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COLLECTION OF THESES

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The methodological opportunities of quantifying the retail mortgage loan's LGD in Hungary

Ph.D. dissertation

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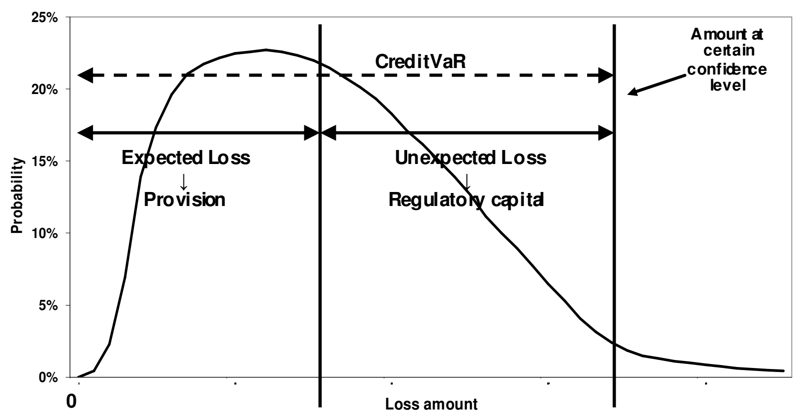
1. Research antecedents and reasoning the theme

The CRD (Capital Requirements Directive) founded on the Basel recommendations put the whole risk assessment of the banks on new bases. It is no exaggeration to state that it generated considerable changes on all risk-relevant areas of the activity of the credit institutions, concerning both the credit risk, the operational risk and the market risk. However, this thesis focus only on a fairly narrow scope not disputing that the particularly complex system of the Basel rules does not enable the dissociation of the areas so categorically. I descend to the particulars only for the proper credit risk which can be defined as the so-called default risk, and I follow this interpretation in the framework of the whole thesis.

The CreditVaR concept serves as a basis for modelling the credit risk according to the Basel recommendations, on the basis of which different prescriptions refer to the assessment of the expected and the unexpected risks: while provision has to be formed for the first one, capital has to be allocated for covering the latter one. The task of the regulatory capital is to protect against the unexpected loss at a given confidence level. It can also be quantified as the difference between a given percentile of the loss distribution and the expected loss (Figure 1). The term "unexpected loss at a given confidence level" derives from that.

Figure 1: The loss distribution of the credit risk



(Self-made figure)

With establishing the CRD it became possible for the credit institutions, if they use the Internal Rating Based (IRB) method regarding the credit risk, then they are allowed to apply their own calculations concerning certain credit risk parameters for quantifying the capital requirement, provided that they meet the assumptions and regulatory prescriptions of the Basel II.

The quantification and the measure of the credit risk are founded on the under-mentioned risk parameters in case of using the Internal Rating Based (IRB) models:

- Probability of Default (PD): the probability that the client becomes non-performing over a one year period.
- Loss Given Default (LGD): the ratio of the loss due to the default of the client to the exposure amount at default.
- Exposure at Default (EAD): the exposure at the default event.
- Maturity (M): the remaining time until the expiration of the deal.

In addition to serving for the objectives of managing the portfolio, the risk parameters also play an important role in calculating the expected and the unexpected loss as well as the Risk Weighted Assets (RWA) eventually.

In the present dissertation I make known certain aspects of calculating the Loss Given Default (LGD), which is one of the most significant components referring to the calculation of the expected loss.

The rating system serving as a basis for the internal rating based method has to provide measurement of the credit risk, classifying and assigning the exposures to pools as well as quantification of the credit risk parameters belonging to them. The classification to grades and pools has to be based on assignment criteria, but the institutions have a relatively large liberty in defining them, because both the CRD and the *Government Decree No. 196/2007 on the Management and Capital Requirement of Credit Risk (Hkr.)* contain only very general prescriptions concerning them. It is expected that the credit institutions lean on the significant risk drivers during the calculations, but there are neither in the CRD nor in the Hungarian regulations any exact prescriptions relating to their scope, so their establishment is the certain institution's task.

