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Abhandlungen

Do Economic Downturns Have an Impact on the Loss Given Default of Mobile Lease Contracts?

– An Empirical Study for the German Leasing Market –

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I. Introduction

Following its introduction in Germany in the early 1960s, leasing has emerged as a considerable means of financing. The importance of leasing in the economy is measured by the leasing quota, which is defined as the leasing share of all investments in capital goods. According to the Federal Association of German Leasing Companies, the leasing quota rose from 2.1 % in 1970 to 17.0 % in 2008.

On the one hand, this popularity offers good chances for growth to leasing companies, but it also poses challenges with regard to their credit risk management. In general, the credit risk associated with a lease contract is similar to that of a collateralized bank loan. The exposure-at-default (EAD) is defined as the present value of the outstanding lease payments plus the residual value of the asset at maturity. The cash-flows after the lessee's default encompass the revenues of the asset disposal as well as payments from other recovery sources.

In order to quantify the credit risk of a leasing contract, three important parameters are required: the above-mentioned EAD, the probability of default (PD), and the loss given default (LGD). A reliable estimation of the expected cash-flows after the default event is an important topic for the credit risk management of a leasing company for the following two reasons:

– The cash-flows from the asset disposal do not only have to cover the outstanding lease payments, but also the residual value of the leased asset.
– Unlike creditors of collateralized bank loans, lessors are allowed to access the leased asset quickly and dispose of it autonomously according to the German insolvency law.

This means that the lessor collects the asset revenues entirely. Therefore, the lessor will be more motivated than the loan creditor to set up an expertise with regard to the asset disposal, which should generally lead to lower losses in the case of default.

These better opportunities with regard to the asset disposal are considered an advantage of leasing over loan financing. In order to benefit from this advantage, leasing companies must be able to estimate their LGDs in a reliable way. The estimation concerns both the single-contract level (with regard to the risk-adjusted pricing of the leasing rentals) and the portfolio-level (with regard to the control of the total risk position of the leasing company). Important questions related to the quantification of the credit risk of a leasing portfolio are the level and distribution of the LGD realizations as well as the identification of factors which can explain differences among LGDs. Within these factors, we distinguish between asset- and contract-related variables on the one hand and systematic variables on the other hand.

In credit portfolio models, the impact of systematic risk factors on the LGD is neglected. In fact, these models assume that the LGDs of the obligors are either constant or independently beta distributed. This assumption has two weaknesses: First, the use of the beta distribution is based on the empirical evidence of prices of defaulted bonds (market recovery). However, loans and the assets for their collateralisation are typically not tradable in the market so that the LGD has to be determined by means of the cash-flows during the workout process (workout recovery). Second, the Basel Committee on Banking Supervision (BCBS) asks for the incorporation of systematic risk factors in the LGD estimation.

In case of the PD, the BCBS prescribes a transformation formula that converts the unconditional PD into a "stress PD" in order to take account of the systematic risk. For the LGD parameter, by contrast, no corresponding formula exists. If the Advanced IRB Approach of Basel II is applied, the adverse economic scenario must be already included in the estimated LGD value, which is referred to as a "downturn LGD". If the LGD proves to increase during downturn periods, the downturn LGD must be used instead of the long-run average LGD.

The contribution of this paper is threefold. First, we provide empirical evidence about the level and distribution of the LGD of mobile lease contracts for different asset types where we use workout recoveries instead of market recoveries. Second, we analyse the impact of macroeconomic conditions on the aggregated LGD and propose a pragmatic method how leasing companies can determine a downturn LGD for their internal risk control. Third, a problem widely neglected in the academic literature is addressed: Debtors classified as defaulted may not fall into an ultimate status of insolvency, but may recover after some time of financial distress and fulfil their debt service as scheduled. Resurrected contracts will occur quite frequently if a default criterion is applied that qualifies contracts as defaulted despite of only minor disturbances. We show that the resurrection rate varies over time and depends on macroeconomic variables. Our data comes from two major German leasing companies and encompasses nearly 54,000 mobile lease contracts regarded as defaulted between 1993 and 2004.

The following section surveys how the LGD is modelled in the credit risk literature and summarizes the empirical evidence concerning the LGD of leasing contracts provided by previous studies. In the third chapter, we present our data set, the default definition, and the procedure for the calculation of the LGD. In addition, we introduce the concept of the "resurrection rate". Section IV is devoted to some descriptive analyses concerning the level and empirical distribution of the LGD. In chapter V, we outline the design of the analysis and introduce several macroeconomic risk factors. Using regression analyses, we investigate in section VI whether the LGDs (as well as the resurrection rates) of different asset types exhibit a cyclical variability or not. In section VII, we propose a simple approach for the estimation of a downturn LGD and demonstrate its application with an empirical example. Finally, section VIII draws a conclusion.

II. Review of the Literature

In the classical option pricing framework developed by *Merton* (1974), the LGD is defined as the difference between the face value of the debt and the value of the firm's assets at the termination date. In contrast to Merton's model, more recent approaches account for the possibility that a default can emerge even before the maturity of the loan. In these approaches, the recovery rate (RR) is either modelled as a constant fraction of the debt (e.g. *Longstaff/Schwartz* (1995), *Zhou* (2001)) or as a percentage of the firm value at default (e.g. *Black/Cox* (1976), *Briys/de Varenne* (1997), *Klein* (1996) or *Ericsson/Reneby* (1998)).

Unlike the above-mentioned structural-form models, reduced-form approaches do not condition the default event on firm characteristics. By contrast, they introduce explicit assumptions on the dynamics of the RR. Concretely, this variable can be modelled in three different ways. In the recovery-of-face-value model, the RR is considered as a fraction of the face value of the debt (e.g. *Das/Tufano* (1996)). According to the usages at the OTC derivatives market, the recovery-of-market-value concept assumes that the creditor receives a payment amounting to a fraction of his claim just before the default of the obligor (e.g. *Duffie/Singleton* (1999)). In the recovery-of-treasury model, the creditor receives a certain quantity of default-free securities which are equivalent to the defaulted debt (e.g. *Jarrow/Turnbull* (1995), *Lando* (1998) or *Madan/Unal* (1998)).

The loss distribution of a credit portfolio significantly depends on the correlation structure between the individual loans. This concerns, on the one hand, the correlation between the default events and the correlation between the LGDs, and, on the other hand, the stochastic dependencies between the PDs and the LGDs. Credit portfolio models only account for the correlation between variations of the obligors' credit worthiness. This is accomplished by the assumption that either the PDs (in Credit Risk+™ and Credit Portfolio View™) or the asset returns (in Credit Metrics™) depend on identical systematic risk factors. In the IRB Approach of Basel II, the dependencies between the PDs are modelled by an asset value model as well.

In all of the above-mentioned approaches, the LGD parameter is treated either as a constant or as a beta distributed random variable. This means that stochastic dependencies between the LGDs (and also between the LGDs and the PDs) are neglected by these models. Hence, the underlying assumption is that the LGD is only influenced by asset- and contract-related characteristics but not by systematic factors.

