest payment *k*
	PV(D) = present value of disbursements	P_l = value of principal repayment *l*
	PV(C) = present value of costs	F_m = value of fee payment *m*
	PV(R) = present value of revenue	G_n = value of guarantee receipt *n*
	OA = outstanding amount at default	S_q = value of collateral (security) receipt *q*
	OI = outstanding interest at default	r = contractual interest rate
	OF = outstanding fees at default	$T_{k, l, m, n, p, \text{ or } q}$ = number of days between event *k, l, m, n, p* or *q* and default
	D_k = value of disbursement *k*	
	C_k = value of cost *k*	T_r = number of days on which the contractual interest rate is based

Table 4 - Determination of loss

3.1.5 Loss given default (LGD), recovery rate (RR) and marginal recovery rate (MRR)

Finally, the LGD is calculated by the determined loss divided by EAD. The recovery rate is simply the inverse of the LGD, so

$$LGD = 1 - RR \tag{3}$$

Therefore studies that focus on LGD or RR are equivalent. Furthermore, it is possible that the recovery of a loan is more than 100% and so instead of a loss a profit is made. Because it is not the intention to make a profit beforehand, the recovery is capped at 100%, which of course results in a minimum LGD of 0%. The full amount of EAD is simply recovered and so there is 0% loss. On the other hand, it is possible that the actual loss is even larger than the EAD due to post-default disbursements or high external costs. This in turn results in a LGD of more than 100%. Because we are interested in real losses and a LGD of more than 100% is rather exceptional and thus interesting, the LGD is not capped at 100%. Loans with a LGD of higher than 100% are called outliers. The number and range of outliers are closely monitored such that they will not cause (too much) distortions in analyzes. Concluding, the LGD ranges from 0% to infinite and so the realized LGD is determined by

$$LGD = Max\left[\frac{EAD + PV(D) + PV(C) - PV(R)}{EAD}, 0\right] \tag{4}$$

Next to the final LGD, the course of the LGD over the post-default period is interesting too, because it gives insight in the recovery process itself. To monitor the course of LGD, marginal recovery rates (MRR) are examined with help of the mortality-based approach, which Dermine and Carvalho (2006) introduced in defaulted bank loan recovery rates and is also used in the study of Koŝak and Poljŝak (2010). The MRR_t indicates the percentage of recover on EAD in a certain period *t* after default, where *t* indicates the year after default. For example, an MRR_1 of 20% indicates that 20% of the total recovery is accomplished within the first year after default and a MRR_5 of 5% means that 5% of EAD is recovered in the 5th year after default. Subsequently, MRR_t is calculated by

$$MRR_t = \frac{PV(R_t) - PV(C_t) - PV(D_t)}{EAD} \tag{5}$$

where MRR_t is the marginal recovery rate in year *t*, $PV(R_t)$, $PV(C_t)$, $PV(D_t)$ are respectively the present values *PV* of revenue *R*, costs *C* and disbursements *D* in period *t* and EAD is the exposure at default. With the MRRs the course of the LGD can simply be monitored by

$$LGD_T = 1 - \sum_{t=0}^{T} MRR_t \tag{6}$$

where LGD_T represent the loss given default at time *T* after default. In this research *t* is monitored in years and ranges from 1 until 5 years after default. Observed cash flows after 5 years of default are summed.

3.2 Independent variables: manageable versus unmanageable factors

The independent variables are the factors that may influence the LGD and are therefore called LGD-determinants. After examining relevant literature and discussing with experts in client defaults within FMO, possible determinants are selected, elaborated and made measurable. An overview is presented in Table 5. A distinction is made between manageable and unmanageable factors. With manageable factors we mean factors that can be managed by the bank during the post-default period. With unmanageable factors we mean factors that cannot be managed by the bank during the post-default period and therefore should be taken as given. This distinction is relevant because analysis between these two factors allows us to investigate to what extend incurred losses on loans are attributable to the management of a bank or in other words are controllable for a bank. Explanations and methods of measurement of the specific factors are presented in Appendix E.

3.2.1 Manageable factors

The manageable factors consist of recovery process characteristics and the business connection between the client and the bank. Interesting would be the difference between manageable factors before the event of default and manageable factors after the event of default. Via multiple process characteristics we try to make a distinction between these two periods. For example, the factor 'insufficient monitoring' is a dummy factor that is used to check if there was insufficient monitoring on the client prior default. On the other hand, the factor 'incorrect judgments' is a dummy factor that is used to check if incorrect judgments were made after the event of default. Furthermore, by adding all default conditions as dummy factors, we can check if a client experienced multiple defaults after the first default, and so we can check if a client experienced objective defaults, subjective defaults or both. Secondly, with the help of the factor 'type of default' we can check if the first default was an objective default or a subjective default. This information is relevant to judge the management of the bank on the management of credit risk, like is the bank prudent or mainly running behind events? Subsequently, the time to emergence is measured. This is the time between default and transfer to Special Operations department. Finally, the duration of default and the intensity of the client relationship are measured as manageable factors.

3.2.2 Unmanageable factors

The unmanageable factors consist of macroeconomic factors, industry conditions, borrower characteristics and loan characteristics. For macroeconomic factors we look to the GDP trend of the country where the client is located, high foreign exchange fluctuations, and the enforceability of the country where the client is located. As industry conditions we look to the type of industry and whether the client experienced distress in the industry during the recovery period. For the borrower characteristic we look to the type and size of the client. Furthermore, we look to the solvency and liquidity of the client just prior default and whether the client received support from other organizations during the recovery period. For the loan characteristics we look to the seniority, security and size of the loan. Finally, whether the loan was part of a syndication is also taken into account.

Manageable factors	**Unmanageable factors**
Recovery process characteristics	*Macroeconomic factors*
- Type of default - Provisioning (dummy) - Restructuring (dummy) - 90 days past due (dummy) - Bankruptcy (dummy) - Time to emergence - Duration of default - Recovery method - Incorrect judgments - Insufficient monitoring	- Average GDP trend - FX fluctuation - Enforceability *Industry conditions* - Type of industry - Industry distress (dummy)
Business connection	*Borrower characteristics*
- Intensity of client relationship	- Type of client - Size of client - Solvency prior default - Liquidity prior default - Support from other organizations
	Loan characteristics
	- Level of seniority - Level of syndication - EAA - EAD - Guarantee coverage - Collateral coverage - Type of collateral

Table 5 - Overview independent variables

3.3 Operationalization

Because the determination of LGD and scoring of the independent variables as described in the previous sections implicates a lot of data and is a time consuming practice, we give specific attention to the operationalization of this research. To gather and structure all the data two templates are developed, called *loss file* and *highlights*. These two templates are used to obtain all date for this research and therefore are the foundation of this research. The two templates are explained in the next sub sections. An overview of the two templates together with their contents is provided in Table 6 and an example of a case with the use of the templates is presented in Appendix F.

3.3.1 Loss files

The loss file is a spreadsheet template designed in Excel and consists of two parts. The first part involves the determination of LGD, while the second part involves the scoring of the independent variables as presented in Table 5 and the client rating scorecard to determine the probability of default factors just prior default.

In the first part of the loss file relevant information about the client and the loan is gathered. And so the loss file starts with the name and ID-number of the client, the type of client, in what region and country the client is located and in what industry it is active. Subsequently, the loan information consists of the name and ID-number of the provided loan, the general ledger unit, type of the loan and general financial information, such as principal amount and interest rates. After the client and loan information, default information is listed which consists of the date of default, outstanding amounts, and the type of default. We should note that from the moment of default all financials are translated to Euros in the template. Next, information of the recovery process is provided. Here, the type of solution, the transfer date to Special Operations department, end date of default, the highest provision amount taken by FMO and made costs after default are listed. Note that the incurred costs after default are discounted to the date of default. After the recovery process information, we monitor the payments after default. Here, there are two choices where the first one is that the loan remains to exist (cure); while the second one is that the loan is terminated (foreclosure). This corresponds with the two defined equations in Table 4 two calculate the present value of the revenue stream after default. Now that the default information, the present value of costs during the recovery process, and the present value of the revenue stream are known, the LGD is calculated by following the equations as described in section 3.1. Because the specific dates of the cash flows are known the marginal recovery rates (MRRs) are calculated as well and graphically presented in a figure.

In the second part of the loss file the defined LGD factors are measured as described in Appendix E. For the recovery process, borrower, loan and industry factors internal documents of FMO are used. This includes client reports, client ratings, loan agreements, correspondence (e-mail), client updates, change requests, transfer files[2] and minutes of the Investment Review Committee. For the macroeconomic factors the databank of The World Bank[3] is used.

3.3.2 Highlights

The second designed template is the highlights. In order to learn from best practices and mistakes from default cases, specific stories are interesting and therefore should be highlighted and studied. To structure these stories the highlight template is constructed, which provides the complete story of a client. And so, while the loss file template is intended per loan, the highlights template is intended per client.

The highlights template consists of three parts: a summary of the storyline, key causes of default and key determinants of loss. The summary starts with general client information, which consists of client name, the different loans the client holds, date(s) of origination, region, country, industry, general ledger unit(s), and type of client. Next, default and LGD information is provided, which consists of the date of default, date of transfer, end date of default, the maximum taken provision, default type, the time in default and the realized LGDs per loan. Thereafter, the client's business is shortly discussed and the course of the loans is set out, including the moment of default and recovery process. After the summary, key causes of default are listed together with the probability of default (or client rating) just prior default. Finally, the highlights end with the key determinants of loss. The main question we try to answer here is why FMO received recoveries or why FMO did not receive any (or much) recoveries.

The information used to construct the highlights comes from internal FMO documents and stories and experiences from employees. Consequently, the data yielded from the highlights are qualitative in the form of case studies. Constructing the highlights is therefore a time consuming practice.

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[2] Transfer files are the files that are used to transfer the client from Front Office to Special Operations department.

[3] http://data.worldbank.org/

Templates		
Loss File (per loan)		**Highlights (per client)**
1	General Client information	Summary of storyline
2	Loan information	- General client, loan and LGD information
3	Default information	- Short outline of client's business
4	Recovery process information	- Summary of recovery period
5 / 6	Cure / Foreclosure	
7	LGD results	
LGD factors	Recovery process characteristics	Key causes of default
	Business connection	- Probability of default just prior default
	Macroeconomic factors	
	Industry conditions	
	Borrower characteristics	
	Loan characteristics	
PD factors	Client Credit Rating Scorecard - Financial Institution - Non-banking financial institution (NBFI) - Corporate - Project Finance	Key determinants of loss

Table 6 – Overview of the *loss file* and *highlights* templates

3.4 Methods of analyzes

The data that have been obtained from the templates is the input for analyzes. All the created loss files are assembled to one database. Subsequently, the database enables the use of quantitative analyzes. On the other hand, the highlights provide qualitative information of all the clients in the sample and so are useful for the study of specific cases.

3.4.1 Quantitative

The constructed database contains all information that is assembled in the loss files. By means of single comparisons the measured factors are analyzed in relation to the corresponding LGDs. This is conducted via single linear regression analyzes, which has the form of:

$$LGD_i = \beta_0 + \beta_1 * factor_i + \varepsilon_i \qquad (7)$$

where β_0 is the intercept, β_1 is the slope parameter (coefficient) and ε_i is the error term. Here β_0 and β_1 are determined such that they provide the best fit for the data points based on the least-squares method (i.e. OLS). And so, a positive β_1 means that the factor is positively related to LGD since a higher score on the factor results in a higher LGD. Subsequently, a negative β_1 means a negative relation between the factor and LGD. Furthermore, the more positive or negative β_1 relatively is (so high [β_1]), the stronger the factor and LGD are related.

The least-squares method is simply the minimization of the sum of squared residuals of the model. The error model ε_i in the single linear regression includes the assumptions of normality ($\varepsilon \sim N(0, \sigma)$) and independent errors. Besides the independent variable (factor) is measured without error. Based on these assumptions a t-test can be conducted for the hypothesis $H_0 : \beta_1 = 0$, which yields a p-value. A significant small p-value means that we reject the null hypothesis and so the corresponding factor is significantly related to LGD following our model. Next to the p-values, the coefficient of determinations R^2 is monitored as well. R^2 is a measure of the fraction of total variation in outcomes that is explained by the linear regression model. A R^2 of one (or 100%) therefore means there is a perfect fit between the factor and LGD in such a way that all data points fall exactly on the linear regression line. R^2 is determined by:

$$R^2 = \frac{var(LGD) - MSE}{var(LGD)} \tag{8}$$

where $var(LGD)$ is the total sample variance of LGD and MSE is the mean squared error which is the residual error variance. Concluding, a high [β_1] combined with a very low p-value and high R^2 as a result of a single linear regression model means that there is a relevant and significant linear relation between the measured factor and LGD.