An overall requirement for assignment to pool is that the concentration should not be disproportionately high. The categories have to be defined and the number of categories has to be appointed in a way, which provides the assignment of homogenous exposures to the same pools, but the numbers of exposures in the certain pools should be sufficient to allow reliable quantification of the risks, enabling the exact and consistent quantification of loss characteristics at grade or pool level. So the regulation prescribes the credit institutions to choose the "golden mean".

Considering that the data series available for the majority of the Hungarian credit institutions are not old and accurate enough for carrying out appropriately consistent estimations, as well as the quantity of the default data is not adequate in many cases, therefore calculating the own LGD values comes up against numerous difficulties.

In the actual Hungarian practice the institutions are not able to take advantage of the theoretical opportunity given by the Basel rules in many cases yet, because the necessary conditions of the secondary market of loans and bonds do not exist. For that very reason the credit institutions have to focus on the historic collecting the internal data and on the basis of them on preparing the most possible accurate predictive models for the sake of exactly quantifying the credit risk parameters on the basis of them.

At the same time the opportunity has a great importance from the viewpoint of the present dissertation that, though the estimations have to be founded basically on the internal data, but external or even common data can be used as well, if it is provable that there is not any significant difference between the internal and external data regarding the assigning processes into grades or pools, as well as the composition of the data (risk profile), or if the differences can be adjusted properly for the sake of completing representativity.

While the literature of the credit risk has been paying notable attention to estimating Probability of Default (PD) for a long time, the quantification of Loss Given Default rate (LGD) has got much less emphasis. Only in the latest few years came modelling the LGD and the recovery rate into the limelight.

Concerning the corporate sector there is already a comprehensive literature about both the theoretical and the empirical LGD modelling, and the more so about modelling the recovery rates, while there are barely a few examples in case of the retail loans in spite of the fact that the retail loan outstandings in whole considerably exceed the amount of the corporate deals.

Considering that the scarcity of data means the largest barrier of the model-building in Hungary, the available database with larger quantity for the loan deals relating to the retail segment implicates more considerable potential in some respects, in comparison with the corporate sector. At the same time there is a rather narrow scope of the information, which is available for the credit institutions, and which can be used as influencing factor of the recovery rate and the LGD in the course of preparing the predictive models hereby.

The aim of my research was to study the characteristic features of the LGD parameter of the retail mortgage loans and to prepare a model for calculating the LGD, which enables the more exact and accurate quantification of this risk parameter than the actual, under domestic conditions. Considering that only the application of the workout LGD methodology has actually the reason for existence in Hungary recently, I also grounded my empirical researches on it.

2. The applied methods

In the course of my research I applied the data of an anonymous commercial bank's database of closed and non-closed retail mortgage loans, as well as the data of the Hungarian Interbank LGD Database.

2.1. The Hungarian Interbank LGD Database

In 2007 the LGD project started being coordinated by the Hungarian Mortgage Association (HMA) and with the participation of five Hungarian banks, with the aim of supporting modelling of the expected losses of mortgage lending based on real loss data. The Hungarian Interbank Retail Mortgage LGD Database, which is the first one founded in Europe, collects the anonymous data about defaulted mortgage deals with the purpose of enabling the participant banks to carry out better-established estimations regarding the mortgage LGD parameter, for the sake of meeting the requirements of the Hungarian regulation in connection with credit risk.

Although the Database was established only in 2008, it contains the data related to 2005, 2006 and 2007 as well, because participant banks undertook to carry out the "primordial uploading", by providing historical data with reference to those three years retroactively.