However, several empirical studies found that the aggregated market LGD depends on changes of the macroeconomic environment. According to *Frye* (2000b), the LGD increases during recessions by 20–25 % compared to periods of normal economic activity. *Hu/Perraudin* (2002) detect a significant correlation between the LGD and the default rate, which suggests that both parameters are driven by a systematic factor. Using data of the US bond market, *Altman* et al. (2005) show that the default rate, together with variables representing the economic cycle and the size of the high-yield bond market, is able to explain a major part of the LGD variation. Furthermore, *Chabaane* et al. (2004) found that the expected portfolio loss as well as risk measures like the value-at-risk or the expected shortfall are underestimated if systematic components are disregarded. Consequently, the assumption of a constant LGD over time does not seem to be realistic.

Models that are able to incorporate systematic risk in the recovery rates have been developed by *Frye* (2000a), *Pykthin* (2003) and *Düllmann/Trapp* (2004). The approach of Frye is based on a one-factor model and the assumption of normally distributed recovery rates. An advantage of this framework is that the factor loadings can be directly interpreted as recovery correlations. In Frye's model, however, the possible outcomes for the RR are not limited to the unit interval.

The model of *Pykthin* (2003) overcomes this drawback by applying a log-normal distribution which ensures that the RR always remains positive. *Düllmann/Trapp* (2004) replace the log-normal distribution by a logistic normal distribution so that the values of RR are restricted to the unit interval. Using market prices of defaulted bonds, they find out that the empirical RR distribution can be approximated quite well by the normal and logistic normal distribution. Furthermore, the authors detect an impact of the systematic risk factor on the recovery rate, which is modelled as a latent variable. The LossCalc model of Moody's (*Gupton/Stein* (2005)) uses an aggregated distance-to-default as a macroeconomic risk factor in order to explain the variation of market recoveries. Moreover, it is shown that the empirical distribution of the RR can be approximated by a beta distribution. *Hamerle* et al. (2006) develop a dynamic approach, in which the market LGD is modelled depending on issuer- and bond-specific as well as macroeconomic variables.

Up to now, there are rather few empirical studies dealing with workout recoveries and their distributional characteristics. Besides, there is little evidence concerning the impact of systematic risk factors on the LGDs of non-tradable securities. Whereas most of these studies are based on bank loans, quite little research has been carried out on the LGD of defaulted lease contracts, especially for the German market.

De *Laurentis/Geranio* (2001) conducted a survey for the European leasing market through three different types of assets (automobiles, equipment, and real estate). The authors calculated LGD averages and volatility levels of nearly 3,000 defaulted contracts and found that leasing companies generally incur rather low losses in the event of default. *Schmit/Stuyck* (2002) confirmed this result for a much larger data set of 37,000 defaulted leases (from twelve companies in six European countries). In addition, they investigated the impact of the age and the term-to-maturity on the average LGD of a given lease portfolio. Using non-parametric tests, they also checked whether there is a relation between the year of default and the level of the LGD. For most of the considered countries and asset types the authors found only weak evidence and concluded that the LGD is quite resistant to a change of the macroeconomic environment. However, the situation in Germany was not considered.

Based on a rather small sample of 1,000 defaulted contracts, De *Laurentis/Riani* (2005) analysed determinants of the LGD for the Italian leasing market. They found that the LGD (on contract level) is affected not only by asset-related variables (for example asset type, original value) but also by non-asset-related variables such as the type of business, the form of organization, and the geographic area of the defaulted lessee. The study conducted by *Schmit* (2004) is devoted to the estimation of the loss distribution and the related risk quantiles for a portfolio of nearly 47,000 mobile lease contracts (thereof about 4,300 defaulted) by applying a non-parametric simulation technique. The same method is used in the work of *Laurent/Schmit* (2005). They simulated LGD distributions of defaulted vehicle leases (6,093 contracts) for different phases of the business cycle. It is shown that the level of the risk quantiles is more or less constant over time and is therefore relatively independent of macroeconomic conditions.

Our article makes a contribution to the literature in several ways. Unlike *Schmit/Stuyck* (2002) or *Laurent/Schmit* (2005), we directly quantify the impact of particular macroeconomic variables on the LGD using regression techniques. Furthermore, with nearly 54,000 defaulted contracts, the following study is based on a very extensive and unique data set. To the best of the authors' knowledge, this is the first empirical study which analyses the LGD exclusively for the German leasing market and according to different asset categories.

III. Data Description

1. Overview

The database used for this study comes from two major German leasing companies and encompasses 53,944 mobile lease contracts that defaulted between 1993 and 2004. The contracts are classified by asset type. Originally, ten different types of assets were distinguished in the data set: cars, fleet vehicles, commercial vehicles, equipment of information and communication technology (ICT), construction machinery, printing ma-

Table 1

Frequency Distribution by Asset Type

Asset Type	*Observations*	*Percent of Total (%)*	
Vehicles	22,567	41.83	–
Cars	17,016	–	31.54
Fleet Vehicles	1,506	–	2.79
Commercial Vehicles	4,045	–	7.50
ICT	19,205	35.60	35.60
Machinery	6,230	11.55	–
Construction	1,265	–	2.35
Printing	465	–	0.86
Plastics	321	–	0.60
Tools	628	–	1.16
Other	3,551	–	6.58
Other Assets	5,942	11.02	11.02
Total	53,944	100.00	100.00

chinery, plastics machinery, tools machinery, other machinery, and other assets.[1] Because of the limited sample size in some asset classes (see table 1), we decided to make a coarser classification of the contracts according to the following four asset types: vehicles, ICT equipment, machinery, and other assets. Table 2 shows the distribution of the defaulted leases over time.

The small number of contracts in 2004 can be traced back to the fact that the process of data collection did not cover the whole year. Apart from information concerning the asset type and the year of default, our database contains several variables that allow for the calculation of the LGD of a contract: risk position of the leasing company at default (exposure-at-default), amount of the revenue from asset resale, and amount of other payments to the lessor after default. For the leases of one company, the exact date of default is known, too.

[1] The category of other assets is quite heterogeneous and contains, for example, medical equipment, containers, fork-lift trucks, or industrial facilities.

Table 2

Frequency Distribution by Default Year

Default Year	*Observations*	*Percent of Total (%)*
1993	5,036	9.34
1994	5,251	9.73
1995	5,312	9.85
1996	5,355	9.93
1997	4,593	8.51
1998	3,729	6.91
1999	3,668	6.80
2000	4,169	7.73
2001	5,121	9.49
2002	7,078	13.12
2003	4,371	8.10
2004	261	0.48
Total	53,944	100.00

2. *Definition of Default and Resurrection Rate*

A crucial issue in the context of the analysis of the LGD is the definition of the default event. The Basel Committee on Banking Supervision applies a rather wide default definition. Accordingly, a default is considered to have occurred if an obligor is past due more than 90 days on any material credit obligation or if another event indicating unlikeliness to pay has taken place. Such an indication could be, for example, that the bank makes a charge-off or account-specific provision, consents to a distressed restructuring of the credit obligation, or has filed for the obligor's bankruptcy.[2]

However, some of these events are not really adequate for leasing contracts. In contrast to a bank, which balances the credit obligation, a leasing company puts the leased asset into its balance sheet. Hence, a charge-off is not a meaningful indication for the lessee's unlikeliness to

[2] See *BCBS* (2006), §§ 452–454.

pay. Furthermore, leasing companies have the right to cancel the contract if the lessee is past due on only two scheduled monthly rentals which corresponds to approximately 60 days. Consequently, a delay of 90 days is also difficult to realize because leasing companies often react earlier on a delay of payment.