Next to the single comparisons, a multivariate analysis is conducted as well. Instead of using only one factor and so one coefficient (β_1), we use multiple factors with each a coefficient to minimize the sum of the squared residuals. From the univariate analysis we selected factors that seem to be relevant in their relation with LGD. Subsequently, the model takes the form of:

$$\begin{aligned} LGD_i = {} & \beta_0 + \beta_1(macroeconomic\ and\ industry\ conditions_i) + \beta_2(loan\ characteristics_i) \\ & + \beta_3(borrower\ characteristics_i) + \beta_4(recovery\ process\ characteristics_i) + \varepsilon_i \end{aligned} \tag{9}$$

where β_0 is the intercept, β_1 represents the slope parameters (coefficient) for every independent macroeconomic and industry factor, β_2 represents the slope parameters for every independent loan characteristic, β_3 represents the slope parameter for every independent borrower characteristics, β_4 represents the slope parameters for every independent recovery process characteristic, and ε_i is the error term which again includes the assumption of normality and independent errors.

With the use of the parameters and the model assumptions we can perform t-tests on every factor included in the model to check their level of significance. This is done by conducting a t-test per factor just as in the univariate analysis, however, with including the other parameters and factors in the model. Consequently, we check the level of significance after accounting affects of the other factors in the model. A very small *p*-value means that the factor is significantly related to LGD in our multiple regression model.

Since the error model is assumed to be normal distributed with independent errors, we can check if the residuals resulting from our multiple regression model are normally distributed as well. This is necessary since the randomness in our model should be equally distributed in order to be valid. By plotting the residuals per factor into a scatterplot, we should see equally spread residuals with a mean of zero and the residuals should be centered at the value of zero. An example of how the residual plots should look like is presented in Figure 1. The bars show that the residuals are equally spread.

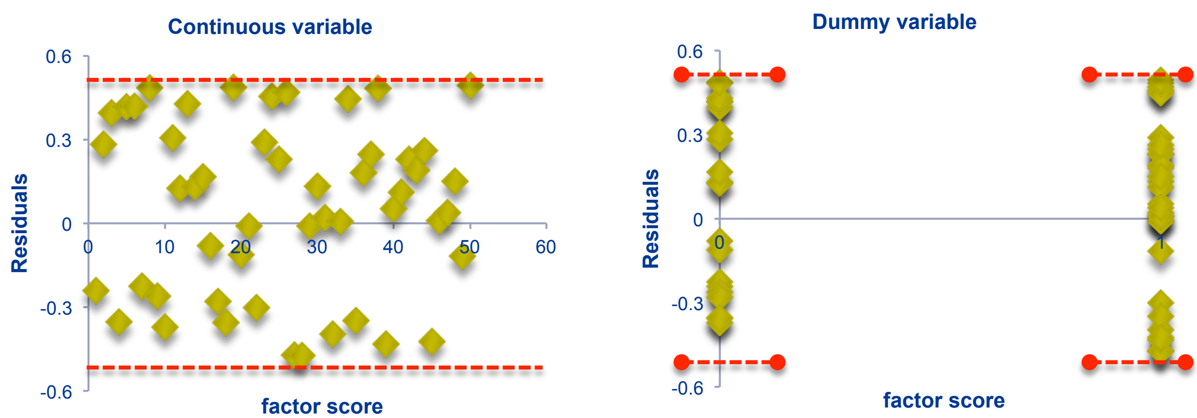

Figure 1 – Example of residual plots based on a normal distributed error model

3.4.2 Qualitative

Next to the quantitative analysis were the measured factors are analyzed, we can use the case studies to conduct a qualitative analysis. By studying the case studies the key causes of default and key determinants of loss are analyzed and grouped by broadly defined concepts in order to better understand relevant factors for the cause of default and recovery process. All constructed highlights are presented in Appendix H.

3.5 Hypotheses

While we need to be careful with benchmarking average LGD with other banks, we believe that manageable factors are important determinants of LGDs. For example, when we compare a client in default with a person who is treated in a hospital, a specialized hospital probably will have fewer losses (mortality rate) than a hospital that is not specialized. However, this reasoning only applies when both hospitals treat clients that have the same degree of illness. Probably, because the specialized hospital is specialized, it will treat clients that have a higher degree of illness than clients in the other hospital, and therefore the mortality rate will just be higher. Therefore, the degree of illness needs to be involved in the analysis in order to say something about the performance of the hospital based on the mortality rate.

Translating this line of reasoning to this research, the unmanageable factors in this research represent the degree of illness of the client in default. We believe that some unmanageable factors or combination of unmanageable factors are able to make the difference between a high or low LGD. Consequently, when you know in advance that certain scores on factors apply to a certain client in default which will probably cause a LGD of 100%, the loss can be minimized by not paying any attention to that client and by taking the current exposure directly as a loss. On the other hand, if an unmanageable factor is often a cause of a high LGD, the bank must wonder whether that unmanageable factor can be changed into a more manageable factor in order to realize lower losses in the future. The first hypothesis is:

1. *Manageable factors as well as unmanageable factors during the recovery process affect the recovery process and so LGD.*

Furthermore, we need to be careful with comparing individual realized LGDs with the expected LGDs, because one specific event may cause a completely different LGD. Because other studies demonstrate this as well, we expect that the realized LGDs are for a large part concentrated at 0% losses and 100% loss and therefore the distribution of LGDs is bimodal. We expect the distribution will be centered to low LGDs, because FMO is seen as prudent by its employees and therefore may have a low threshold for taking provisions on specific loans. Therefore the second hypothesis is:

2. *The distribution of realized LGDs is a bimodal distribution, with a magnitude of loans with very low LGDs and a little lower magnitude of loans with very high LGDs.*

While many studies on LGD are focused on the U.S. or West-European market and FMO is active in emerging markets and developing countries, we expect that other unmanageable factors apply as determinants of LGDs than those studies proved or suggested. For example, we believe that the enforceability of countries is an important determinant for the loss on loans, because when the enforceability of a specific country is very low, it is possible that the involved collateral cannot be obtained and therefore is worthless. Consequently, while the bank believed it had a good collateral position, in practice it was worthless which in turn had a significant effect on the realized LGD.

Because emerging markets and developing countries are seen as more instable than developed countries, we believe macroeconomic factors highly affect the realized LGDs. Furthermore, we believe that factors that are seen as indirect guarantees highly affect the realized LGDs as well, because FMO provides loans that are on average more risky which indirectly causes a higher dependence on co-lenders and shareholders or governmental support. These propositions are summarized in the last hypothesis.

3. Macroeconomic factors, support from other organizations, position within co-lenders and the level of syndication highly affect the LGD of loans in emerging markets and developing countries.

In the next chapter, Chapter 4, the created sample is discussed in order to put the analysis and its results into context. Subsequently, Chapter 5 presents de results of the quantitative (univariate and multivariate analysis) and qualitative (case studies) analyzes.

CHAPTER 4

Sample

After months of data gathering and investigating specific cases the sample for this research is created. Because of the magnitude of work, another intern was attracted to help gathering the data. Differences in the interpretations of causes and determinants are, as much as possible, minimalized by the standardization of this research via the templates.

This chapter discusses the composition of the sample. First, general information of the sample and the distribution of LGD are presented. Thereafter, the distribution per general ledger unit, region, country, industry, type of client and year of origination and default is discussed. An overview of the sample is presented at the end of this chapter in Table 7.

4.1 General sample information

Initially, 84 companies with 113 loans of resolved or closed defaults in the period 2006-2012 were identified that initially seemed to be useful. Equity investments and grants were not useful and therefore were already excluded from the existing data. Finally, after checking data availability and due to time constraints, 73 loans of 52 clients are investigated and incorporated in this research. Because for one case too less information was available for the case study, 51 highlights are constructed, which are presented in Appendix H.

To 15 of the 52 clients multiple loans were provided, and 48 of the 73 loans were senior loans and so 25 were subordinated loans. Of the 15 clients with multiple loans, 10 clients did hold a senior loan together with a subordinated loan. Furthermore, a small majority of 39 loans were secured by a guarantee, by collateral or both, and so 34 loans were unsecured.

The 52 clients are spread across multiple industries and countries around the world. The clients are divided by 9 industry groups, spread over 31 countries in the regions Latin America & the Caribbean (LAC), Africa, Europe & Central Asia (ECA), Asia, and Global. Furthermore, the 73 loans are provided in a total of 10 different currencies, but USD and thereafter EUR clearly dominate. The smallest provided loan was EUR 123,000 while the largest provided loan was approximate EUR 28.5 million. The average size of the loan or EAA (Exposure at Approval) is approximate EUR 6.5 million and so the total committed amount of the sample is approximate EUR 473 million. The oldest loan of the sample was contracted in 1976, while the most recent loan was contracted in June 2012.

The distribution of EAD corresponds with the distribution of EAA. The average EAD of the 73 loans is EUR 5.37 million, while the average EAD per client is EUR 7.54 million. Next, the majority of the loans and clients had an EAD that is less than average. This is evidenced by a smaller median of EUR 4 million and EUR 5.6 million respectively for the EAD of loans and clients. The total EAD of the complete sample amounts to EUR 392 million, which is EUR 81 million less than the total EAA of the loans (EUR 473 million).

The average LGD of the sample is 22%, while the median is 0%. Therefore, the majority of the loans in the sample experienced a LGD of 0%. When the total exposure and recovery is determined per client, the LGD results in 28%, and again the median is 0%. The distribution of LGD in buckets of 10% is presented in Figure 2. The magnitude of the clients and loans with a LGD of less than 10% is clearly visible. However, there is also a (smaller) magnitude of clients and loans with a LGD higher than 90% as well. Concluding, we see a bimodal distribution with the majority of the loans with very low LGDs and a magnitude of loans with very high LGDs.

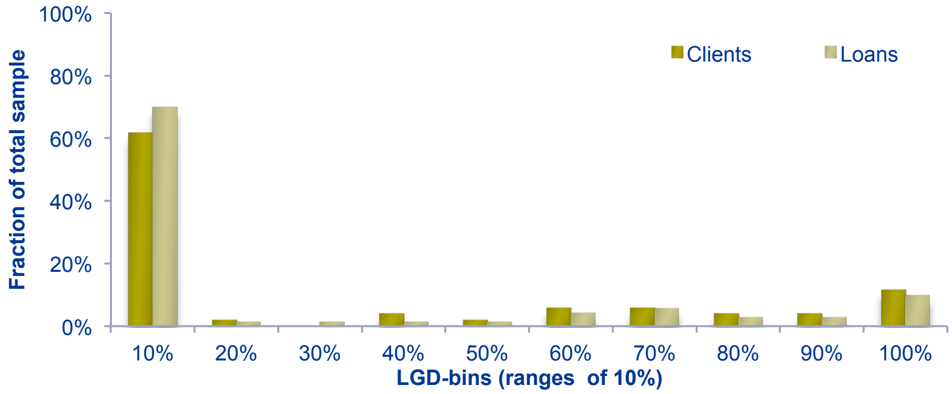

Figure 2 - Distribution of LGD

4.2 Distribution per general ledger unit (GL-Unit)

Within FMO loans are provided from different sources (general ledger units). The majority of the FMO provided loans are from FMO's own account. This GL-Unit is called 'FMO A'. Consequently, the majority of the loans in sample (53 of 73 loans) are from FMO A as well. Other GL-Units in this sample are part from the management of government funds. The government funds include MASSIF, Infrastructure Development Fund (IDF), Access to Energy Fund (AEF), and Facility Emerging Markets (FOM) and are all dedicated to specific sectors in poorer or least-developed countries. Of the sample, 11 loans were provided from FOM, 7 loans from MASSIF, and one from IDF and AEF.

The differences in GL-Unit are important, since the different sources imply different goals and therefore different risk appetites. Especially, the difference between FMO A and the management of government funds is important, because losses from FMO A loans are all for FMO, while losses from government funds are not or are for a large part covered by state guarantees. Furthermore, government funds loans are often smaller and are provided to smaller clients than for FMO A loans. For example, FOM is intended for the stimulation of Dutch enterprises to invest in emerging markets and developing countries.

Consequently, we see dispersion in the LGDs per GL-Unit. Loans from FMO A and MASSIF result on average in low LGDs (10% and 1%, respectively), while FOM, IDF and AEF result on average in very high LGDs (81%, 86% and 75%, respectively). Furthermore, the average EAD of FMO A loans is indeed higher than average (EUR 6.4 million), while the average EAD for the government funds is less than average, except for the one loan provided from IDF (EUR 9.9 million).

4.3 Distribution per region and country

Such as the total loan exposure of FMO, the 52 clients are well spread around the world. The majority of the sample (28 loans) is allocated to Europe and Central Asia (ECA), while the minority of the sample (6 loans) is allocated to Global. In turn, the LGD of these two regions are on average the highest with a LGD of 29% for ECA and 69% for Global. Furthermore, the loans allocated to Africa (10 loans), Asia (12 loans) and Latin America & Caribbean or LAC (17 loans) result in a below average LGD of 7%, 18% and 4%, respectively. The loans allocate to Africa, ECA and Global did have a lower than average EAD, while the loans allocated to Asia and LAC did have a higher than average EAD. The distribution of LGD per region is presented in Figure 3. Furthermore, the sample is spread of 31 countries. Russia, China, Argentina, South Africa and Georgia are represented with the most loans in the sample with 10, 7, 5, 5 and 4 loans, respectively.