The LGD Database is able to admit data in the appropriate structure, pertaining to the participant banks' defaulted mortgage loans. From the constitutional aspect the dataset consists of three parts *(HMA [2008])*:

a) basic data of the non-performing mortgage loans, data in connection with the claims derived from the deals, as well as recovery and loss data.
b) data of the real estates referring to these deals, as well as data of realization of the real estate value,
c) basic data which enable to join deals and related real estates together, as well as value data.

There can be different relational connections between deals and real estates. In most cases only one particular real estate pertains to each deal (1:1 relation), but occasionally there are more than one real estate collateral behind a particular deal (1:n), or the same real estate serves as collateral for more than one deal (m:1).[1] These relations appear in the system in a way that each deal or each real estate occurs only once in the table of deals or real estates, but that table which contains the connective data represents each link as separate record, so if two real estates serve as collateral of a particular deal, then these result in two records in the table of connections, and it can be recognized from the deal and real estate identification numbers which deal they pertain to.

For the banks which comply with the obligation to provide data, the credit risk analysts or the other staff-members who are charged with this function and are in possession of the right for downloading and password, can download them as anonymous data in pre-specified format whenever they wish. There are not any restrictions in connection with the frequency of downloadings, but only those data can be accessed which relate to the already closed periods, therefore the quantity of downloadable data from the system do not change during a particular quarter. On 30th June 2011 the Hungarian Interbank LGD Database contained 1770 deals and 1719 real estates, which constituted 1881 records because of the 1:n and m:1 relationships between the deals and the real estates.[2]

In the course of my empirical researches I had respect only to those deals, in case of which the default event occurred after 31st December 2003, because the bank database, on which the most considerable part of my analyses rested, also contains only the deals whose default event occurred after December of 2003. In addition to that I picked out from the database the deals as well, in case of which not residential real estate (or not only residential real estate) serves as collateral.

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[1] Theoretically the occurrence of m:n relation is also possible.
[2] 30th June 2011 was the closing date of the last quarter which preceded the carrying out my empirical analyses, thus I consider as actual the state of the database at this time.

The reason behind these adjusting steps was that only those data should be applied in the course of the empirical analyses, which are directly comparable with the data of the bank database. Namely according to the *71. § (1) Paragraph of the Hkr.* one of the important base conditions of using the common database is that it has to reflect the portfolio representatively, relating to which the common data are applied.

2.2. The bank's database

The dynamic growth of the bank's retail mortgage loan portfolio until 2008 is mainly the result of the general boom on the Hungarian lending market during the past few years. The government subsidized mortgage loan program, which started in 2001, intensively increased the credit taking appetite of the people, then in December 2003 when the Government continued to enhance this policy, several credit institutions decided to launch foreign currency credit lending to take the advantages of the low level of the interest rates. Subsequently the foreign currency denominated loans incrementally took the place of HUF loans, almost displaced them.

The turning befell in the autumn of 2008, when the credit institutions executed serious lending restrictions on account of the financial crises. Due to the drastic HUF depreciation CHF credit lending has practically been stopped, and as a consequence of the crisis and the restrictions only minimal new volume had been disbursed during 2009 and 2010. According to these changes in lending policy, the total exposure of the retail mortgage loans did not grow on in the last two years.

The CRD prescribes the use of the so-called downturn LGD in order to calculate the risk weighted assets, in the course of which also the changes arising from the cyclicality of the economic conditions have to be taken into account. Considering that due to the crisis, which started in September 2008, a considerable proportion of the portfolio is derived from the economic downturn period, so in the course of calculating the LGD further adjustment is not necessary to reflect the impact of the economic recession.

In this subsection I present the data, sorting on the basis of the data sources, which I used in the course of calculating the LGD.