The two leasing companies of our data set define a lease contract as defaulted when it accesses their legal departments. Usually, a contract is transferred to the legal department if the leasing company has unilaterally cancelled the contract or the lessee has filed for bankruptcy, whichever happens earlier.[3] In the context of the Basel II definition, the access date to the legal department can be considered to be an event indicating the lessee's unlikeliness to pay. Thus, our default criterion is compatible with the regulations of Basel II. Compared to a 90-days past due, it is, however, a little more severe as it takes effect earlier.

The application of this default definition includes the possibility that a lease contract is transferred to the legal department first, but leaves it again at a later date. This case can occur if the contract has been cancelled, but the lessee did not actually default and the agreement is re-fulfilled duly. Within our study, a contract that leaves the legal department is called "resurrected". In our data set, we can determine for each lease contract whether it was resurrected or not. We now introduce the so-called resurrection rate, denoted by *XR*, which describes the extent of resurrections for a given portfolio of lease contracts. Thus, *XR* is defined by:

$$XR = \frac{\text{Number of resurrected contracts}}{\text{Number of accesses to legal department}}$$

As shown in table 3, resurrection is a quite frequent phenomenon in our data set. According to the different asset types, the resurrection rates range from 20.71 % (machinery) to 39.13 % (other assets). Overall, more than every fourth contract leaves the legal department because it was re-fulfilled correctly.

With regard to the analysis of the LGD, it is essential to distinguish between resurrected and non-resurrected (i. e. definitely defaulted) contracts because they describe different economic circumstances. Whereas the cash-flows of definite defaults basically come from the asset or col-

[3] Since this definition was set by the leasing companies themselves, we are not able to investigate the impact of different default criteria in our study.

Table 3

Resurrection Rates *(XR)* by Asset Type

Asset Type	*Observations*	*Not resurrected*	*Resurrected*	*XR (%)*
Vehicles	22,567	16,752	5,815	25.77
ICT	19,205	14,181	5,024	26.16
Machinery	6,230	4,940	1,290	20.71
Other	5,942	3,617	2,325	39.13
Total	53,944	39,490	14,454	26.79

lateral disposal, the payments from resurrected contracts consist of the regular (re-)fulfilment of the lease. Since we focus our analysis on the disposal risk of the leasing company, it is appropriate to consider only such cases where the contract was terminated before maturity and a resale of the leased asset actually took place. Thus, the sample for the analysis of the LGD in the following chapters amounts to the 39,490 non-resurrected contracts.

3. Definition and Measurement of the LGD

In general, the LGD is defined as the fraction of credit exposure that cannot be recovered in the event of the borrower's default. Several studies also use the term recovery rate (RR), which equals one minus LGD. Since leasing claims are typically not traded in the market, the LGD of a defaulted lease contract cannot be obtained from market prices after the default event as in the case of bonds. Instead, all relevant cash-flows resulting from the workout-process must be first identified, then discounted at the default date and finally divided by the exposure-at-default. This way of measurement is referred to as workout LGD.

In our data set, the workout cash-flows consist of the revenues from the resale of the leased asset at the secondary market as well as payments from other recovery sources such as other collateral or rentals that have been paid after the default event. This happens, for example, if the insolvency practitioner decides to fulfil the leasing contract after the opening of the insolvency proceedings. Since the data set only provides insufficient information about the costs within the workout process (for example, broker fees, legal costs, or asset repossession costs), we do not consider them for the calculation of the LGD. The LGD of an individual lease contract is determined by the following formulas:

$$\mathrm{LGD} = 1 - \mathrm{RR} = 1 - \frac{\text{Present Value (Resale Revenue + Other Recoveries)}}{\mathrm{EAD}}$$

where

$$\begin{aligned}\mathrm{EAD} = \ & \text{Discounted residual value of the asset at maturity} \\ & + \text{Discounted outstanding rentals up to maturity} \\ & + \text{Compounded overdue rentals.}\end{aligned}$$

For discounting respectively compounding at the default date, the leasing companies used the yield (internal rate of return) of the particular lease contract.

IV. Descriptive Analyses

Before we analyse the relationship between the LGD and the macroeconomic environment, we present the results of several descriptive analyses in this chapter. First, we look at the shape of the empirical LGD distribution. Figure 1 shows the histograms for the different asset types. For reasons of illustration, only those values that lie within the interval $[-1,5;\ +1]$ are computed.

The four diagrams indicate that the LGD distributions are widely bimodal with peaks occurring at 0 % and at around 100 %. In other words, the most likely results imply losing nothing or almost everything. This phenomenon is quite typical for workout LGDs and also consistent with the findings of other empirical studies.[4] In the case of vehicles, machinery, and other assets we can observe that the left mode (at 0 %) is higher than the right one, which means that lower LGDs are more common. For ICT equipment, in contrast, higher values tend to occur more frequently.

Besides, it can be observed that the distributions are not completely symmetric, but exhibit certain skewness towards negative LGDs (left-skewness). This is caused by the presence of negative LGD realizations. If the LGD is measured using the workout method, negative LGD values can occur frequently. If a given lease contract has a rather low EAD, but

[4] See, for example, *Laurent/Schmit* (2005), *Asarnow/Edwards* (1995) or *Eales/Bosworth* (1998).

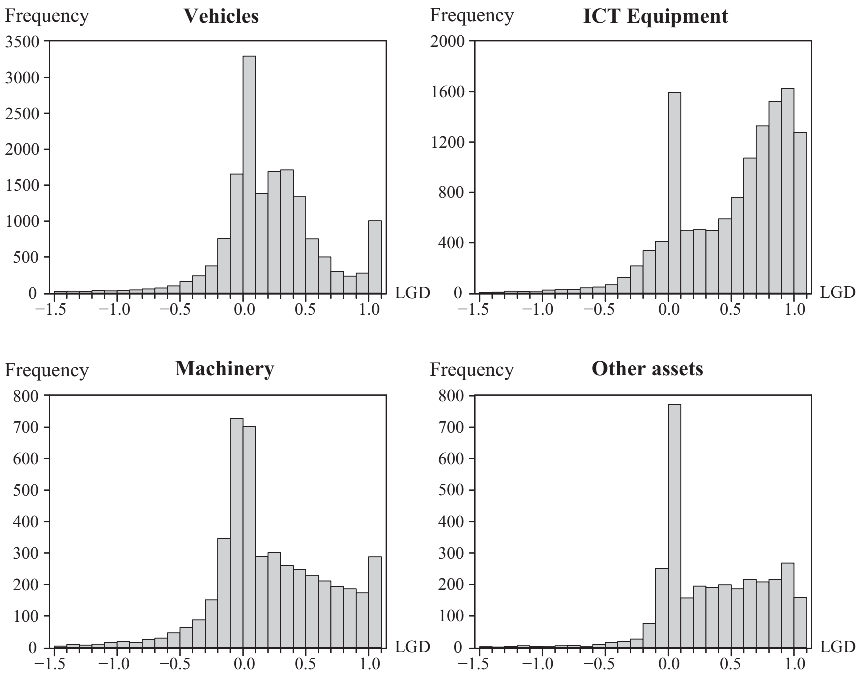

Figure 1: Empirical LGD Distribution by Asset Type
(non-resurrected contracts only)

the leasing company achieves a high recovery from asset resale, the resulting LGD can be lower than zero.[5]

Next, we focus on the comparison of LGD levels among different asset classes. Table 4 exhibits several summary statistics of the LGD distribution according to the type of the leased asset.