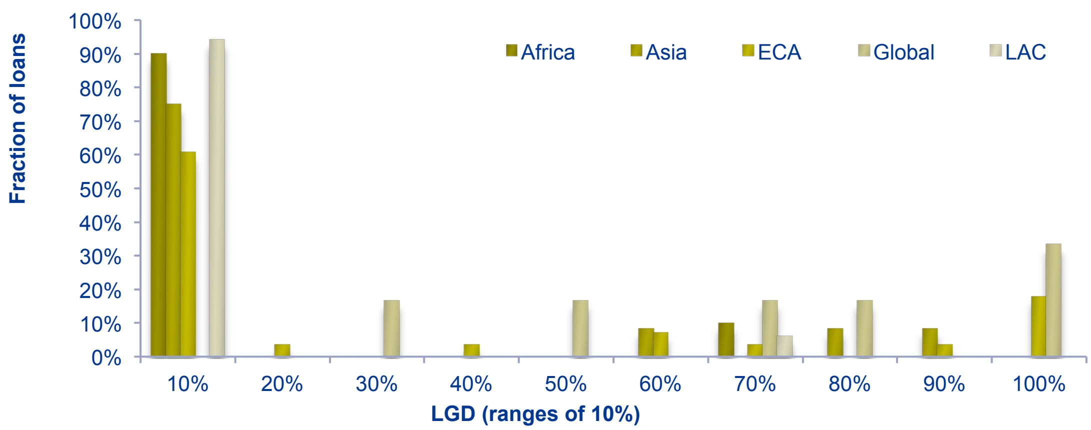

Figure 3 – Fraction of loans per LGD-bin per region

4.4 Distribution per industry and type of client

The sample is divided into 9 industries, where the finance, consumer products and agriculture sectors dominate with respectively 26, 11 and 10 loans. The sectors capital goods, energy, materials, telecom, transport & logistics and utilities are less presented in the sample. The sectors utilities, material, capital goods, consumer products and energy present higher than average LGDs, while the sectors agriculture, finance, telecom and transport & logistics present lower than average LGDs.

To determine probability of defaults, FMO uses different scorecard that are developed for different types of clients. A distinction between four clients is made: financial institutions, non-banking financial institutions (NBFIs), corporates and project finance. The majority of the loans (42) in the sample were provided to corporate clients, and these resulted on average in the highest LGD of 33%. The other three types of client resulted in lower than average LGDs. The 21 loans provided to financial institutions resulted in an average LGD of 5%, the 6 loans provided to NBFIs resulted in an average LGD of 14% and the 4 loans that were provided as project finance resulted in an average LGD of only 1%. The distribution of the different types of client and LGD is presented in Figure 4. In the very low LGD region we see indeed that relative less corporates resulted in low LGDs and that 17% of the corporates resulted in a LGD of more than 90%, which in turn results in a relative high average LGD.

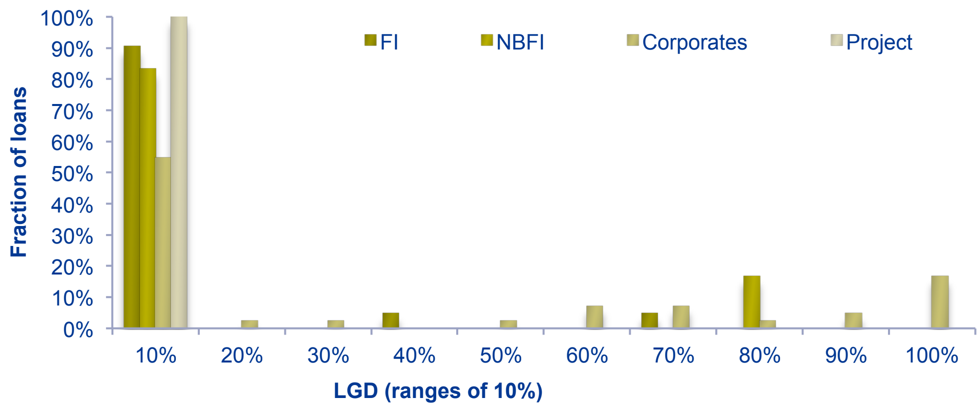

Figure 4 – Fraction of loans per LGD-bin per client type

4.5 Distribution per year of origination and default

Since cases that were resolved in the period between 2006 and 2012 are investigated in the sample, the years of origination and default are spread. The oldest loan was contracted in 1976, but the majority of the loans were contract from 2005. The first default in our sample occurred in 1993, and so this default process took quite some time (but resulted in a los of 0%). The latest default occurred in 2012, and so this default was closed very quickly (with a loss of 100% however). In 2008, a magnitude of defaulted loans (28 loans) in our sample is presented. This is due to the many provision FMO took in the end of 2008 to prepare itself for the financial crisis. Especially loans to financial institution in countries that were expected to be vulnerable for the effects of the crisis (mainly in Eastern Europe) were selected and provisioned. However, due to the many provisions the average LGD remained limited with only 7%. The years 2001, 2006, 2007, 2009 and 2012 present an LGD that is above average. Especially 2007 and 2009 stand out with relatively many loans (5 and 9 loans) and a relative high LGD of 78% and 41%, respectively.

4.6 Conclusion

This chapter presented the sample in order to understand the dispersion within the sample. This is necessary to interpret the results of specific factors that may affect the losses on loans. An overview of the sample is presented in Table 7. Here, you find the LGDs, number of loans, EADs and the standard deviations of the LGDs per GL-Unit, type of client, region, industry and year of default. The next chapter discusses the findings of factors that may affect the losses on loans.

Category	LGD	Number of loans	EAD *(EUR x million)*	St. Dev (LGD)
Sample	**22%**	**73**	**5.4**	**36%**
Per GL-Unit				
FMO NV	10%	53	6.4	23%
FOM	81%	11	1.0	27%
IDF	86%	1	9.9	-
MASSIF	1%	7	4.3	2%
AEF	75%	1	0.4	-
Type of client				
Financial Institutions	5%	21	6.4	16%
NBFIs	14%	6	4.3	31%
Corporates	33%	42	5.2	41%
Project Finance	1%	4	3.3	1%
Region				
Africa	7%	10	4.4	21%
Asia	18%	12	5.8	33%
ECA	29%	28	4.9	41%
Global	69%	6	1.8	31%
LAC	4%	17	7.7	16%
Industry				
Agriculture	21%	10	4.4	33%
Capital Goods	44%	5	4	44%
Consumer products	39%	11	5.5	47%
Energy	33%	5	3.7	36%
Finance	4%	26	6.1	15%
Materials	48%	4	3.4	56%
Telecom	0%	4	8.4	0%
Transport and Logistics	1%	4	4.2	1%
Utilities	61%	4	6.0	44%
Year of default				
1993	0%	1	3.4	-
2001	50%	3	4.0	-
2002	22%	2	3.4	-
2003	18%	3	6.7	-
2004	0%	5	2.8	-
2005	10%	7	4.9	-
2006	50%	2	3.3	-
2007	78%	5	1.4	-
2008	7%	28	7.2	-
2009	41%	9	3.8	-
2010	21%	4	6.2	-
2011	3%	3	9.5	-
2011	100%	1	0.3	-

Table 7 – Overview Sample

CHAPTER 5

Findings

In this chapter the findings of the analyzes of the measured factors in relation to LGD are presented. We start with quantitative results where univariate and multivariate analyzes are conducted. Thereafter, qualitative results are presented by means of key causes of default and key determinants of loss. Finally, this chapter ends with a conclusion.

5.1 Univariate analysis

The individual factors that are measured are analyzed in their relation to the determined LGDs. An overview of the descriptive statistics and single linear regression results per factor is presented in Table 8. First, the macroeconomic and industry conditions are assessed, thereafter, loan characteristics, borrower characteristics, recovery process characteristics and, at last, the probability of default outcomes.

5.1.1 Macroeconomic and industry conditions

Following the single linear regression results the GDP trend, FX appreciation and enforceability have a positive relation with LGD, while FX depreciation has a negative relation with LGD. Consequently, all these results are counterintuitive, while the factors FX appreciation and enforceability even show significant results with a level of significance of (or *p*-value smaller than) 5% and 1%, respectively. This means that FX appreciation of the local currency against the Euro and enforceability are significantly related to LGD, where a high FX appreciation and a better enforceability score tend to result in a higher LGD. The same conclusion results for industry distress. Here, the linear regression results in a counterintuitive result as well, since when a client experiences industry distress the LGD tends to be lower following the model. This result is significant with a level of significance of 10%.

5.1.2 Loan characteristics

When we look to the loan characteristics factors we see that all factors are negatively related to LGD. This means that a senior loan, a syndicated loan, a higher EAA or EAD, a guarantee coverage and a collateral coverage all tend to result in lower LGDs. Here, the seniority, EAA and EAD results are significant with a significance level of 1%, and the collateral result is significant with a significance level of 5%. Furthermore, the high negative coefficient of approximate 40% of the seniority factor combined with a high relative R^2 of 0.271 is interesting, since this means that, on average, a senior loan recovers about 40 cents more on a dollar than a subordinated loan. Concluding, since β_1 and R^2 are relatively high, while the *p*-value is very low in case of the factor seniority, this seems to be a very relevant factor in relation to LGD.

5.1.3 Borrower characteristics

For the borrower characteristics we see some significant results as well. Especially a worse solvency and/or liquidity position just prior default has its effect on the LGD, since the LGD tends to increase as well (positive β_1*'s)*. Furthermore, the size of the client shows a significant result too, however the negative coefficient (β_1) is so small that we can conclude that size of a client does not affect the LGD at all. This result is combined with a relative high R^2 (0.152) and low *p*-value (0.000). On the other hand, support from other organizations shows a relative strong relation with LGD. A loan that gets support from another organization recovers, on average, about 19 cents more on a dollar than a loan that gets no support. However, the *p*-value and R^2 are not that convincing since the *p*-value is 0.097 (10% level of significance) and R^2 is only 0.038. Furthermore, the variable multiple support shows counterintuitive results, which are far from significant (R^2 = 0.001 and *p*-value = 0.785).

5.1.4 Recovery process characteristics & business connection

The factors that cover the types of default show significant results in their relation with LGD. When the first default type of a loan was a taken provision by FMO, the LGD tends to decrease significantly (β_1 = -0.828). And so, when the first default involves a delayed payment obligation, a restructuring or liquidation, the LGD tends to become significantly higher. Subsequently, an objective default or multiple defaults are positively related with LGD as well. However, these two factors are highly correlated (correlation factors is 0.9), because when a loan experiences an objective default, FMO will almost always take a provision, which directly results in multiple defaults. Concluding, when a loan is restructured and/or a client is 90 days past due a payment obligation and/or is bankrupt, the LGD tends to increase significantly. Since the R^2-values are relative high and *p*-values are significant small for these factors, it seems that these factors are relevant factors in relation to LGD.

Furthermore, if we look to the factor liquidation, we see that 18% (mean = 0.18) of the loans were liquidated, which in turn resulted in significantly (*p*-value = 0.000) higher LGDs compared to loans that were not liquidated. The average difference in LGD between liquidated loans and non-liquidated loans is approximate 69% following the linear regression results (β_1 = 0.685). Besides, R^2 shows a good result as well (0.546). This means that approximate 55% of the LGDs is explained by the linear regression between the factor liquidation and LGD.

At last, we see that the duration of default and incorrect judgments are positively related with LGD as well and show significant results (*p*-values are 0.049 and 0.001, respectively). Consequently, a longer duration of default and an incorrect judgment during the recovery process tend to result in higher LGDs. However, following the linear regression the LGD tends to increase with only 0.2% per year in default (β_1 = 0.002), while an incorrect judgment results on average in an increase in LGD of 46% (β_1 = 0.458).

5.1.5 Probability of default

When we look to the probability of default scores and the one year determined probability of defaults we do not see significant results (*p*-values are 0.200 and 0.122, respectively). However, the relation between the two factors and LGD is intuitive. A better score of the PD-scorecard results in a lower LGD, while a higher PD tends to result in a higher LGD. These results comply with the findings of the borrower characteristics factors, since the client's solvency, liquidity and likelihood of support is also incorporated in the PDscorecards of FMO. This implies that we should expect a positive relation between PD and LGD, and so the PD and LGD do affect each other. But, the direct relation between PD and LGD is not significant.