(a) Application data

The first block is composed by the application data, whose majority respects to the clients, who apply for the loan, and the minor part comes from the characteristics of the deals at the origination. On the basis of the greatly expansive dataset which was available, I produced the structured data table containing the following elements:

Table 1: Basic data at the application (known at the date of origination of the deal)

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
deal_id	Deal identification number.
start_term	The duration term of the deal according to the contract (number of months).
loan_purpose	Purpose of the loan.
loan_amount_lcy	Loan amount which was applied for and paid out (in HUF).
coapplicant_flag	Dummy variable which indicates whether there is a co-applicant.
first_instalment	The original monthly repayment amount (in HUF).
full_name	The full name of the client.
gender	The gender of the client.
citizenship	The citizenship of the client.
birth_settlement	The birth place of the client.
start_age_months	The age of the client at the origination of the deal (number of months).
marital_status	The marital status of the client.
education_level	The education level of the client.
Home_settlement	The name of the settlement of the client's living place.
landline_phone_flag	Dummy variable which indicates whether the client has a landline phone.
mobile_phone_flag	Dummy variable which indicates whether the client has mobile phone.
start_address_months	The duration of living at the given permanent address at the origination of the deal (number of months).
Empl_industry	The industry of the client's employer.
Empl_type	The type of the client's employment.

Table 1 (continuation): Basic data at the application (known at the date of origination of the deal)

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
empl_position	The working position of the client.
empl_term	The type of the client's labour contract.
start_work_months	The duration of working for the given employer at the origination of the deal (number of months).
applicant_net_income	The monthly net income of the client.
total_household_income	The total monthly income of the household of the client.
earners_number	The number of earners in the household of the client.
dependents_number	The number of dependents in the household of the client.
existing_ca_flag	Dummy variable which indicates whether the client has a current account.
existing_card_flag	Dummy variable which indicates whether the client has a credit card.
existing_ovd_flag	Dummy variable which indicates whether the client has an overdraft.
existing_loan_flag	Dummy variable which indicates whether the client has another credit.
interest	The original lending rate of the deal.
apr	The Annual Percentage Rate of the deal at the origination.

(Self-made table)

Considering that the Annual Percentage Rate (APR) was not available in case of all deals, imputation became necessary. In the framework of that I quantified the average APR values for each month, currency and deal type according to the purpose of the loan then I refilled the missing values with them.

(b) Behavioural data

While the application data give a static image about the characteristics of the certain deals and clients, the behavioural data show the run of some treats of the deals concerning the whole duration of the loans from time to time.

The bank's database, which was disposable for me, held the behavioural data of the deals relating to the last workday of each month on deal level. Considering that I focused on the retail mortgage loans in the course of my research, I filtered the data according to the type of the client and the product group. In order that to make it possible to investigate the impact of changing the materiality threshold (5th Hypothesis), I defined dummy variables to indicate whether the given deal was voted non-performing in the actual month in case of applying the different materiality thresholds. Beyond that I also constructed indicator codes for the sake of indicating the reason of the default concerning each materiality threshold which I examined. On the basis of all that I made up the data table with the under-mentioned content:

Table 2: The behavioural basic data of the deals

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
deal_id	Deal identification number.
basic_number	Client identification number.
product	Type of the product.
product_description	Sub-type of the product.
application_type	Category according to the type of the application.
exposure_lcy	The actual exposure at the end of the month (in HUF).
exposure_ccy	The actual exposure at the end of the month (in the original currency of the deal).
principal_lcy	The actual principal amount at the end of the month (in HUF).
principal_ccy	The actual principal amount at the end of the month (in the original currency of the deal).
start_principal_lcy	The disbursed loan amount (in HUF).
start_principal_ccy	The disbursed loan amount (in the original currency of the deal).
dpd	The number of days past due at the end of the given month.
past_due_amount_lcy	The delayed amount at the end of the given month (in HUF).
past_due_amount_ccy	The delayed amount at the end of the given month (in the original currency of the deal).
defaulted_minwage	Dummy variable which indicates whether the deal has default status in the given month according to the materiality threshold, which is defined by the lowest monthly minimum wage.
default_reason_minwage	The indicator variable which indicates the reason of the default according to the materiality threshold which is defined on the basis of the lowest monthly minimum wage.
defaulted_huf50000	Dummy variable which indicates whether the deal has default status in the given month according to the materiality threshold of HUF 50000.
default_reason_huf50000	The indicator variable which indicates the reason of the default according to the materiality threshold of HUF 50000.
defaulted_huf20000	Dummy variable which indicates whether the deal has default status in the given month according to the materiality threshold of HUF 20000.
default_reason_huf20000	The indicator variable which indicates the reason of the default according to the materiality threshold of HUF 20000.
defaulted_huf2000	Dummy variable which indicates whether the deal has default status in the given month according to the materiality threshold of HUF 2000.
default_reason_huf2000	The indicator variable which indicates the reason of the default according to the materiality threshold of HUF 2000.