It strikes that the LGD averages for ICT equipment are much higher compared to the other asset classes. A reason for this result might be that many ICT assets (e.g. computer hardware) are subject to steady technological progress. Therefore, they suffer from a rapid decrease in value which leads to higher losses in case of default. For vehicles and machinery assets, by contrast, the LGD average values are rather low. This might be explained by relatively stable market values in case of machinery and liquid secondary markets for vehicles (e.g. cars).

[5] In our data set, we observe a rather high number of negative LGDs in all asset classes. More than every fifth contract (21.92 %) exhibits a LGD below zero.

Table 4

Descriptive Statistics of the LGD by Asset Type (non-resurrected contracts only)

Asset Type	*Observations*	*Mean (%)*	*Median (%)*	*Standard Deviation (%)*
Vehicles	16,752	20.51	17.61	52.31
ICT	14,181	61.84	70.77	46.93
Machinery	4,940	24.16	12.70	58.16
Other	3,617	34.05	42.75	53.73
Total	39,490	31.59	32.57	56.22

Arithmetic means and standard deviations are weighted by the EAD of the contract.

The mean of the entire sample of defaulted leases amounts to 31.59 %. Compared to the minimum LGD for collateralized exposures in the Foundation IRB Approach of Basel II, which is 40 %[6], this figure is somewhat lower. Table 5 summarizes the results of other empirical studies concerning the LGD of lease contracts and bank loans. A direct comparison between workout LGDs among different surveys cannot be carried out without difficulties because the exact evaluation of the LGD often differs with regard to the default definition, the choice of the discount factor, and the cash-flows determining the recovery value.

The studies dealing with lease contracts, however, confirm our findings that the level of the LGD varies significantly depending on the type of the leased asset. In general, assets with relatively stable market values (for example real estate or machinery) and assets traded on liquid secondary markets (vehicles) benefit from lower LGDs. In contrast, for assets that lose value quite rapidly (such as ICT equipment) higher losses can be observed. The relation between lease contracts and bank loans is ambiguous. Some authors suggest that leasing companies benefit from lower LGDs than banks because of their better understanding of the secondary markets and the assets themselves.[7] Against the background of the figures from table 5, however, this hypothesis cannot be confirmed in general.

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[6] See *BCBS* (2006), § 295. Leases other than those that expose the bank to residual value risk will be treated in the same way as exposures collateralized by the same type of collateral (see *BCBS* (2006), § 523).

[7] See, for example, *Schmit/Stuyck* (2002), p. 24 f.

Table 5

Selected Empirical Studies Concerning the LGD of Lease Contracts and Bank Loans

Lease Contracts

	Number of Defaults	LGD by Asset Type (%)		
		Vehicles	Equipment	Real Estate
De Laurentis/Geranio (2001)	2,804	0.4–48.3	14.3–71.7	2.0–39.2
De Laurentis/Riani (2005)	1,118	39.0	55.0	16.0
Laurent/Schmit (2005)	3,503	–0.4	–	–
Schmit (2004)	4,263	20.0	22.7–55.1	–
Schmit/Stuyck (2002)	37,259	3.6–35.2	26.2–55.3	5.3–43.9

Bank Loans

	Number of Defaults	LGD (%)
Araten et al. (2004)	3,761	39.8
Asarnow/Edwards (1995)	831	34.8
Davydenko/Franks (2008)	2,280	39.0
Eales/Bosworth (1998)	5,782	27.0–31.0
Grunert/Weber (2005)	120	28.1
Moody's (2009)	Period 1982–2005	35.8

V. Design of Analysis

1. Methodology

The macro-economy is supposed to have an impact on the average LGD of all contracts that defaulted within a given period. Hence, we aggregate the individual LGDs into a time series of averages by calculating the exposure-weighted arithmetic means with regard to a specific asset type.[8] Because of the limited sample size and the heterogeneous charac-

[8] This procedure is geared to the studies of *Altman* et al. (2005), *Hu/Perraudin* (2002) or *Schmit/Stuyck* (2002) who also use aggregated values for the analysis of the LGD over time.

ter of the segment of other assets, we focus on only three asset types: vehicles, ICT equipment, and machinery.

In our data set, both companies provided information about the default year of their leasing contracts. The exact date of default, however, is only known for the contracts of one leasing company. As we want to look at the entire sample of contracts, our analyses are basically built on annual LGD averages. Besides, we calculated series of quarterly averages based on the contracts of one company.[9] Of course, the results for annual and quarterly data are not directly comparable, but we think they can serve as a good robustness check.

Since the year 2004 was not covered completely in the collection of the data, and the number of observations is accordingly very low (see table 2), our observation period encompasses 11 years (1993 to 2003). For the analysis on quarterly level, we focused on the period between the first quarter of 1993 and the second quarter of 2003, which corresponds to 42 observations. The series of aggregated LGD for the different asset classes are presented in figure 3 (appendix). Table 9 (appendix) shows the number of contracts entering the calculation of annual and quarterly averages.

Following the methodology of *Altman* et al. (2005), we use a linear regression approach in order to quantify the impact of the macroeconomic environment on the LGD. Theoretically, a panel regression model[10] could also be applied in order to analyse individual (cross-sectional) LGD determinants in addition to macroeconomic effects. Unfortunately, such a model is not applicable in our context, because the data set does neither provide information concerning contract characteristics nor lessee-related features. Hence, we could not include individual effects on the LGD in our model. However, we are convinced that such an extension would not yield any significantly different results as leasing – unlike bank loans – is a rather homogeneous product with most of the variations among contracts captured by asset class. Individual characteristics such as seniority or lessee-related variables are supposed to be of less importance.[11] Hence, we think that our approach is quite adequate for

[9] We passed on analyses on monthly basis because in some months there are too few defaulted contracts for the calculation of meaningful averages.

[10] See, for example, *Hamerle* et al. (2006).

[11] This hypothesis is supported by *De Laurentis/Riani* (2005) who come to the conclusion that a considerable proportion of the LGD variability remains unexplained even if a lot of individual features are taken into account.

the underlying research question. Accordingly, we use the aggregated LGD as dependent variable and macroeconomic risk factors, generally denoted with *RF,* as regressors.

As the magnitude of resurrections influences the average LGD, it might also be important for leasing companies to know which factors are responsible for the variation of the resurrection rate XR, which was introduced in chapter III.2. Therefore we also performed regressions with XR as a dependent variable. In our data set, however, the variable XR can only be analysed on an annual basis. Since the leasing company, that provided the exact default date of their lessees, registered a rather small number of resurrections in their data, we did not have enough contracts to obtain meaningful results on a quarterly or monthly level. The general form of the regression equations is given by:

$$LGD_t = \alpha + \sum_{i=1}^{K} \beta_i RF_{i,t} + \varepsilon_t \qquad \text{respectiveley} \tag{1}$$

$$XR_t = \gamma + \sum_{i=1}^{K} \delta_i RF_{i,t} + \omega_t \qquad \text{for } t = 1, \dots T. \tag{2}$$

The regression coefficients α, β, γ and δ are estimated by the method of ordinary least squares (OLS).[12] K is the number of risk factors, T denotes the number of observations and ϵ respectively ω the regression residuals. In order to guard against possible autocorrelation and heteroscedasticity of the residuals, we compute Newey-West standard errors.[13]

According to the equations (1) and (2), we initially estimated specifications with both one and multiple risk factors. However, in the multivariate context, the problem of multicollinearity emerges since the regressors are rather highly correlated with each other. This is also economically plausible, because the considered variables describe similar circumstances. Consequently, the regression results become biased if more than one regressor is included into the model. The Schwarz Bayesian Information Criterion, which describes the trade-off between the goodness-of-fit and the number of estimated parameters, also indicates that univariate models should be preferred. Therefore, we only present the results of regressions with one risk factor in the following sections.