Univariate analysis results

	Descriptive Statistics						Single linear regression results			
Factor	*N*	*Mean*	*Median*	*St. Dev.*	*Min*	*Max*	β_1 *(coeff.)*	β_0 *(intercept)*	R^2	*p-value*
Sample LGD	73	0.22	0	0.36	0	1	-	-	-	-
Macroeconomic conditions										
GDP trend	73	-0.03	-0.02	0.05	-0.15	0.08	0.857	0.241	0.015	0.303
FX depreciation	73	0.55	1	0.50	0	1	-0.133	0.290	0.035	0.115
FX appreciation**	73	0.04	0	0.20	0	1	0.469	0.198	0.069	0.025**
Enforceability***	73	1.99	2	0.84	1	4	0.179	-0.138	0.178	0.000***
Industry conditions										
Distress*	73	0.45	0	0.50	0	1	-0.163	0.291	0.053	0.051*
Loan characteristics										
Seniority***	73	0.67	1	0.47	0	1	-0.393	0.481	0.271	0.000***
Syndicated	73	0.38	0	0.49	0	1	-0.006	0.220	0.000	0.945
EAA***	73	6.49	5.50	5.28	0.12	28.50	-0.028	0.400	0.173	0.000***
EAD***	73	5.37	4.04	4.66	0.01	23.10	-0.027	0.365	0.128	0.002***
Guarantee	73	0.12	0	0.37	0	2	-0.120	0.232	0.015	0.295
Collateral**	73	0.70	0	0.79	0	2	-0.133	0.310	0.087	0.011**
Borrower characteristics										
Size***	73	238.74	102	318.66	0.07	1409	-0.000	0.322	0.152	0.001***
Solvency score***	73	2.55	2	1.14	1	4	0.102	-0.042	0.106	0.005***
Liquidity score**	73	2.66	3	1.07	1	4	0.080	0.005	0.057	0.042**
Support*	73	0.85	1	0.36	0	1	-0.194	0.382	0.038	0.097*
Multiple Support	73	0.29	0	0.46	0	1	0.025	0.210	0.001	0.785
Default type***	73	0.95	1	0.23	0	1	-0.828	1.000	0.282	0.000***
Objective Default***	73	0.60	1	0.49	0	1	0.354	0.004	0.238	0.000***
Multiple Default***	73	0.56	1	0.50	0	1	0.380	0.004	0.283	0.000***
Time to emergence	52	7.31	2.3	11.77	-11.8	43.4	-0.004	0.334	0.015	0.380
Duration of default**	72	38.28	33.6	37.19	0.1	181.1	0.002	0.123	0.015	0.049**
Liquidation***	73	0.18	0	0.39	0	1	0.685	0.096	0.546	0.000***
Incorrect judgments***	73	0.10	0	0.30	0	1	0.458	0.174	0.145	0.001***
Insufficient monitoring	73	0.19	0	0.40	0	1	0.117	0.195	0.017	0.273
Intensity of client relationship	73	2.19	2	0.59	1	4	0.101	-0.004	0.028	0.155
Probability of default										
PD-score	70	45.19	43.57	11.79	13.92	80.44	-0.005	0.426	0.024	0.200
PD	70	0.14	0.12	0.14	0.00	1.00	0.472	0.145	0.035	0.122

** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

Table 8 – Descriptive statistics and single linear regressions results

5.2 Multivariate analysis

5.2.1 Results

Next to the single linear regression analyzes per measured factor a multiple linear regression is conducted as well. A linear regression is conducted with the factors that showed relevant results in the single linear regression. Here, with relevant we mean a non-zero coefficient (β_1) and a p-value of less than 10%. The identified relevant factors and the results of the multiple regression are presented in Table 9. By selecting the non-zero coefficients (β_i's) the multiple linear regression model results in:

$$\begin{aligned} LGD = {} & 46\% - 16\% * FX\ appreciation + 5\% * enforceability + 3\% * ind\ distress - 11\% * seniority + 0.3\% * EAA \\ & - 5\% * collateral - 2\% * solvency + 2\% * liquidity - 11\% * support - 37\% * default\ type + 14\% \\ & * mult.default + 38\% * liquidation + 33\% * inc.judge + \varepsilon \end{aligned}$$

We see from the regression results that the factors seniority, default type, multiple default, liquidation, and incorrect judgments are the only factors that show a p-value of less than 10%, and so show significant results. Since these factors also showed significant results in their univariate analysis, it seems that these factors are stronger factors in their relation to LGD than the other measured factors. Remarkable are the results of the recovery process characteristics, because these show relatively high coefficients (β_i's) combined with significant results.

The coefficient of determination or R^2 of the multiple linear regression is 0.761. This means that approximate 76% of our data points is explained by our multiple regression model. This R^2 is significantly larger than those obtained in the univariate analysis and so the combination of the factors as presented in the model is a better predictor for LGD than the factors individual.

5.2.2 Residuals

As explained in Chapter 3, the error term in the regression model is assumed to be normal distributed with a mean of zero. Consequently, the residuals of our model should be normal distributed as well. The residuals per factor resulting from our multiple linear regression model are graphically presented in Appendix G. From these figures we see that residuals for all factors are between -0.6 and 0.6, where the range of LGD is of course from 0 to 1. For some factors the residual figure looks acceptable, since the residuals look equally scattered over the factor scores with the majority of residuals around zero. This approximately applies to the factors seniority, solvency, support and incorrect judgments. For the other factors, the residuals seem to be distributed differently. Factors with diverging residuals over the scores are liquidity, default type and multiple default. Factors with converging residuals over the scores are FX appreciation, EAA, collateral, and the size of client.

Multivariate analysis results

Factor	β_i *(coeff.)*	*p-value*	*Lower 95%*	*Upper 95%*
Macroeconomic and industry conditions				
FX appreciation	-0.158	0.323	-0.477	0.160
Enforceability	0.052	0.124	-0.015	0.118
Industry distress	0.033	0.576	-0.084	0.150
Loan characteristics				
Seniority*	-0.107	0.099*	-0.236	0.021
EAA	0.003	0.614	-0.008	0.014
Collateral	-0.047	0.210	-0.121	0.027
Borrower characteristics				
Size	-0.000	0.494	0.000	0.000
Solvency score	-0.020	0.471	-0.074	0.035
Liquidity score	0.023	0.389	-0.030	0.075
Support	-0.108	0.152	-0.258	0.041
Recovery process characteristics				
Default type**	-0.367	0.046**	-0.728	-0.007
Multiple default**	0.143	0.028**	0.016	0.269
Duration of default	0.000	0.870	-0.002	0.001
Liquidation***	0.380	0.000***	0.199	0.560
Incorrect judgments***	0.333	0.000***	0.164	0.502
Intercept**	0.463	0.032**	0.042	0.884
N	72			
R-Squared	0.761			

* 10% level of significance
** 5% level of significance
*** 1% level of significance

Table 9 – Multiple linear regression results

5.3 Key causes of default

After thoroughly investigating the default cases and constructing the default stories of the client, key causes of defaults were selected per client. Subsequently, the identified causes were allocated to broadly defined issues, namely management & corporate governance (CG) issues, crisis, shareholder or parent company issues, and finally other environment issues. These findings are discussed in this section.

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5.4 Key determinants of loss

Next to the key causes of default, key determinants of loss per client were selected as well. After analyzing the key determinants of loss, the determinants were grouped by shareholder or parent support, management and CG, recovery process, third party support and other environmental matters. Furthermore, we should note that a key determinant of loss could have a positive effect or have a negative effect on the loss. In the defined groups both positive and negative effects are involved.

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5.5 Conclusion

This chapter presented the findings of the conducted quantitative and qualitative analyzes of this research. First the single defined independent variables are analyzed in their relation to LGD by means of linear regressions. Thereafter, relevant variables were selected and a multivariate analysis is conducted by means of a multiple linear regression. Furthermore, key causes of default and key determinants of loss are discussed on a qualitative base.

The results of the univariate analyzes shows counterintuitive results for macroeconomic and industry conditions. Consequently, we cannot indicate relevant relations between macroeconomic conditions, industry conditions and LGD. However, we did found relevant results for loan characteristics, borrower characteristics, recovery process characteristics, business connection and the probability of default in relation to LGD. Especially, seniority, collateral, solvency prior default, liquidity prior default, support from other organizations, default type, objective/multiple defaults, liquidations and incorrect judgments are strongly related to LGD following the univariate analyzes.

However, following the results of the multivariate analyzes especially loan characteristics and recovery process characteristics seem to have strong power in their relation to LGD. The seniority of the loan, the type of default and whether a loan experiences multiple defaults, liquidation or an incorrect judgment are strongly related to the LGD following the results of the multiple regression analysis.

On the other hand, when we follow the specific stories of the clients in the sample and check specific key causes of defaults we see that borrower characteristics and macroeconomic or environmental issues play an important role. Especially, the quality of management, corporate governance structure and position of the main shareholder or parent company are relevant borrower characteristics for the cause of default.

Furthermore, when we look at key determinants of loss we see that borrower characteristics and macroeconomic or environmental issues do play an important role for recovery or losses too. Subsequently, the recovery process seems to play a significant role in the recovery process as well.

CHAPTER 6

Conclusion

This research on LGD is conducted within FMO since FMO did not have insight into realized losses on loans or loss given defaults (LGDs). The reasons to understand historical LGDs are to improve the capital adequacy of the bank and to learn from best practices and mistakes. The main research question is therefore stated as:

What are realized LGDs of FMO's loan portfolio and what are their determinants?

This chapter discusses the conclusions that arise from the conducted research. First, we reflect on the research steps. Thereafter, we discuss our main findings and reflect them to other studies. Lastly, recommendations for FMO are presented, which answers the last stated sub question.

6.1 Research steps

After a preliminary literature study it became clear that the study on LGD is not straightforward since different methods and definitions are applied in available LGD-studies. Furthermore, FMO did not have developed a standardized approach to determine realized LGDs as well. Consequently, this LGD-research is designed from the ground and so specific care is provided to the design, set up and execution of the research. This is seen back in the stated sub questions that divided the research into the set up face, execution face, analyzes face and reflection face.

First, the question of how LGD should be determined is answered, together with what factors are expected to affect LGD. This resulted in the used definitions, methods and measurable factors. The factors are grouped by macroeconomic factors, industry conditions, loan characteristics, borrower characteristics, recovery process characteristics and the business connection between the bank and the borrower. To finalize the set up face of the research two templates are designed such that the data could be gathered in a structured way. These templates are the *loss file* and the *highlights*. The loss file is designed for all quantitative data on loan level, while the highlights is designed for case studies on client level.

After the set up face, the research is executed. After months of data gathering with the support of the templates the sample is created. Furthermore, the analysis part is prepared by setting the methods of analyzes and by stating hypotheses, which are stated as:

1. *Manageable factors as well as unmanageable factors during the recovery process affect the recovery process and so LGD.*
2. *The distribution of realized LGDs is a bimodal distribution, with a magnitude of loans with very low LGDs and a little lower magnitude of loans with very high LGDs.*
3. *Macroeconomic factors, support from other organizations, position within co-lenders and the level of syndication highly affect the LGD of loans in emerging markets and developing countries.*

After creating the sample, the LGDs are analyzed by means of the measured factors. This is done by univariate and multivariate analyzes with the use of linear regressions based on the least-squares method. Furthermore, the highlights are used as case studies and so are analyzed on a qualitative base.

6.2 Findings

In total, a LGD-sample of 73 loans of 52 clients is created, which is broadly dispersed over regions, countries and industries. The average LGD of the sample is 22% with a high standard deviation of 36%, which is indeed bimodal distributed with a magnitude of loans with a very low LGD (< 10%) and a little magnitude of loans with a very high LGD (> 90%). Consequently, our second hypothesis is confirmed. Furthermore, the average LGDs differ between the available general ledger units of FMO. With general ledger we mean from which account the loan is provided. FMO provides loans from its own account, which is the GL-Unit *FMO*

NV, but manages also some government funds. These are the GL-Units *FOM*, *IDF*, *MASSIF* and *AEF*. Because there is a different risk apatite between the GL-Units, especially for some government funds, we see high differences in terms of LGD. Next, we note differences in LGD between regions as well. *Africa*, *Asia* and *Latin America and the Caribbean* (*LAC*) show lower than average LGDs, while *Europe and Central Asia* (*ECA*) and *Global* provided higher than average LGDs. The high average LGD in *ECA* is partly explained by the large number of *FOM*-loans that are provided to entrepreneurs in *ECA*. If we look to different industry groups we see that there is some dispersion in LGDs too, however for some industry groups only a few loans are incorporated. The *finance*, *consumer products* and *agriculture* industries are best represented, which complies with the total loan portfolio of FMO. The LGDs in the *finance* industry are lower than average, while the LGDs in the *consumer products* industry are higher than average and *agriculture* industry are average. The low average LGD in the *finance* industry is partly explained by the many provisions FMO took as a precaution of the global financial crisis. Consequently, many defaults due to the taken provisions finally resulted in no losses and so the average LGD result is low.

The results for the univariate analyzes show some significant results but also some counterintuitive results. All macroeconomic and industry factors show counterintuitive results, where high appreciation of the local currency against the Euro, enforceability score and industry distress even show significant relations. On the other hand, loan and borrower characteristics provide intuitive results. Especially, the seniority of the loan and the solvency and liquidity of the borrower just prior default show relevant relations with LGD, where a senior loan and better solvency and liquidity scores are related to lower LGDs. Next to the loan and borrower characteristics, the recovery process characteristics and business connection show relevant results. The first relevant intuitive factor is whether the client experienced an objective default and or multiple defaults. This means that when a loan is restructured and/or a client is 90 days past due a payment obligation and/or is bankrupt, the LGD tends to increase significantly. The second relevant intuitive relation is that the LGD tends to increase if the loan is liquidated. Other solutions, like a cure, restructuring or full prepayment therefore result in lower LGDs. Next, we found that a longer duration of default and incorrect judgments during the recovery process result on average in higher LGDs and, lastly, the probability of default scores show intuitive but not significant results.

By selecting the factors that show relevant results in the univariate analyzes a multivariate analysis is conducted. As a result, the seniority of the loan, the default type, multiple defaults, whether the loan was liquidated or not and incorrect judgments show significant results in the multiple linear regression model. Consequently, a senior loan and a taken provision as default type tend to result in lower LGDs, while multiple defaults, a liquidation of the loan and incorrect judgments tend to result in higher LGDs. Concluding, loan and recovery process characteristics seem to be strongly related to LGD.