Table 2 (continuation): The behavioural basic data of the deals

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
defaulted_huf0	Dummy variable which indicates whether the deal has default status in the given month according to the materiality threshold of HUF 0.
default_reason_huf0	The indicator variable which indicates the reason of the default according to the materiality threshold of HUF 0.
write_off_lcy	The loss which has been written off in the given month.
ccy	The original currency of the deal.
start_date	The date of the origination of the deal.
maturity_date	The contractual maturity date of the deal.

(Self-made table)

In the course of working up the subtypes of the deals *(product_description)* I attempted to establish quite homogeneous groups, because I assumed that significant differences can be experienced among their LGD values. The circumscription served the purpose to enable me to filter out the deals from the analysis which were concerned by restructuring or secured by life insurance. I considered as concerned by restructuring not only the deals which the clients claimed for restructuring their already existing loans (successor deals), but the ones as well, which served as ancestors deals. This was necessary, because in the case of these loans the same default definition could not have been applied, thus the testing of the impacts of changing the default definition (1st Hypothesis) would have become impossible. The disposability of the client identification number *(basic_number)* technically enabled me the joining of the concerned deals to each other.

The circumscription of the categories according to the type of the application *(application_type)* was justified by the fact that the maximum LTV-ratio is considerably higher in the case of the loans which are based on income verification, than in the case of the purely collateral-based financings, so I also presupposed significant differences concerning the risk level. I investigated the impact of this feature on the LGD values in the course of the 3rd Hypothesis.

(c) Data referring to the collaterals

Also monthly level data were obtainable for me concerning each collateral underlying the deals. In order to make the recoveries of the loan deals, which were examined by me, comparable with the recoveries of the Hungarian Interbank LGD Database, I tried to construct a data table which possesses equivalent content to the Hungarian Interbank LGD Database (Table 3), according to the pieces of information about the collaterals. In the case of some data fields (for example the floor-space, the number of rooms, the year of the building and the renovation) the lack of data was so considerable that it could not have been handled by imputation reliably, thus finally I left out these variables from the analysis.

Table 3: The basic data referring to the collaterals

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
collateral_id	Collateral identification number.
deal_id	Deal Identification number.
appraisaldate	The date of the original appraisal (prior to the disbursement of the loan).
revaluedate	The date of the latest revaluation which is effective in the given month.
priorcharge_amount	The sum of the prior charges on the collateral (in HUF).
start_collvalue	The realization value of the collateral at the origination of the deal.
loancoll_value	The realization value of the collateral at the end of the given month.
start_marketvalue	The market value of the collateral at the origination of the deal.
marketvalue	The market value of the collateral at the end of the given month.
zipcode	The zip code of the real estate which serves as collateral.
settlement	The name of the settlement of the real estate which serves as collateral.
realestate_type	The type of the real estate which serves as collateral.
material	The building type of the real estate which serves as collateral.

(Self-made table)

All through the categorization according to the type of the real estate *(realestate_type)* and the building type *(material)* I kept the requirement in view that the same grouping should come up as the one which exists in the Hungarian Interbank LGD Database for the sake of making feasible the comparison of the recoveries.