[12] We performed our estimations using EViews (version 5.1).
[13] See *Verbeek* (2000).

2. Macroeconomic Risk Factors

From a theoretical point of view, we can expect that a bad economic situation, represented, for example, by a negative GDP growth rate or a strong increase of the insolvency rate, may cause decreasing prices at the secondary markets and therefore higher LGDs (negative relationship). In contrast to the LGD, we guess that resurrection rates are positively correlated with the business cycle. In times of economic upturns, distressed firms' future prospects are assessed more optimistically leading to an increasing proportion of contracts leaving the legal department. On the contrary, downturn situations should imply lower resurrection rates.

We now list some macroeconomic risk factors that we reasoned could be potential drivers of the LGD and XR. The theoretically expected effect of the respective variable on the LGD is indicated by the sign "+" or "−" in parentheses. In case of XR, the effects are vice versa.[14]

– *GDP* (−): Growth rate of the real gross domestic product in comparison to the preceding period.

– *DD* (+): Dummy variable for economic downturns (downturn dummy). *DD* takes the value of 1 during downturn periods and 0 otherwise. We define downturn periods in the following way: Years of negative GDP growth (1993 and 2003) and quarters which are within a sequence of at least three consecutive quarters of negative GDP growth (I/1993, IV/2002, I/2003 and II/2003).

– *INV* (−): Growth rate of the real equipment investment in comparison to the preceding period. This variable might be in a more direct relationship to the secondary markets than the GDP.

– *INS* (+): Growth rate of the German company insolvency rate (only considered for analyses of annual data).

– *IFO* (−): IFO Index of Business Situation (only considered for analyses of quarterly data).

[14] For the acquisition of the data we used the information system "Genesis Online" of the German Federal Statistic Office (www.destatis.de) and the sources of the IFO Institute for Economic Research (www.ifo.de).

VI. Results

1. Loss Given Default

In this paragraph, we present the results of our analyses concerning the impact of the macroeconomic environment on the LGD. First, we focus on the asset class of vehicles. If we consider the evolution of the annual series of the LGD averages and the GDP growth rate (top left in figure 3), we can recognize a first evidence for the expected negative relationship between these two variables. When the GDP growth was high during the expansion period in 1999/2000, the LGD averages decreased. In contrast, the LGDs of vehicles were rather high in times of recessions (1993 and 2002/2003). The estimation results of the regression analyses, which are given in table 6, confirm the evidence form the graphs.

For annual data, the coefficient of the GDP is negative and significant at the 5 %-level. Accordingly, a decrease of the GDP growth rate by one percentage point leads to an increase of the average LGD by 3.65 points. The highly significant coefficient of the downturn dummy indicates that the LGD average in the two recession years is about 15 percentage points higher than in times of normal GDP growth. The coefficients of the IFO index as well as the insolvency rate are also significant with the theoretically expected sign which strengthens our hypothesis that the LGDs of vehicle leases might be influenced by macroeconomic conditions.

Even if they are performed on different sample sizes, the regression results for quarterly averages are largely in line with those for annual data. Except for the GDP, all considered variables exhibit a significant influence on the LGD. Especially the IFO index, whose coefficient is significant at the 1 %-level, turns out to be a meaningful risk factor.[15]

Next, we turn to the asset classes of ICT equipment and machinery. In contrast to the vehicle segment, it is difficult to recognize a clear evidence from the graphical representations in figure 3. This observation is confirmed by the estimation results from the regressions. It strikes that most of the coefficients of the macro-variables under consideration are not significantly different from zero. Besides, the values of R^2 in all regressions are very low compared to the estimations for vehicles. Since they do not provide further insights, we refrained from presenting the result tables for these two asset categories.

[15] Compared to annual data, the values for R^2 are much lower what can be explained by the higher volatility of the quarterly series.

Table 6

Estimation Results for Asset Class Vehicles

Asset Class Vehicles, Dependent Variable: *LGD*								
Regressors	Annual Data ($T = 11$)				Quarterly Data ($T = 42$)			
Intercept	25.342***	17.485***	21.149***	14.990***	19.153***	17.236***	18.909***	96.131***
	(2.154)	(2.147)	(1.494)	(3.085)	(2.191)	(2.301)	(1.998)	(26.803)
GDP	–3.653**				–2.327			
	(1.395)				(2.125)			
DD		15.451***				11.116**		
		(2.391)				(4.481)		
INV			–0.673***				–1.427**	
			(0.156)				(0.668)	
INS				0.447***				
				(0.136)				
IFO								–0.837***
								(0.281)
R^2	0.295	0.596	0.430	0.387	0.018	0.099	0.111	0.185

The symbols *, **, and *** indicate significance at a level of 10, 5, and 1 % respectively. Newey-West-corrected standard errors of the coefficients are denoted in parentheses.

Economic reasons for the different findings can be manifold. The cashflows of defaulted ICT contracts, for example, contain a rather high fraction of recovery payments which are not related to the resale of the asset (e. g. late rentals). To what extent lessees are able to continue to pay their rentals after the default event often depends more on the policy of the insolvency practitioner than on the macroeconomic environment. Many machinery assets can be characterised by a high asset specificity, which means that they have rather few opportunities for alternative use and therefore relatively poor demand. Consequently, the LGD is more strongly influenced by the properties of the secondary markets than by the overall economic situation.

Generally, variables with a direct link to the specific secondary markets could be analysed additionally to the above-mentioned macroeconomic indicators. However, the precise quantification is a challenging task since these markets are either very fragmented and illiquid (e. g. machinery) or extremely heterogeneous (e. g. vehicles). In the case of the latter category, detailed information concerning the properties of the leased cars (e. g. year of construction, model type, etc.) would be necessary in order to account for different market developments such as special effects due to series changes. Unfortunately, we could not investigate that issue any further because of limitations in our data set.

In the course of our analyses, we have also tested the impact of timelagged risk factors on the LGD. However, we could not find a clear evidence for a specific lag structure which is more appropriate to explain the LGD variation compared to the non-lagged realizations. A possible reason for this result might be the fact that the intervals between the default and the reselling date (recovery lag) are probably not identical for all considered assets. Since the recovery lags are not given in our data set, we did not analyse this question in greater detail.

If we compare our findings, it is obvious that the impact of the macroeconomic environment on the LGDs is rather different among the three asset types. In the case of vehicle leases, we found some evidence that the LGDs react quite sensitively to the variation of several risk factors. By contrast, the average LGDs of ICT equipment and machinery are time-varying as well, but they do not seem to depend on general economic conditions.