Next to the quantitative analyzes, a qualitative analysis based on case studies is conducted too. All case studies are presented in Appendix H. Key causes of default and key determinants of loss are highlighted and grouped into broadly defined issues. Main causes of default are allocated to management and corporate governance issues of the borrower, crisis, and to a lesser extend shareholder or parent company issues. Remaining causes of default are grouped to other environment issues. Key issues in the management or corporate governance structure of the borrower can be defined as weak risk management practices, conflicting roles between Board of Directors and shareholders and inadequate business models or strategies. Main determinants of loss are allocated to shareholder or parent support, management and corporate governance and to a lesser extend the recovery process, third party support and finally other environmental issues.

Following the results from the quantitative and qualitative analyzes we conclude that the manageable and unmanageable factors during the recovery process affect the LGD and so our first hypothesis is true. Especially in the case studies we see that specific decisions or action by the bank affect the LGD. A liquidation of the loan as a solution of the default situation results in average on higher LGDs, and so liquidation should be avoided to minimize losses. However, in certain cases liquidation is the only option left, for example when the client is filed for bankruptcy. Furthermore, our third hypothesis is for a large part not true since we did not find (intuitive) relations between macroeconomic factors, syndications and LGD. In our multivariate analysis we even found no significant results between macroeconomic factors and LGD. On the other hand, we did see in specific case studies that sovereign events could have its affect on LGD, but that macroeconomic factors seem to be more relevant as a cause of default. Furthermore, from the case studies we did see that support from other organizations is relevant for the LGD. This might be closely related to whether the business is able to continue its operations (in the long term) and so other parties are still interested in the business of the client. Lastly, the position of the bank within co-lenders seemed to be difficult to quantify and to analyze. However, in certain case studies we did see that the grouping and support of co-lenders (for example a rescue finance package) finally resulted in a full recovery (and so low LGD), but also that disagreement between co-lenders can result in high losses.

6.3 Reflection

Due to differences in methods and definitions in LGD-studies direct benchmarking of LGD results make little sense. But, if we look to the average LGD of our sample, we see that it corresponds with other LGD studies on corporate loans. The majority of the LGD-studies namely report an average LGD around 20-30% (Chalupka & Kopecsni, 2008; Grunert & Weber, 2009). Furthermore, we showed that the used definition of default in LGD-studies matters since we found a relation between objective defaults and LGD. This means that the LGD tends to increase when an objective default is noted and so a subjective default only (a taken provision) lowers the average LGD result. Consequently, by following the definition of default as Basel II prescribes prudent banks will show lower average LGDs than less prudent banks. This should subsequently be compensated by higher probability of defaults. Therefore we state that direct benchmarking of LGDs should be accompanied with benchmarking PDs, while differences in definitions must be clear.

The distribution of LGD also corresponds with other studies. We found a bimodal distribution with a concentration on either low or high LGDs, like the studies of Asarnow & Edwards (1995), Carty & Lieberman (1996) and Felsovalyi & Hurt (1998), *inter alia*, reported as well. While other studies found relevant relation between macroeconomic factors and LGD, we found counterintuitive results and so possibly other factors are the cause of these counterintuitive results in our sample. Emery, et al. (2004) and Grunert & Weber (2009) did not find relevant relations between macroeconomic factors and LGD as well. The same holds for industry distress. While certain studies found intuitive results for industry distress in relation to LGD (Carey, 1998; Frye, 2000a, 2000b; Hu & Perraudin, 2002; Emery, et al., 2004; Acharya, et al., 2007; Chalupka & Kopecsni, 2008; Khieu, et al., 2012; Mora, 2012), we found the counterintuitive result that the LGD tends to decrease when the client experiences industry distress. This result is possibly explained by the high number of subjective defaults (taken provisions as a precaution) due to industry distress. Consequently, the average LGD results remained low. On the other hand, we did found differences between broadly defined industry groups. The finance industry, however, resulted in low average LGDs, while other studies state that defaulted loans provided to the finance industry result in higher LGDs and higher PD-rates due to contagion risk (Dermine & Carvalho, 2006; Mora, 2012). Again, a possible explanation of our low LGD result is the many subjective defaults that occurred at FMO-clients in the financial industry due to the global financial crisis. Furthermore, significant results on other industry groups are limited due to our small sample divided over relative many industry groups.

In this research loan characteristics seem to be relevant in relation with LGD. Especially, the seniority of a loan comes forward as a relevant factor, which corresponds with the major finding of Gupton et al. (2000). Khieu, et al. (2012) even found that loan characteristics are more significant with LGD than borrower characteristics and in particular the seniority and collateral of the corresponding loan. For the collateral position of the loan we found this intuitive result as well in the univariate analysis. But, we found a different result for the size or EAD of the loan. The majority of LGD-studies found a positive relation between size and LGD, which means that larger loans tend to result in larger LGDs (Carty & Lieberman, 1996; Felsovalyi & Hurt, 1998; Emery, et al., 2004; Dermine & Carvalho, 2006; Chalupka & Kopecsni, 2008; Bastos, 2010; Khieu, et al., 2012). We found a negative relation between size or EAD and LGD, which is also found by Koŝak & Poljŝak (2010). The reason for their results can be found in the differences of collateralization between the small and large loans. This is partly true for our sample as well, but secondly, loans that are provided from government funds are typically smaller and involve a different (higher) risk apatite. This is possibly reflected in our LGD results as well.

Next to loan characteristics, we found results for borrower characteristics that comply with other studies too. This involves in particular the solvency and liquidity of the borrower just prior default. A better solvency, liquidity, creditworthiness or leverage results in lower LGDs, which is also found by Castle & Keisman (1999), Emery, et al. (2004), and Grunert & Weber (2009). Furthermore, our result on the positive relation between support from other organizations and LGD is not found in other studies. It is simply not a discussed topic in other studies, but following our results and especially qualitative results it might be an important factor for forecasting LGDs.

As is stated before, recovery process characteristics are not well covered in LGD studies. Our results show that recovery process does matter, which is also stated by Gupton, et al. (2000) Khieu, et al. (2012), and Mora (2012). Especially the type of solution of the default case seems to be an important factor for LGD, where liquidation should be avoided to minimize loss. Incorrect judgments and the intensity of the client relationship seem to be relevant as well, but still these are difficult to quantify and therefore these results are rather biased.

6.4 Recommendations

The recommendations for FMO following from this research are divided into three parts: follow up, short term and long term. The first recommendation is to continue increasing the LGD sample. This research with its findings is based on 73 loans of 52 clients only. With a significant increase of the sample, better results and so a more valid model can be obtained. Nonetheless, the research is constructed with the *loss file* and *highlights* in such a way that the bundling of default and LGD information can be done on a continuous base. First steps to embed this process in the organization are already taken during the execution of this research and so this should be continued.

The second recommendation is that the constructed highlights per client should be available in a safe way so they can be studied for 'best practices and mistakes'. Additionally, what will be very meaningful is expanding the highlights with the main issues that came forward during the approval state of the loan (by Investment Review Department and Investment Committee). As a result, you then have a summary of the client and the default process, key issues at loan approval stage, key causes of default and key determinants of loss combined on one page only.

The last recommendation, which is intended as long term, is the improvement of the LGD-scorecard. The current used LGD scorecard consists of loan characteristics only (seniority and security). Following the results of this research especially loan characteristics, borrower characteristics and the recovery process are relevant for the LGD. Since loan characteristics are already incorporated, the LGD-scorecard might be improved by adding borrower characteristics and recovery process characteristics as well. However, we should notice here that loan characteristics might change much less than borrower and recovery process characteristics and so by incorporating these characteristics in the LGD-scorecard, LGD-forecasts might fluctuate much more. Therefore, implementation and monitoring issues should be checked accurately.

Furthermore, by increasing the sample of default and LGD information, other factors might be seen as relevant as well. At least once per year the loss-database must be validated and analyzed. This will result in a much more relevant database that can be better compared or enforced by databases of other Development Financial Institutions, like the Global Emerging Markets database (GEMs). If improvements of LGD-forecasting are desirable in short time, the link between and use of GEMs and maybe other databases (like Moody's) should be investigated next.

CHAPTER 7

Discussion and further research

Every research design has its assumptions and limitations. Especially in creating models to make a simplification or simulation of reality, assumptions are necessary. This last chapter of this master thesis reflects on the research design by discussing the used assumptions and its limitations. To complete, we discuss certain topics that are recommended for further research in the field of Loss Given Default and credit risk in general.

7.1 Limitations

This research on LGD of FMO's loan portfolio consisted of two research analysis designs: a cross-sectional analysis and a case study analysis. The major issues in cross-sectional research designs are i) the weakness at the level of explanatory, causal analysis and ii) the sample size. Therefore, both issues should be taken into account in our quantitative findings. With the results of the regression analyzes we found relevant relations, but we should be careful with stating causal relationships. Next, our regression analyzes are based on 73 loans, which is rather small if one takes the large number if independent variables into account. As a result, while we found relevant results in our sample, we should be careful with generalizing and extrapolating these results.

To overcome the issue of causal relationships the research is extended by case studies. While case studies are time consuming, it provides a complete story of specific cases (Yin, 2009). Subsequently, the case studies are in particular relevant for the learning experience of FMO. But we should note that the case studies are conducted with the best available historical information within FMO. Therefore, relevant information might be excluded from certain cases since it was not available. Interviewing employees of FMO about recent cases made these stories complete, but for older cases information might be lost.

Other issues related to this research are the identification of variables and the operationalization of the research. By a thorough literature study factors that may affect or explain LGDs are selected and made measurable. But, since there are no predefined explanatory factors of LGD, important factors still might be excluded in this research. Next, by explaining how the selected factors are measured in combination with the standardization of the data gathering with the designed templates, the research design and execution is clear and can be repeated any time at any place. Only the issue of data availability remains. This research is conducted within FMO where loan and client information was well available.

7.2 Further research

Following this research and its limitations further research on LGD is recommended. These can be divided into research on definitions in LGD-studies, combining and comparing data of LGD-studies, methods of analysis and manageable factors as determinants of LGD.

Since the determination of LGD is dependent on several definitions, the generalization of findings remains an issue. Consequently, findings are mainly based on data of one institution where only a relative small sample size is obtainable. This applies to this study as well. Therefore, a general accepted methodology or a method to be able to compare studies with a different LGD-dataset must be investigated. We believe this should be a complete comparison of bank's credit risk practices and so involves the comparison of LGD in combination with PD, EAD and all needed definitions and methods.

While quantitative analyzes in this study is based on linear regression with the least-squares method, it is however not known what analyzes methods provides the best result in LGD-studies. Therefore, further research is recommended to compare different analysis methods especially when the sample size is increased significantly. Possibilities of other methods are, for example, a logistic regression (or log-log model) and the use of quasi-maximum likelihood estimators (QMLE) (Dermine & Carvalho, 2006; Chalupka & Kopecsni, 2008). However, there is no well-excepted method of analysis for LGD, and so this requires further research.

As we stated in this research recovery process characteristics in relation to realized LGDs are underexposed in research on LGD. With this study we tried to emphasize the importance of the management of the bank on realized corporate loan losses. This involves as well the monitoring and studying of realized losses as well as the ability of the bank to minimize losses by good management. Therefore, we definitely encourage more research on the management of recovery processes of corporate loans. Especially comparative studies on the recovery process between different financial institutions are recommended.

Finally, in default cases and the recovery process there is a grey area, which is the period just prior default. With the grey area we mean that a bank might be able to prevent a default and so the recovery process is not applicable since no real default happened. However, the bank possibly minimized its loss to prevent the default by good management and so these actions are related to the PD instead of LGD. Direct management factors of a bank may therefore be related to both PD and LGD. Further research on this 'grey area' between PD and LGD is therefore needed and recommended as well.

Bibliography

Acharya, V. V., Bharath, S. T., & Srinivasan, A. (2007). Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries. *Journal of Financial Economics, 85*(3), 787-821.

Altman, E., Resti, A., & Sironi, A. (2001). Analyzing and Explaing Default Recovery Rates. *The International Swaps & Derivatives Assocation, December*, 1-97.

Altman, E., Resti, A., & Sironi, A. (2004). Default recovery rates in credit risk modelling: A review of the literature and empirical evidence. *Economic Notes, 33*(2), 183-208.

Asarnow, E., & Edwards, D. (1995). Measuring loss on defaulted bank loans: A 24-year study. *The Journal of Commercial Lending, 77*(7), 11-23.

Bade, B., Rösch, D., & Scheule, H. (2011). Default and recovery risk dependencies in a simple credit risk model. *European Financial Management, 17*(1), 120-144.

Bastos, J. A. (2010). Forecasting bank loans loss-given-default. *Journal of Banking & Finance, 34*(10), 2510-2517.

Bennett, R. L., Catarineu, E., & Moral, G. (2005). Loss given default validation. In BIS (Ed.), *Working Paper No. 14: Studies on the Validation of Internal Rating Systems* (Vol. May, pp. 68-93). Basel.

BIS. (1999). *A new capital adequacy framework*. Basel: Basel Committee on Banking Supervision. Bank for International Settlements.