(d) Recoveries and direct costs

I constructed a data table from the recovery amounts and the indirect costs as well. In addition to the deal identification number, the currency and the amounts given in the original currency of the deal I also disposed the date of the paying-up of the recovery and the occurring of the cost, and considering that the whole process of LGD estimation grounds on HUF-amounts, I exchanged the recoveries and the costs from the original currency of the deal to HUF on the exchange rate effective at their emergence date. The table below shows the content of the data table, which was constructed in this manner.

Table 4: Recoveries and direct costs

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
deal_id	Deal identification number.
ccy	The original currency of the deal.
repayment_date	The value date of accounting the recovery or the indirect cost.
principal_lcy	The principal recovery amount (in HUF).
interest_lcy	The interest recovery amount (in HUF).
charge_lcy	The charge recovery amount and the accruing direct cost (in HUF).
principal_ccy	The principal recovery amount (in the original currency of the deal).
interest_ccy	The interest recovery amount (in the original currency of the deal).
charge_ccy	The charge recovery amount and the accruing direct cost (in the original currency of the deal).

(Self-made table)

(e) Macroeconomic data

For the sake of investigating the effects of the general macroeconomic situation on the LGD I collected some indicators which I considered as potential LGD influencing factors in the course of my empirical research. The Hungarian Central Statistical Office's (HCSO) STADAT Database served as a source of the majority of the data, while the probabilities of defaults are results from the internal estimations of the bank.

Table 5: Macroeconomic basic data

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
month	The month which the macroeconomic indicators refer to.
unempl_rate	Quarterly average unemployment rate (STADAT 3.10.).
min_wage	The official lowest monthly minimum wage (STADAT 2.1.40.).
avg_netincome	Average monthly net income: until December 2007 the 12-month moving averages calculated from the yearly averages (STADAT 2.1.34.1., STADAT 2.1.34.2.), from January 2008 the monthly figures according to the HCSO (STADAT 2.1.37.).
CPI	Yearly consumer price index: until December 2006 the 12-month moving averages calculated from the yearly averages (STADAT 3.6.1., 2.1.41.), from January 2007 the monthly figures according to the HCSO (STADAT 3.6.1.).
cum_CPI	Fixed-base consumer price index according to the STADAT 3.6.1. (base: January 2001).
realwage_index	Yearly real wage index: the quotient of the 12-month moving average calculated from the change of the average monthly net income (avg_netincome) and the yearly consumer price index (CPI).
cum_realwage_index	Base ratio of the monthly real wage according to the realwage_index (base: January 2001).
cum_GDP_growth	Base ratio of the GDP-growth: base ratio which is calculated from the increasing of the seasonally adjusted GDP values on a quarterly basis (STADAT 3.1.6.), using geometric average (base: January 2001).
GDP_growth	Yearly GDP-growth index: 12-month moving average of the yearly GDP-growth indices which are calculated from the cum_GDP_growth.
HomeEquity_PD	Average PD of the mortgage equity withdrawals at the given month.
HousingLoan_PD	Average PD of the home loans at the given month.
avg_PD	Average PD of the mortgage loans at the given month.

(Self-made table)

In addition to the data enrolled in the table I also used the central bank base rates in the course of estimating the LGD, but considering that they occasionally changed during the month as well, I linked the values of the central bank base rate of the proper currency effective at the time of default event and the values of them effective on 30th June 2001 directly to the certain deals.

In the course of my analyses I made the estimates and built the regression models using the data made known previously.

2.3. Definitions and assumptions

The presented data tables contain the deals which are in normal status (not in default status) as well, therefore in the next step I defined the date of all default events of each deal, and I created a data table (Table 2) from the behavioural data which comprehends only the non-performing deals. I think it is important to note that if a certain deal has "cured" after the default, then later on it became non-performing again, I handled all default events separately, so I considered all default events as particular cases from the viewpoint of estimating the LGD.