2. Resurrection Rate

In the following section, we analyse the resurrection rates according to their cyclical variability. At first, we consider the graphical representation of the annual resurrection rates for vehicles, ICT equipment, and machinery (see figure 4 in the appendix). This plot suggests that the XRs of the three asset categories exhibit a rather similar pattern over time. Besides, the graph shows that the resurrection rates seem to be highly correlated with the growth rate of equipment investment which is a first evidence that they could depend on the macroeconomic environment.

Now, we focus on some selected results of univariate regression analyses, which are exhibited in table 7. The equipment investment as well as the insolvency rate prove to be very significant, with the expected sign in all three asset segments. By contrast, the GDP seems to have a weaker influence on XR. The corresponding coefficient is only significant for machinery contracts. The downturn dummy is not significant in all regressions; therefore we do not provide these results. As in the case of the LGD, the results of multiple regressions are not meaningful, which is attributed to the multicollinearity of the risk factors.

Summarizing our findings concerning the resurrection rate, we can recognize some evidence for a cyclical variability on annual level. In contrast to the LGD, the XRs probably depend on the financial situation of the particular lessee rather than on the type of the leased asset. This might explain the similar results for the three asset segments. Since our data set does not contain any information on characteristics of the lessees, we cannot investigate this issue any further within this study.

VII. Estimation of a Downturn LGD

1. Basic Idea

The Basel II capital rules are basically intended to cover the risk of unexpected credit losses. Since economic downturns represent a material source for such unexpected losses, the risk parameters in the Advanced IRB approach have to be conditioned on conservative macroeconomic scenarios. For the PD, the Basel Committee prescribes a transformation formula that converts the unconditional PD into a conditional PD which refers to an adverse state of the economy. For the LGD parameter, by

Table 7

Estimation Results for Resurrection Rates

Annual data ($T = 11$), Dependent Variable: *XR*									
Regr.	*Vehicles*			*ICT Equipment*			*Machinery*		
I'cept	23.148*** (4.026)	25.568*** (1.621)	32.160*** (2.049)	25.383*** (1.976)	25.912*** (1.130)	29.016*** (1.590)	17.442*** (1.326)	20.262*** (0.863)	26.464*** (1.249)
GDP	2.398 (1.642)			0.690 (0.788)			2.585** (1.326)		
INV		0.704*** (0.202)			0.334** (0.115)			0.592*** (0.086)	
INS			–0.480** (0.157)			–0.226*** (0.067)			–0.459*** (0.058)
R^2	0.167	0.618	0.586	0.039	0.398	0.371	0.313	0.705	0.865

The symbols *, **, and *** indicate significance at a level of 10, 5, and 1 % respectively. Newey-West-corrected standard errors of the coefficients are denoted in parentheses.

contrast, the BCBS has deliberately passed on a concrete formula. The main reasons are the lack of broad empirical evidence about the behaviour of the LGD during downturn periods as well as little consensus within the banking industry concerning appropriate methods to incorporate macroeconomic conditions in the estimated LGD.

Hence, the corresponding paragraph in the framework document is rather vague. According to § 468, the BCBS only requires that the estimated LGD for a certain facility must reflect economic downturn conditions, where necessary, to capture the relevant risks.[16] Besides, it says that this LGD, henceforth called "downturn LGD", cannot be less than the long-run default-weighted average LGD[17] of the underlying data observation period for that type of facility. This means that a (more conservative) downturn LGD must be used instead of the long-run average if the LGD proves to raise during downturn periods.

In the following, we propose a simple procedure for the determination of a downturn LGD that fulfils the requirements of the above-mentioned paragraph.

In this regard, we want to emphasize that the aim of our approach is not the estimation of an exact value for the downturn LGD in a strict regulatory sense.[18] The main intention is to show how leasing companies (and, of course, other financial institutions that apply the IRB approach) can use empirical insights concerning the LGD variation over time for internal risk management purposes. The general idea is to estimate the downturn LGD, denoted with LGD^*, subject to K macroeconomic (i.e. systematic) risk factors:

$$LGD^* = f(RF_i) \qquad i = 1, ..., K. \tag{3}$$

An important condition for the application of this approach is the existence of a stable (significant) relationship between the LGD and the particular risk factor(s), for example, in terms of a regression model. Besides, the possible danger of multicollinearity must be kept in mind if more than one single risk factor is used. Concretely, we estimate a reali-

[16] See *BCBS* (2006), § 468, and *BCBS* (2005).

[17] The notion "'default-weighted'" means that the average LGD must be weighted by the number of defaults.

[18] A deeper investigation of that issue would necessitate further information concerning the correlation structure between the PD and the LGD as well as their consequence for the allocation of regulatory capital. Since our data set is limited to the LGD, an analysis of these aspects, however, is not topic of this article.

zation of *LGD** by substituting a sufficient unfavourable realization of the particular risk factor into the estimated equation. Assuming our linear regression model from (3), possible values for the downturn LGD can be calculated as follows:

$$LGD^{*} = \hat{\alpha} + \sum_{i=1}^{K} \hat{\beta}_i \cdot RF_i \qquad i = 1, ..., K \tag{4}$$

The coefficients $\hat{\alpha}$ and $\hat{\beta}_i$ are obtained from historical data, $\widetilde{RF}_i$ represents the critical realization of the risk factor(s). Examples for critical realizations could be either the worst case within the observation period (or even from a longer data history, if available) or selected empirical quantiles of the historical distribution of the particular risk factor. By choosing different risk factors as well as critical realizations, the internal risk management can determine a range of possible outcomes for a downturn LGD. Thus, our approach combines theoretical considerations concerning a meaningful scenario with empirically-founded evidence about the behaviour of the LGD during downturn situations.

2. Empirical Example

Finally, we demonstrate the estimation of a downturn LGD with an example based on our data set. We consider the asset class of vehicles, because here we could find a significant influence of several risk factors on the LGD. In order to have a larger number of observation points, we base our calculations on the estimation results for quarterly data (table 6).

As risk factors, we consider the three variables for which we could find significant relationships with the LGD: the downturn dummy, the equipment investment, and the IFO index. In addition to the most adverse realization of the particular risk factor within the observation period ("worst case"), we take the 5 %-quantile and the 10 %-quantile of the univariate historical distribution as critical values. Table 8 provides some estimated downturn LGDs according to equation (4). In addition to the univariate models, we also performed two bivariate regressions with *IFO* and *DD* respectively *IFO* and *INS* as systematic risk factors. Because of the above-mentioned multicollinearity problem, however, the corresponding results for *LGD** are primarily intended to illustrate the procedure.

Table 8

Downturn-LGD for the Asset Class Vehicles According to Different Risk Factors

Downturn-LGD (LGD^*) in %			
Risk factor(s)	*Realization of $\widetilde{RF}$*		
	Worst case	5 %-Quantile	10 %-Quantile
DD	28.35	28.35	28.35
INV	25.76	24.96	22.57
IFO	24.91	24.66	24.52
IFO and *DD*	29.21	29.00	28.88
IFO and *INV*	26.84	26.30	25.19

It is quite evident that in the worst case scenario the downturn LGD is higher than in the less restrictive scenarios. For the downturn dummy, the critical realization is $DD = 1$ in all three cases. Hence, LGD^* is always identical with a value of 28.16 %. If we combine two risk factors, it must be noted that the corresponding values for the downturn LGD are not directly comparable to the single-factor case. Instead, the bivariate probability for a joint occurrence of the univariate scenarios would have to be considered for an interpretation in the strict sense.[19]

According to the requirements in Basel II, the downturn LGD must be higher (more conservative) than the so-called long-run default-weighted average LGD, which amounts to 20.33 % in our sample (I/1993–II/2003). However, this average LGD would underestimate the true risk in an adverse situation because the LGD increases. Therefore, one of the values for the downturn LGD from table 8 should be used as an internal estimate for this asset class. Our results for LGD^* are throughout higher than 20.33 %, which means that the Basel II requirements are formally fulfilled.