BIS. (2001). The Basel Capital Accord. *Consultative Paper, Bank of International Settlements, January*.

BIS. (2006). International convergence of Capital Measurement and Capital Standards. *Basel Committie on Banking Supervision: Bank for Internaitonal Settlements, June*, 1-347.

Carey, M. (1998). Credit Risk in Private Debt Portfolios. *The Journal of Finance, 53*(4), 1363-1387.

Carey, M., & Gordy, M. (2001). Systematic Risk in Recoveries on Defaulted Debt. *Unpublished Working Paper presented at the 2001, Financial management Association Meetings, Toronto, October 20, 2001*.

Carty, L. V., & Lieberman, D. (1996). Defaulted Bank Loan Recoveries. *Moody's Special Comment, November*.

Chalupka, R., & Kopecsni, J. (2008). Modelling bank loan LGD of coprorate and SME segments: A case study. *IES Working Paper 27/2008. IES FSV. Charles University*.

Dermine, J., & Carvalho, C. N. (2006). Bank loan losses-given-default: A case study. *Journal of Banking & Finance, 30*(4), 1219-1243.

Düllmann, K., & Trapp, M. (2004). Systematic Risk in Recovery Rates - An Empirical Analysis of U.S. Corporate Credit Exposures. *EFMA 2004 Basel Meetings Paper*, 1-35.

Emery, K., Cantor, R., & Arner, R. (2004). Recovery rates on North American syndicated bank loans, 1989-2003. *Special Comment, Moody's Investors Service.*

Felsovalyi, A., & Hurt, L. (1998). Measuring loss on Latin American defaulted bank loans: A 27-year study of 27 countries. *Citibank portfolio strategies.*

FMO. (2013). Financials. Retrieved 28 April, 2013, from http://www.fmo.nl/financials

Franks, J. R., de Servigny, A., & Davydenko, S. (2004). A comparative analysis of the recovery process and recovery rates for private companies in the UK, France, and Germany. *Standard and Poor's Risk Solutions, June, 2004.*

Fridson, M. S., M.G., C., & Okashima, K. (2000). Recovery Rates: The Search for Meaning. *Merrill Lynch & Co., High Yield Strategy.*

Frye, J. (2000a). Collateral damage. *Risk Magazine, 13*(4), 91-94.

Frye, J. (2000b). Depressing recoveries. *Risk Magazine, 13*(11), 69-73.

Frye, J. (2003). A false sense of security. *Risk Magazine, 16*(8), 63-67.

Grunert, J., & Weber, M. (2009). Recovery rates of commercial lending: Empirical evidence for German companies. *Journal of Banking & Finance, 33*(3), 505-513.

Guo, X., Jarrow, R. A., & Lin, H. (2008). Distressed debt prices and recovery rate estimation. *Review of Derivatives Research, 11*(3), 171-204.

Guo, X., Jarrow, R. A., & Zeng, Y. (2009). Modeling the recovery rate in a reduced form model. *Mathematical Finance, 19*(1), 73-97.

Gupton, G. M., Gates, D., & Carty, L. V. (2000). Bank-loan loss given default. *Moody's Investors Service, Global Credit Research, November 2000*, 69-92.

Hu, Y. T., & Perraudin, W. (2002). The dependence of recovery rates and defaults. *Mimeo, Birbeck College.*

Jarrow, R. (2001). Default Parameter Estimation Using Market Prices. *Financial Analysts Journal, 57*(5), 75-92.

Jokivuolle, E., & Peura, S. (2000). A Model for Estimating Recovery Rates and Collateral Haircuts for Bank Loans. *Bank of Finland Discussion Papers 2/2000*.

Khieu, H. D., Mullineaux, D. J., & Yi, H. C. (2012). The determinants of bank loan recovery rates. *Journal of Banking and Finance, 36*(4), 923-933.

Koŝak, M., & Poljŝak, J. (2010). Loss given default determinants in a commercial bank lending: An emerging market case study. *Zbornik Radova Ekonomskog Fakultet au Rijeci, 28*(1), 61-88.

Miu, P., & Ozdemir, B. (2006). Basel requirements of downturn loss given default: modeling and estimating probability of default and loss given default correlations. *Journal of Credit Risk, 2*(2), 43-68.

Mora, N. (2012). What determines creditor recovery rates? *Federal Reserve Bank of Kansas City.*

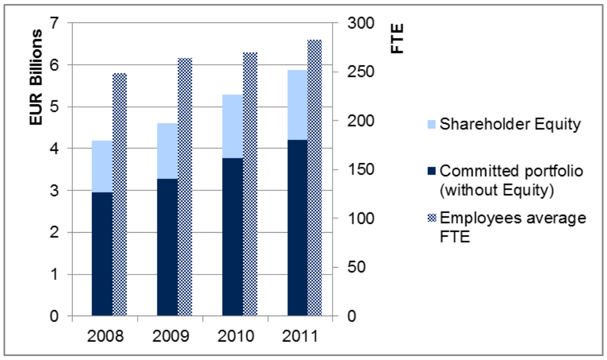
van de Castle, K., & Keisman, D. (1999). Recovering your money: losses from defaults. *Standard & Poor's CreditWeek, June 16*, 29-34.

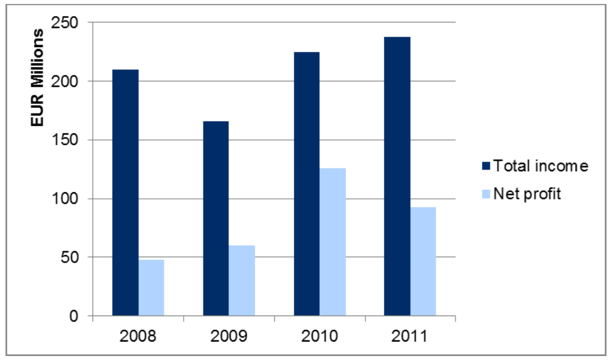
Yin, R. K. (2009). *Case Study Research: Design and Methods*: Sage Publications.

Appendices

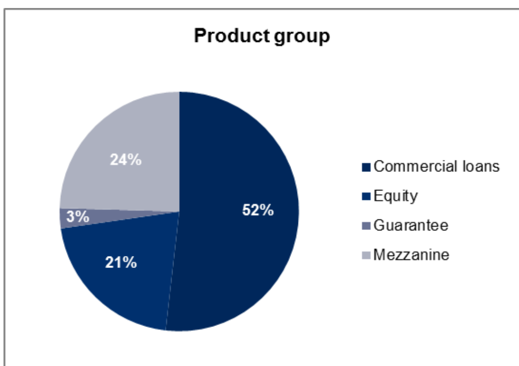
Appendix A: FMO figures

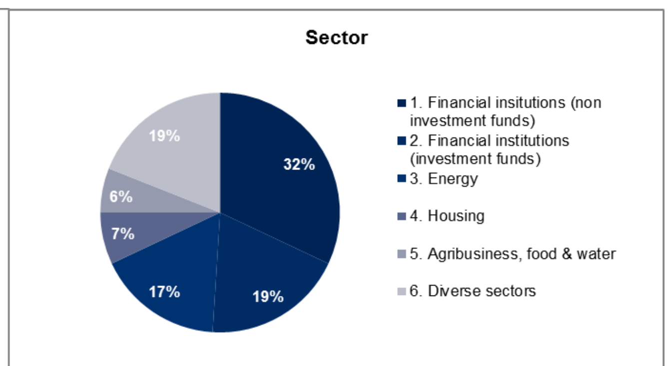
Committed portfolio, shareholders equity, FTE, total income and net profit

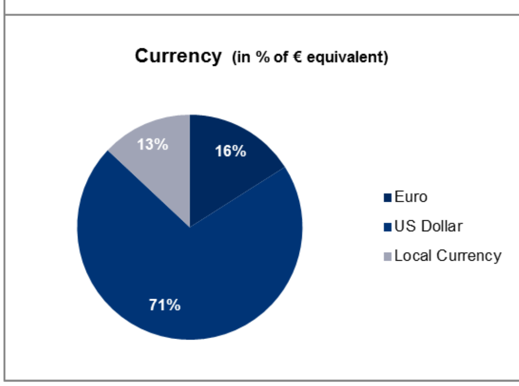


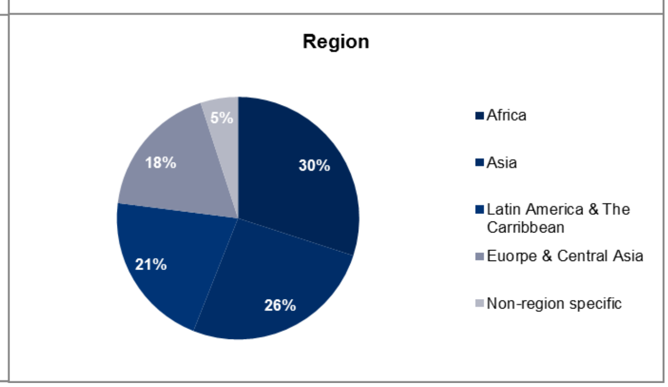


Committed portfolio per product group, sector, currency and region as of 2011









Appendix B: Literature research approach

Searching method

To perform a good literature review it is necessary to define and justify the following components: choice of research databases, keywords, selection criteria and prioritisation criteria.

Research database

Online scientific databases are used to search for relevant articles for the research. Initially, Web of Science is used since it covers relevant journals in the field of credit risk, risk management, finance, banking and economics. Secondly, Google Scholar and Scopus are used to search for any missed relevant articles.

Keywords used

During the preliminary research possible keywords have been identified that would lead to interesting articles. These are presented in the following tag cloud. The value of using a keyword is indicated with the size of the text.

After the search on these keywords a forward and backward research is conducted to find additional relevant articles. This feature is available in Web of Science, Google Scholar and Scopus.

1. Selection and prioritization criteria
2. Identified articles have to satisfy the following four criteria in or der to be useful.
3. Article is written in English or Dutch.
4. The full text is available.
5. The article is published in a journal with a focus on financial risk, banking, or economics.
6. The topic of the article is related to credit risk and loss given default or recovery rate.

After relevant articles are selected that meet the selection criteria the articles are scored by prioritization criteria in order to define the degree of relevance of these articles. The prioritization criteria are chosen so that they together represent the ideal article that is useful for this research. The prioritization criteria and their corresponding weight and scoring indicators are presented in the following table. Note that all scores are transformed as a fraction of the maximum points possible for those criteria.

#	Prioritization criteria	Weight	Score			
			0 point	1 points	2 points	3 points
1	Times cited	0.15	< 10	>10	>50	
2	Publication date	0.5	< 2006	>2006		
3	Focus on LGD/RR of loans	0.1	None	Mentioning	Part of analysis	Only focus
4	Focus on LGD/RR determinants	0.25	‘	‘	‘	‘
5	Focus on LGD/RR forecasting models	0.05	‘	‘	‘	‘
6	Focus on LGD/RR calculation	0.15	‘	‘	‘	‘
7	Focus on downturn LGD	0.05	‘	‘	‘	‘
8	Focus on emerging markets	0.10	‘	‘	‘	‘
9	Empirical evidence	0.10	No	Yes		

Subsequently, the articles that score at least 0.6 with the prioritization criteria are initially selected for the literature research. However, other slightly less prioritized articles may still contain relative information for the research and so these are not excluded in advance.

Selection of articles

Initially, by searching with the keywords only resulted on many hits because of the connection with certain keywords with the science in chemistry and medicine. Therefore all hits were narrowed on the topic 'credit risk' only and next articles in the topic of bank, finance and economics were selected only. This resulted in less than 100 articles and after a first scan on topic and titles, 41 articles were selected. After a forward and backward research and applying the selection criteria, 67 articles remained. By reading the abstracts and screening the articles, the prioritization criteria were applied. After calculating the overall scores, 25 articles scored a 0.5 or higher and 15 articles a 0.6 or higher. These articles are presented in the next table and are thoroughly analyzed to set up the literature review.