To select the non-performing deals, in the first step I had to define the mere default event.

(a) The default event

The CRD and the Hungarian prescriptions *(Hkr. 68-69. §)* served as a basis for defining the term "default event".

The calculation of the number of the days past due (DPD) is fundamental to the definition of default. If a client fails to meet one or more instalments of the certain loan, this deal becomes delinquent. The counting of the DPD starts with the first day when an instalment is overdue, so the DPD measures the number of days since the due date of the earliest and currently unpaid past due obligation. If later on the client pays money on his account, then this covers the oldest arrear at first, namely the oldest past due obligation is satisfied foremost, then the other instalments one after the other. If the arrear is paid in full, the deal becomes to normal status again and the DPD is restored to 0.

The establishment of the term "materiality threshold" was needed for the sake of not considering the deals as non-performing in cases when the amounts in arrears are negligible or when the delays occur because of technical reasons. In the basic model the highest delayed amount which is not defined as delinquent (the overdue amount is considered as immaterial) is the minimum of the under-mentioned values:

- the lowest monthly minimum wage effective at the time of becoming delayed,
- 2% of the obligations of the client, and
- one monthly repayment instalment.

It means that counting the days past due (DPD) starts on the day, when the overdue obligations exceed this calculated amount. The most common reason for going into default status is that the DPD for the deal goes above 90, and at the same time the total past due obligation exceeds the prescribed materiality threshold. If the client executes a payment thereafter, and therefore the DPD decreases below 90, then this results in the "recurring" of the deal. The case is an exception to this rule, when the delay of the deal with a material past due amount reaches 181 days, namely in this case the total exposure becomes due, consequently later on the deal is considered as defaulted irrespectively of its current DPD and past due obligation until its closing.

There are two further efficient causes of qualifying the deals as non-performing: the decease of the client and the fraud. The decease of the client results in the deal is becoming to default status, but if the inheritor takes over the loan, then the deal get to normal status again. Also the fraud (for example manipulating the evaluation of the collateral) generates the qualifying as non-performing, but this default status is irrecoverably, it results in the total exposure is becoming due immediately.

So generally speaking a deal is considered as defaulted in the basic model if either of the below conditions holds:

- The client is in delay for more than 90 days with the instalments of the deal, and the past due obligation is more than the lowest monthly minimum wage effective at the time of becoming delayed or 2% of the obligations of the client or one monthly repayment instalment.
- The client was in delay for more than 180 days with instalments of the deal at any time, and the past due obligation exceeded the lowest monthly minimum wage effective at the time of becoming delayed or 2% of the obligations of the client or one monthly repayment instalment.
- It is inferential that the loan will not be paid back, because the client died or a fraud occurred.

If any of these conditions obtain in connection with a loan of a client, then all the other loans of the given client is also considered as non-performing (cross-default), so the term "default status" acts in my empirical analysis as a client-level category.

The 4th Hypothesis was directed towards survey, how the change of the materiality threshold influences the LGD values. For the sake of that I decided to use four different alternative materiality thresholds (HUF 50000, HUF 20000, HUF 2000, HUF 0), but for the comparability I left unchanged the other parameters of the default definition (DPD-counting, cross-default, consideration of the other default reasons), so enabling the separate investigation of the effects derived from modifying the materiality threshold.

Considering that in the course of estimating the LGD the exposure at the date of the default event means the reference point, I quantified both this amount and the reasons behind the non-performing status, then I joined them to the behavioural data of the deals.