Figure 2 illustrates the comparison between the historical LGD averages, the long-run default-weighted LGD and the downturn LGD, based on realizations of the risk factors *DD* and *IFO* at the (univariate)

[19] Compared to the univariate quantiles, this probability is typically smaller, whereas the exact value depends on the correlation between the risk factors. However, this difference should be rather small in our case, since the macroeconomic variables are highly positively correlated.

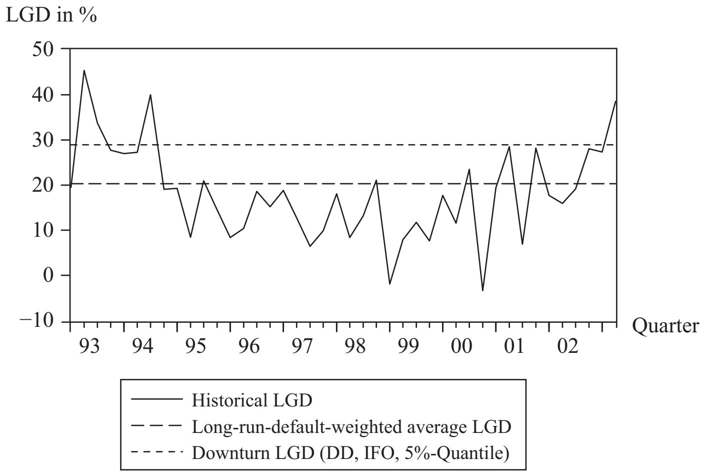

Figure 2: Comparison between Historical LGD, Long-Run Default-Weighted Average and Downturn LGD

5 %-quantile of each historical distribution. The graph shows once again that the risk of an adverse economic situation can be incorporated in a more conservative manner if the downturn LGD is used instead of the long-run average.

VIII. Conclusion

In this paper, we provided empirical evidence concerning the LGD of defaulted lease contracts belonging to different asset classes. Based on a unique data set from the German leasing market, we carried out different descriptive and explorative analyses.

First, we found that the level of the LGD varies significantly depending on the type of the leased asset. In general, assets with relatively stable market values (machinery) and assets traded on liquid secondary markets (vehicles) benefit from lower LGDs. In contrast, for assets that lose value quite rapidly (such as ICT equipment), higher losses can be observed. Furthermore, the empirical distribution of the LGD can be characterized by a bimodal shape with modes at 0 % and 100 % as well as by the frequent occurrence of negative LGD realizations.

Our empirical results suggest that the impact of the systematic risk factors on the aggregated LGD varies considerably from one asset class to another. For vehicle leases, we could find some evidence for a significant cyclical variability of the LGD, which is contradictory to the studies of *Schmit/Stuyck* (2002) and *Laurent/Schmit* (2005). This result might be due to the fact that the market for used vehicles, particularly for cars, is quite well-developed and liquid. Thus, demand and supply are rather sensitive to changes of the economic situation. By contrast, the LGDs of ICT equipment and machinery react by far more weakly on the macro-variables under consideration. A possible explanation could be the high fragmentation and the illiquidity of the corresponding secondary markets.

In addition, we pointed out how a downturn LGD for a certain asset segment can be calculated in a quite simple and intuitive way. Our approach is a rather flexible tool for the internal risk management which combines theoretical considerations and empirically-founded evidence about the behaviour of the LGD during downturn situations. We demonstrated the proposed procedure with an empirical example for vehicle leases and different macroeconomic risk factors. Our estimated downturn LGDs always exceed significantly the long-run default-weighted average, which is in line with the requirements of Basel II.

Furthermore, we introduced the concept of the resurrection rate, which measures the extent of resurrections due to a reversal of the default event. In the leasing industry, resurrections are a quite frequent phenomenon since the underlying default criterion usually qualifies contracts as defaulted despite of only minor disturbances. According to their cyclical variability, we found out that the resurrection rates in all asset classes are significantly influenced by several systematic risk factors.

On the whole, the findings of our study provide useful insights for the internal credit risk management of leasing companies, especially for those who comply with the Advanced IRB Approach of Basel II for internal reasons. However, it is necessary that leasing companies intensify their efforts to collect more detailed data and make them available for further research on that subject, especially with regard to the development of a comprehensive LGD estimation model according to the requirements of the IRB Approach. By means of such a model, leasing companies could establish a rating system for the LGD (in analogy to the widely-used rating systems for the default probability) which can assign an estimated LGD for each new leasing contract.