First Author	Year	Title	Journal	Cited by	Score
Kosak and Poljsak	2010	Loss given default determinants in a commercial bank lending: an e	Zbornik radova Ekonomskog fakultet	0	0.83
Khieu	2012	The determinants of bank loan recovery rates	Journal of Banking & Finance	8	0.78
Dermine	2006	Bank loan losses-given-default: A case study	Journal of Banking & Finance	87	0.78
Chalupka	2009	Modelling bank loan LGD of corporate and SME segements: A case	Czech Journal of Economics and Fir	12	0.76
Mora	2012	What determines creditor recovery rates?	Economic Review	1	0.69
Bastos	2010	Forecasting bank loans loss-given-default	Journal of Banking & Finance	32	0.64
Schuermann	2004	What do we know about loss given default?	Working Paper, Federal Reserve Ba	216	0.67
Grunert	2009	Recovery rates of commercial lending: Empirical evidence for Gern	Journal of Banking & Finance	64	0.65
Altman	2009	Default Recovery Rates and LGD in Credit Risk Modeling and Prac	In: Jones, S., Hensler, D.: Advances	59	0.65
Gupton	2000	Bank loan loss given default	Moody's Investors Service	129	0.65
Hurt and Felsovalyi	1998	Measuring loss on Latin Amercian defaulted bank loans, a 27-year	The Journal of Lending and Credit R	49	0.64
Emery et al.	2004	Recovery Rates on North American Syndicated Bank Loans, 1989-	Moody's Investors Service	16	0.64
Acharya	2007	Does Industry-wide Distress Affect Defaulted Firms? - Evidence fro	Journal of Financial Economics	258	0.63
Hu and Perrauding	2002	The dependence of recovery rates and defaults	Risk Control limited. Februari	124	0.63
Frye	2003	A false sense of security	Risk Magazine	62	0.60
Dullmann and Trapp	2004	Systematic risk in recovery rates - an empirical analysis of US corp	EFMA 2004 Basel Meetings Paper	84	0.58
Altman	2004	Default recovery rates in credit risk modelling: A review of the literat	Economic Notes	158	0.58
Bennett et al.	2005	Loss given default validation	pp. 60 - 93	6	0.58
Gupton	2002	LossCalc: Moody's Model for Predicting Loss Given Default (LGD)	Moody's KMV	113	0.58
Van de Castle et al.	1999	Recovering your money: Insights into Losses from Defaults	Standard and Poor's Credit Week, Ju	36	0.54
Gupton	2005	Advancing loss given default prediction models: how the quiet have	Economic Notes	20	0.54
Franks	1994	A comparison of Financial Recontracting in Distressed Exchanges a	Journal of Financial Economics	408	0.52
Altman	2006	Default Recovery Rates: A Review of the Literature and Recent Em	Journal of Finance Literature	59	0.52
Altman	2001	Analyzing and explaining default recovery rates	ISDA Report	125	0.52
Jokivuolle	2003	Incorporating collateral value uncertainty in loss given default estim	European Financial Management	85	0.50

At last, a tag cloud of the prioritized articles is presented below in order to check whether the general topics of the articles fit well and reflect the tag cloud of the initial keywords.

Appendix C: Definition of Default by Basel II (BIS, 2006)

A borrower is considered to have defaulted if any of the following events have taken place.

- The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held).
- The obligor is past due more than 90 days on any material credit obligations to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstandings.

The elements to be taken as indications of unlikeliness to pay include:

- The bank puts the credit obligation on non-accrued status.
- The bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure.
- The bank sells the credit obligation at a material credit-related economic loss.
- The bank consents to a distressed restructuring of the credit obligation where this is likely to result in a diminished financial obligation caused by the material forgiveness, or postponement, of principal, interest or (where relevant) fees.
- The bank has filed for the obligor's bankruptcy or a similar order in respect of the obligor's credit obligation to the banking group
- The obligor has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation to the banking group.

Appendix D: Overview of studies

Article	LGD Determination	Determinants	Sample data	Analysis	Results
(Acharya, et al., 2007)	- Market LGD	- Contract characteristics - Firm characteristics - Industry Q - Industry distress - Industry characteristic - Macroeconomic and bond market conditions	More tan 300 non-financial, public and private defaulted U.S. companies. Period: 1982-1999 Source: S&P's Credit Pro database (Portfolio Management Data)	-OLS regression	- Industry conditions, in particular industry distress
(Bastos, 2010)	-Discounted cash flow approach (r= charged interest rates)	- Loan size - Collateral - Personal guarantee - Manufacturing sector - Trade sector - Service sector - Lending rate - Age of firm - Rating - Missing rating - Years of relationship	374 loans granted to SMEs Period: 1995-2000 Source: Banco Comercial Portugues (BCP)	Fractional response regress -Log-log regression - Logistic regression Nonparametric regression - Tree model	- Regression trees give better results for shorter recovery horizons of 12 and 24 months, while fractional response regression gives better results for longer horizons.
(Chalupka & Kopecsni, 2008)	- Discounted cash flow approach (r = premium for each asset class of collaterals)	<u>Counterparty related factors:</u> - Industry classification, age of company, year of default, year of company origination, year of loan origination, length of business connection <u>Contract related factors:</u> - type of contract, EAD, interest rate, tenure, number of different types of contracts <u>Collateral related factors:</u> - collateral type, collateral value by type, aggregate collateral value, collateral value relative to the EAD, number of collaterals, diversification of collaterals	Historical closed files Period: 1989-2007 Source: Anonymous commercial bank from Central Europe	Symmetric logit and asymmetric log-log link functions for ordinal responses as well as for fractional responses Fractional responses - Beta inflated distribution - QMLE	- Value of collateral - Loan size - Year of loan origination Log-log models in some cases perform better
(Dermine & Carvalho, 2006)	-Discounted cash flow approach (r= charged interest rates)	-Size of the loan - Type of guarantee/collateral support - Industrial sectors - Default year - Age of the firm - Number of years of relationship - Annual GDP rate of growth - Frequency of default in the industry sector - Rating of borrower - Interest rate on loan	374 default cases , which are all SMEs based in the south of Portugal, including Lisbon Period: 1995-2000 Source: Banco Comercial Portugues (BCP)	-Mortality analysis - OLS - Log-log - QMLE	- Size of the loan - Collateral - Industry sector - Year dummies - Age of the firm

(Emery, et al., 2004)	- Market approach Average bid price one month after default.	Firm/loan characteristics - Secured versus unsecured, loan rating one day prior, loan rating one year prior, loan debt cushion, issuer's capital structure, issue amount, loan default type, loan seasoning, bonds default before loans, number of tranches Macroeconomic/industry factors - Moody's SG default rate, industrial production growth, Ba/Treasury spread, industry type, industry distress	202 issuers over 370 North American defaulted syndicated loans. Period: 1989-2003 Source: Moody's Loan Default Database.	-Univariate analysis - Regression analysis	- Debt cushion - Issue amount - Industry distress - Seasoning
(Frye, 2003))	- Market LGD Prices are observed as the bid-side average two to eight weeks after the default event.	- Default rate	859 bonds and loans of U.S. non-financial issuers Period: 1983-2001 Source: Moody's Default Risk Service Database	- Univariate analyzes	-Increase of LGD when default rate increases - Risk is especially great for low LGD debt types
(Grunert & Weber, 2009)	- workout LGD (r = last interest rate before default event)	Variables referring to hypotheses - Value of collateral - Creditworthiness of the borrower - Size of the company - Intensity of the client relationship Control variables - Industry classification - Form of company - Continuation of the company - EAD - Economic conditions (GDP and unemployment rate)	120 companies in default Period: 1992-2003 Source: One large German bank	- Univariate analyzes - Linear Regression	-High quota of collateral leads to a higher recovery rate - Risk premium of borrower and the size of the company is negatively related to recovery rate. - Borrowers with intense client relationship with the bank exhibit higher recovery rate.
(Gupton, et al., 2000)	- Market LGD Secondary market price quotes of bank loans one month after the time of default	- Seniority of loan - Influence of a firm's having multiple loan obligations - Influence of broad industry groups - Moody's firm ratings - Timing	181 defaulted bank loans (121 defaulted issuers) Period: 1989-2000 Source: Moody's	- Univariate analyzes	- Presence of multiple loans with borrower's debt structure negatively influence recovery of senior unsecured loans - Nature of bankruptcy filing affects LGD - Defaults with average LGD levels are among the longest to resolve - Presence of security - Moody's ratings (at default) - No significant influence of industry groupings on LGD

(Hu & Perraudin, 2002)	- Market LGD Recovery rates are defined as the ratio of the market value of the bonds to the unpaid principal.	- Industry dummies - Domicile dummies - Seniority dummies - A dummy reflecting whether the issuer has support from some other organization.	958 long-term bond defaults (no bank loans). Period: 1971-1999 Source: Moody's Corporate Bond Default Database	- OLS regression - Inverse Gaussian regressions - Kernel estimates of loss distributions - Extreme Value Theory estimates	-Recoveries tend to be low when default rates are high. - Support from other organizations lowered LGD.
(Felsovalyi & Hurt, 1998)	- Workout LGD Since loan-specific contractual lending rate was not available, yearly average interest rates on non-U.S. C&I loans are used.	- LGD during sovereign events - Year of default - Size of default	1,149 defaults on commercial and industrial (C&I) bank loans in 27 countries in Latin America Period: 1970-1996 Source: Citibank		- Larger loans higher LGD - Presence of economic groups that affect LGDs - Diversity in economic environment (sovereign events) over the period is not reflected in the variation of LGD
(Khieu, et al., 2012)	-Discounted settlement value (r = effective interest rate) - Trading prices (30-day after default)	<u>Loan characteristics:</u> - Loan size, loan types, collateral <u>Recovery process characteristics:</u> - Prepackaged bankruptcy, time to emergence <u>Borrower characteristics:</u> - Firm size- Cash flows, asset tangibility & leverage, prior defaults <u>Macroeconomic conditions, industry and PD:</u> - GDP, industry distress, cross-section variation across industry, PD	Actual recovery of 1364 observations (loans) of North American commercial and industrial firms. Period: 1987-2007 Source: Moody's Ultimate Recovery Database	-Univariate analysis - Multiple regression: OLS & QMLE	- Loan characteristics more significant than borrower characteristics - Firm leverage before default (negatively on recoveries) - Secured loans, especially collateral like inventories and accounts receivable - Loans with prior defaults yield higher recovery - Prepackaged bankruptcy increases recoveries - Macroeconomic conditions
(Košak & Poljšak, 2010)	- Discounted cash flow approach (r = average interest rate on Slovenian Tolar denominated loans)	<u>Collateralization factors:</u> - type of collateral, value of collateral <u>Type of industry variable</u> <u>Macroeconomic factors:</u> - Annual GDP growth rates and year of default <u>Other factors:</u> - Maturity factor (short/long-term loans) - Last available loan rating - Recovery method - Size of the loan exposure	124 defaulted SMEs Period: 2001-2004 Source: Commercial bank operating in Slovenian banking market	- Mortality -based approach - GLM (Generalizes linear models)	Significance of: - Type of collateral - Type of industry - Last available loan rating - Recovery method - Size of the loan exposure

(Mora, 2012)	- Market LGD Recovery is measured by the market value of defaulted debt as a percentage of par, one month after default.	<u>Market specific</u> - Defaulted amount - Default rate - Real GDP growth - S&P 500 stock return <u>Industry conditions</u> - Industry Q (Market to book) - Industry stock return - Industry distress indicator	Defaulted U.S. corporate debt securities. Period: 1978-2010 Source: Moody's Default Risk Service	- Descriptive statistics - Regression	Recovery rate depends on systematic and industry wide factors.
(van de Castle & Keisman, 1999)	- Market LGD	- Collateral type - Instrument type - Subordinated Debt cushion	829 debt instruments Period: 1987-1997 Source: S&P's Credit Loss Database	- Multiple regression model	Type of debt, collateral type and subordinated debt cushion are determinants

Appendix E: Definition and measurement of factors

Manageable factors

Recovery process characteristics

Type of default	The type of default following the Basel II definitions of default, which is used by FMO. When multiple definitions apply, the definition that occurs as first is the type of default.

Score	Description
1	Provisioning
2	Restructuring
3	90 days past due payment obligation
4	Bankruptcy of client

Provisioning (dummy)	This dummy checks if a provision was taken on the specific loan account.

Score	Description
0	No provision
1	A provision was taken

Restructuring (dummy)	This dummy checks if the loan is restructured during the course of default.

Score	Description
0	No restructuring
1	Loan is restructured

90 days past due (dummy)	This dummy checks if the client was 90 days past due on any payment obligation during the lifetime of the loan.

Score	Description
0	Client was not 90 days past due on a payment obligation
1	Client was 90 days past due on a payment obligation

Bankruptcy (dummy)	This dummy checks if the client went into an official bankruptcy position.

Score	Description
0	Client was not in bankruptcy position
1	Client was in bankruptcy position

Time to emergence	The time it took before the client in default got special attention. This is measured as the time difference in days between default-date and transfer-date to Special Operations department.
Duration of default	The time it took to close the default process. This is measured as the time difference in days between default-date and closing-date of the loan or closing-date of the charge-off.
Recovery method	There are four recovery methods identified, which get the following scores.

Score	Description
0	Nothing changed to the loan
1	A prepayment is agreed to foreclose the loan
2	The loan is restructured
3	The loan is liquidated

Incorrect judgments (dummy)	Whether operational mistakes or failed expectations occurred within the bank in the post-default process. Measured as a dummy variable.

Score	Description
0	No incorrect judgments after default
1	Incorrect judgments did occur after default

Insufficient monitoring (dummy)	Whether the client was insufficiently monitored prior default. Measured as a dummy variable.

Score	Description
0	Client was sufficiently monitored
1	Client was insufficiently monitored

Business connection

Intensity of client relationship	The intensity of client relationship is difficult to monitor and measure. Once per year a client is reviewed and the client rating is updated. While there is no scoring for the client relationship, existing difficulties in the relation do often come forward. Furthermore, in interviews the intensity of the relationship is asked. Finally, the intensity of client relationship is scored as follows:

Score	Description
1	Excellent relationship
2	Good relationship
3	Partly unsatisfactory relationship
4	Unsatisfactory relationship

Unmanageable factors

Macroeconomic factors

Average GDP trend	The average GDP trend is determined by the difference between the average GDP growth over the 5 years prior default, and the average GDP growth over the post-default period. To calculate the average GDP growth annual GDP growth factors are used.
FX fluctuation	FX fluctuation is used to check if major devaluations or inflations happen during the lifetime of the facility. An FX fluctuation is measured as follows.