Appendix

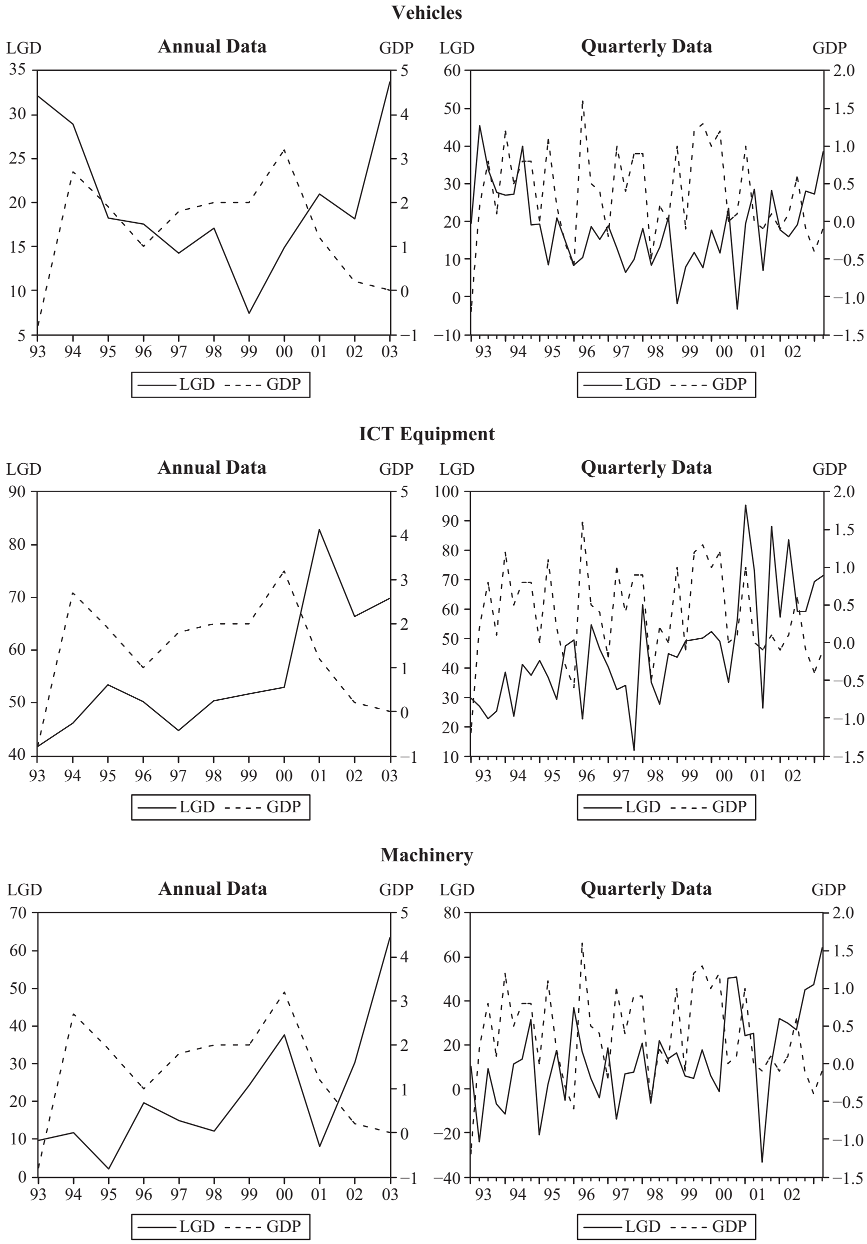

Figure 3: Evolution of the LGD and the GDP over Time for Asset Classes Vehicles, ICT Equipment, and Machinery

Table 9

Number of Contracts for the Calculation of Annual and Quarterly LGD Averages

Asset Type	Annual Averages ($T = 11$, 1993–2003)	Quarterly Averages ($T = 42$, 1993 Q1–2003 Q2)
Vehicles	16,697	7,748
ICT Equipment	14,152	4,181
Machinery	4,929	2,702

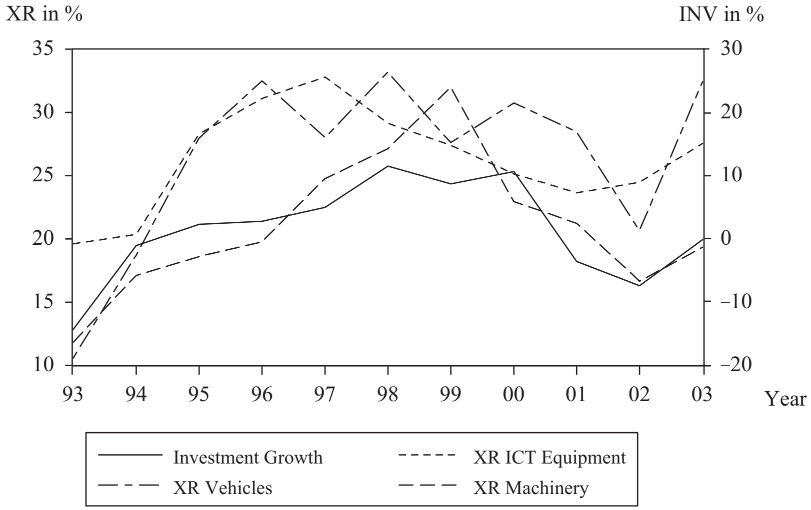

Figure 4: Evolution of the Annual Investment Growth and the Resurrection Rates over Time for the Asset Types Vehicles, ICT Equipment, and Machinery

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Summary

Do Economic Downturns Have an Impact on the Loss Given Default of Mobile Lease Contracts? – An Empirical Study for the German Leasing Market –

Along with the probability of default, the loss given default (LGD) is a crucial variable for the quantification of credit risks. According to the German insolvency law, lessors are allowed to access the leased asset quickly and dispose of it autonomously if the lessee encounters a default. In order to benefit from this advantage over creditors of collateralized bank loans, a reliable estimation of the LGD is of special importance for leasing companies.

Using an extensive and unique data set from two major German leasing companies, we analyse the LGD of mobile lease contracts. The contribution of our paper is threefold: First, we extend the empirical evidence about the level and distribution of the LGD according to different asset types. Second, we investigate the impact of macroeconomic conditions on the aggregated LGD and propose a method how leasing companies can determine a downturn LGD for their internal risk control. Third, we address the phenomenon that contracts can "'resurrect'" from default after some time of financial distress, which has been neglected in academic research so far.

Our results suggest that the level of the LGD varies considerably depending on the asset type and that the empirical LGD distribution can be characterized by a bimodal shape. Concerning the impact of the macro-economy on the LGD, we could identify a significant relatíonship for vehicle leases only. Regarding the resurrection rate, we found empirical evidence for a cyclical variability in all asset categories. On the whole, the findings of our study provide useful insights for the internal credit risk management of leasing companies. (JEL G21, G28)

Zusammenfassung

Reagieren die Verlustquoten von Mobilien-Leasingverträgen auf einen konjunkturellen Abschwung? – Eine empirische Untersuchung für den deutschen Leasingmarkt –

Die Verlustquote im Insolvenzfall (Loss Given Default, LGD) gehört neben der Ausfallwahrscheinlichkeit zu den zentralen Größen bei der Quantifizierung von Kreditrisiken. Für Leasinggesellschaften stellt der LGD dabei eine besonders wichtige Variable dar: Das deutsche Insolvenzrecht ermöglicht es dem Leasinggeber, bei Nichterfüllung des Leasingvertrages durch den Leasingnehmer sehr schnell auf das Leasingobjekt zuzugreifen und es selbstständig zu verwerten. In den besseren Verwertungsmöglichkeiten wird ein Vorteil von Leasing gegenüber der Kreditfinanzierung gesehen. Um diesen Vorteil nutzen zu können, müssen Leasinggesellschaften in der Lage sein, den LGD zuverlässig zu schätzen.

Unter Verwendung umfangreichen Datenmaterials zweier großer deutscher Leasinggesellschaften wird im vorliegenden Artikel der LGD von Mobilien-Leasingverträgen analysiert. Die Autoren sehen den Beitrag zur Literatur auf den folgenden drei Gebieten: Erstens erfolgt eine Erweiterung der empirischen Erkenntnisse über die Höhe und Verteilung des LGD in Bezug auf unterschiedliche Objektkategorien. Zweitens wird der Einfluss systematischer Risikofaktoren auf den zeitlich aggregierten LGD getestet und darauf aufbauend eine Möglichkeit zur Bestimmung eines „Abschwung-LGD“ für die interne Risikosteuerung vorgeschlagen. Drittens wird das Phänomen thematisiert, dass Leasingverträge, die als ausgefallen eingestuft wurden, zu einem späteren Zeitpunkt „wiedergesunden“ können, was in der akademischen Literatur bislang vernachlässigt wurde.

Die empirischen Ergebnisse zeigen, dass die LGD-Verteilung eine bimodale Gestalt aufweist und das LGD-Niveau in Abhängigkeit der Objektkategorie stark variiert. Ein signifikanter Einfluss makroökonomischer Risikofaktoren auf den LGD konnte lediglich im Fahrzeug-Segment nachgewiesen werden. Dagegen finden sich in allen betrachteten Kategorien Hinweise auf eine Konjunkturabhängigkeit der Wiedergesundungsquote. Die Studie ist für Leasinggesellschaften von praktischer Relevanz im Hinblick auf eine verbesserte Ausgestaltung ihres internen Risikomanagements für den LGD.