Score	Description	Measure
-1	High devaluation	Local currency devaluated with more than 30% on USD
0	Neutral	Local stayed within -30% - 30% boundaries on USD
1	High inflation	Local currency inflated with more than 30% on USD

Enforceability

FMO developed an enforceability factor per country. The enforceability factor is based on a dataset of the World bank, which reports on governance indicator for countries. It is based on three indicators: rule of law, control of corruption and regulatory quality. These indicators can be find here: http://info.worldbank.org/governance/wgi/index.asp

Furthermore, in a limited number of countries FMO has a preferred creditor status. These countries are monitored separately and therefore get a score of 5.

Score	Enforceability factors
1	=<25
2	>25 and =<50
3	>50 and =< 75
4	>75
5	Preferred creditor status in country

Industry conditions

Type of industry

General industry class in which the client is mainly active.

Industry class
Agriculture
Capital Goods
Consumer products
Energy
Finance
Material
Telecom
Transport & Logistics
Utilities

Industry distress (dummy)

Whether industry distress is noticed in which the client is active. It is measured as a dummy variable.

Score	Description
0	No industry distress noticed
1	Industry distress noticed

Borrower characteristics

Type of client

FMO makes distinction among four different types of client, which are scored as follows:

Score	Description
1	Financial Institutions
2	Non-banking financial institutions (NBFI)
3	Corporates
4	Projects

Size of client

The size of clients is measured in different ways due to the different client types.

Type of client	Measure
FI and NBFI	Generated annual revenue in EUR
Corporates	Total assets in EUR
Projects	Total budget of project in EUR

Solvency prior default

The solvency measures the ability of the client to survive in the long run. It is measured as total assets divided by total liabilities. A difference is measures as applied between corporates and financial institutions.

Score	**Description**	Corporates	Banks and NBFIs
1	Excellent	Solvency: >=45%	BIS ratio: < 8%
2	Good	Solvency: 30>=45%	BIS ratio: > 8%<10%
3	Partly unsatisfactory	Solvency: 20>=30%	BIS ratio: > 10%<14%
4	Unsatisfactory	Solvency: <20%	BIS ratio: > 14%

Liquidity prior default

The liquidity measures the ability of the client to pay short-term debt. Current ratio or liquidity coverage ratio is used to measure the liquidity, which is current assets divided by current liabilities:

Score	**Description**	Current rate	Liquidity coverage ratio
1	Excellent	>=1.7	>=1.6
2	Good	1.3>=1.7%	1.3>=1.6
3	Partly unsatisfactory	0.8>=1.3	0/7>=1.3
4	Unsatisfactory	0 < 0.8	0 < 0.7

Support from other organizations

Support from other organizations is seen as an indirect guarantee, because shareholders or governments may support the client when it encounters difficulties. It is measured as follows:

Score	**Description**
0	No direct support from other organization
1	Support from shareholders
2	Support from co=lenders
3	Support from government or guarantee system

Position within co-lenders

The position within co-lenders is defined as how many co-lenders are involved in the default of the client, which may indicate how many stakes are applicable.

Score	**Description**
0	FMO is only lender
1	Client has less than 5 lenders
2	Client has 5 to 10 lenders
3	Client has more than 10 lenders

Loan characteristics

Level of seniority

Support from other organizations is seen as an indirect guarantee, because shareholders or governments may support the client when it encounters difficulties. It is measured as follows:

Score	**Description**
0	Sub-ordinated loan
1	Senior loan

<table>
<tr><td>Level of syndication</td><td>The level of syndication is defined as whether the provided loan is part of a syndication and in particular if the provided loan is part of a syndication with IFC* or IBRD**.
<table>
<tr><th>Score</th><th>Description</th></tr>
<tr><td>0</td><td>No syndication</td></tr>
<tr><td>1</td><td>Loan is part of syndication</td></tr>
<tr><td>2</td><td>Loan is part of syndication with IFC or IBRD</td></tr>
</table>
* IFC is International Finance Corporation, which is part of the World Bank Group.
** IBRD is International Bank for Reconstruction and Development, also part of World Bank Group.
</td></tr>
<tr><td>EAA</td><td>Exposure at approval, which is the total commitment of the facility in EUR x million</td></tr>
<tr><td>EAD</td><td>Exposure at default, which is the total exposure at default in EUR x million</td></tr>
<tr><td>Collateral coverage</td><td>The percentage of the exposure that is covered by the collateral.
<table>
<tr><th>Score</th><th>Collateral coverage</th><th>Description</th></tr>
<tr><td>0</td><td>>0%-24%</td><td>No securities, strong pari-passu with other creditors, negative pledge, potential to receive material securities, collater coverage <25%</td></tr>
<tr><td>1</td><td>25%-49%</td><td>Collateral coverage up to 49%</td></tr>
<tr><td>2</td><td>50%-74%</td><td>Collateral coverage up to 74%</td></tr>
<tr><td>3</td><td>75%-99%</td><td>Collateral coverage up to 99%</td></tr>
<tr><td>4</td><td>100%-149%</td><td>Collateral coverage up to 149%</td></tr>
<tr><td>5</td><td>150%-199%</td><td>Collateral coverage up to 199%</td></tr>
<tr><td>6</td><td>200% and over</td><td>Collateral coverage 200% and above</td></tr>
</table>
</td></tr>
<tr><td>Type of collateral</td><td>Liquidity of the assets that are part of the collateral received
<table>
<tr><th>Score</th><th>Description</th><th>Examples</th></tr>
<tr><td>0</td><td>None</td><td>There is no collateral</td></tr>
<tr><td>1</td><td>Low</td><td>Accounts receivable, assignment of receivables or sub loans, machinery and equipment, pledge of shares private company, licenses, telecom switch, package of collateral received for project</td></tr>
<tr><td>2</td><td>Medium</td><td>Real estate, land, pledge of shares listed company, leasing assets</td></tr>
<tr><td>3</td><td>High</td><td>Real estate or land in an a-location, pledge of highly liquid shares listed company</td></tr>
<tr><td>4</td><td>Excellent</td><td>Pledge of bank accounts</td></tr>
</table>
</td></tr>
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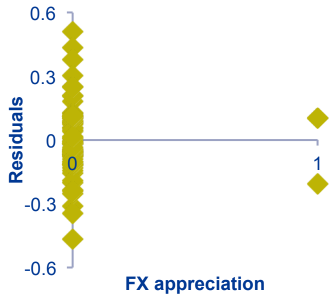
Appendix F: Example of a client

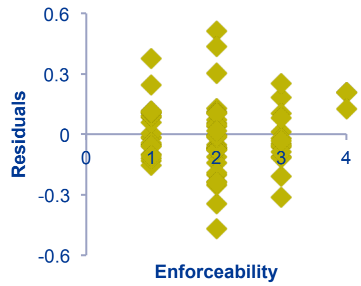
Highlights

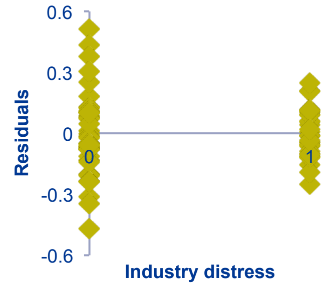
Loss file

Appendix G: Residuals of multiple linear regression analysis

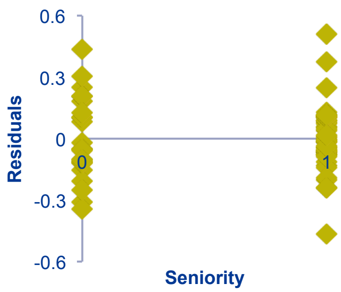
Macroeconomic and industry conditions

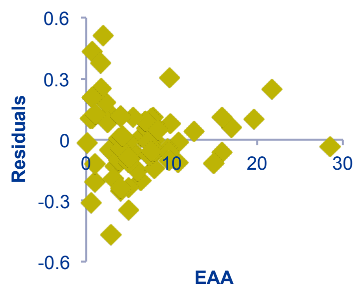


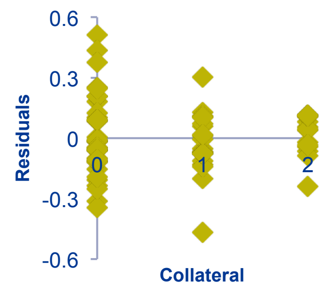




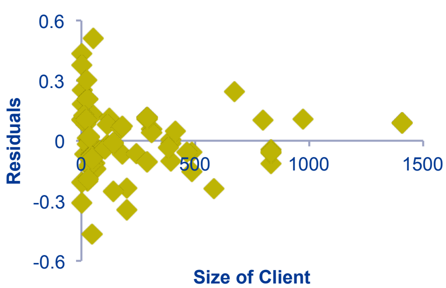
Loan characteristics

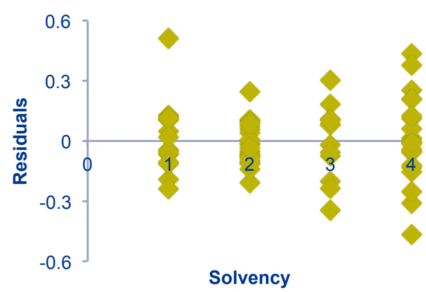


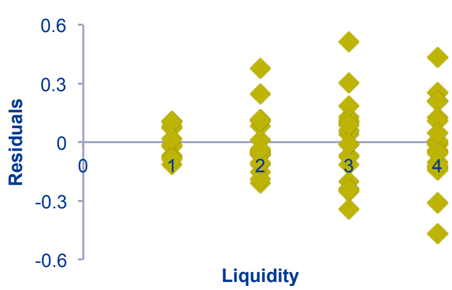


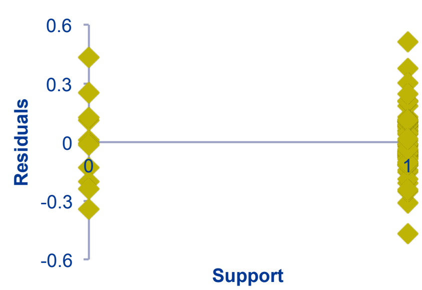


Borrower characteristics

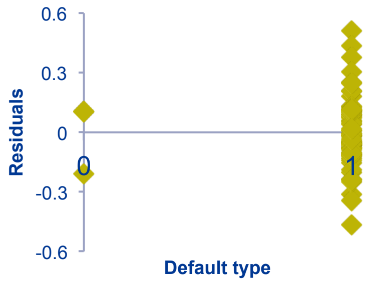


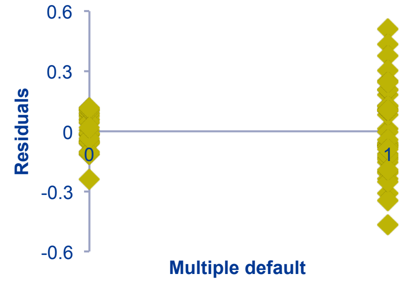


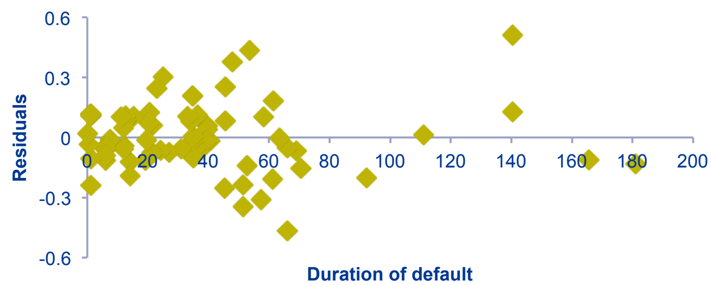


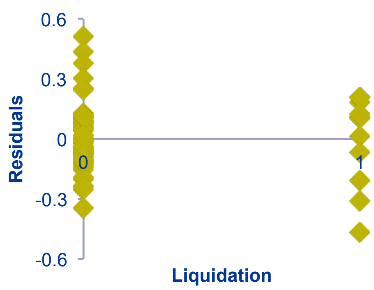


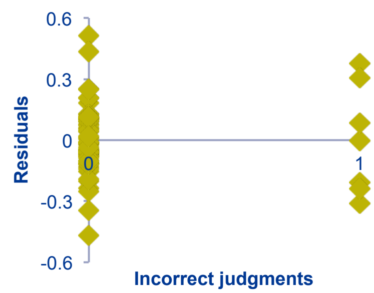
Recovery process characteristics











Appendix H: Highlights Bundle

This appendix contains the highlights (summaries) of all clients that were investigated in this research. Per highlight first key client and LGD information is presented, thereafter a (short) summary of the complete process. Finally, key causes of default, the client rating just prior default and key determinants of the loss are presented. We should note that these highlights are created by us with the best-obtained internal information of FMO. Used documentations are for example IRC-minutes (Investment Review Committee), client rating reports, transfer notices, ending notices, historical documentations obtained from the client (such as financial information) or other available memo's. Furthermore, for some recent cases FMO employees were interviewed for their own experience with the client.

First an overview of the clients with key information is provided. Thereafter all highlights are presented in alphabetical order.

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