Table 6: Data about the default

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
default_date	The date of the default event of the deal.
default_month	The period of the default event of the deal (year, month).
months_to_default	The duration from the origination of the deal to the default event (number of months).
defaulted_exposure_lcy	The exposure of the deal at the date of the default event (in HUF).
orig_default_reason_minwage	The indicator variable at the date of the default event which indicates the reason of the default because of arrears according to the materiality threshold which is defined on the basis of the lowest monthly minimum wage.
orig_default_reason_huf50000	The indicator variable at the date of the default event which indicates the reason of the default because of arrears according to the materiality threshold of HUF 50000.
orig_default_reason_huf20000	The indicator variable at the date of the default event which indicates the reason of the default because of arrears according to the materiality threshold of HUF 20000.
orig_default_reason_huf2000	The indicator variable at the date of the default event which indicates the reason of the default because of arrears according to the materiality threshold of HUF 2000.
orig_default_reason_huf0	The indicator variable at the date of the default event which indicates the reason of the default because of arrears according to the materiality threshold of HUF 0.
defaulted_per_start_exposure	The proportion of the exposure at the default and the disbursed amount.
reason_fraud	Dummy variable which indicates whether the deal is considered as defaulted because of fraud.
reason_death	Dummy variable which indicates whether the deal is considered as defaulted because of death.
reason_pastdue_minwage	Dummy variable which indicates whether the deal is considered as defaulted according to the materiality threshold which is defined on the basis of the lowest monthly minimum wage.
reason_pastdue_huf50000	Dummy variable which indicates whether the deal is considered as defaulted according to the materiality threshold of HUF 50000.
reason_pastdue_huf20000	Dummy variable which indicates whether the deal is considered as defaulted according to the materiality threshold of HUF 20000.
reason_pastdue_huf2000	Dummy variable which indicates whether the deal is considered as defaulted according to the materiality threshold of HUF 2000.
reason_pastdue_huf0	Dummy variable which indicates whether the deal is considered as defaulted according to the materiality threshold of HUF 0.
default_age_months	The age of the client at the date of the default event of the deal (number of months).
default_address_months	The duration of living at the given permanent address at the date of the default event (number of months).
default_work_months	The duration of working for the given employer at the date of the default event (number of months).
default_fx_rate	The exchange rate of the deal's currency at the date of the default.
default_unempl_rate	Unemployment rate at the date of the default.
default_min_wage	The lowest monthly minimum wage at the date of the default.
default_avg_netincome	Average monthly net income at the date of the default.
default_realwage_index	Yearly real wage index at the date of the default.
default_CPI	Yearly consumer price index at the date of the default.
default_GDP_growth	Yearly GDP-growth index at the date of the default.

(Self-made table)

(b) Calculating the net recoveries on deal level

The measurement of the recoveries involves all cash recoveries and non-cash items regardless of their source (for example payment from the clients, repossession or selling of the collaterals). Relating to the certain recoveries only the date of the coming-in and the amount were available in the database which I examined, thus the different handling of the distinct types of the recoveries was not feasible, but considering that the Collection Department keeps a separate file about the deal identification numbers of the loans, in case of which the real estate, which served as collateral, has been sold, it became possible for me to compare the recoveries of the Hungarian Interbank LGD Database with the recoveries of the deals which I examined.

I treated the penalty fees and penalty interests as well as internal (for example phone call, reminder letter) and external collection costs as negative cash flows in the course of calculating the LGD. Considering that some costs could not be associated with the individual deals (indirect costs), and therefore the concrete deal-level cost amount is not disposable, I allocated the total collection costs of the given month evenly between the deals which are actually in default status each month. The consideration in the background of this decision is that the portfolio, examined by me, contained only retail mortgage loans, in connection with which the intensity of the collection process was not significantly influenced by either the loan amount, or the exposure at the date of the default event, or other similar factor, on the basis of which the proportioning is practicable and logically reasonable.

In the next step I linked each deal with the obtainable recoveries and direct costs on deal level, as well as the monthly overheads computed from the indirect costs, which I calculated in a way that I divided the total indirect collection costs, which occurred in the certain months, with the quantity of the deals which were in default status in the given month. In order that I will be able to examine the effect of using the different discount rates on the LGD values (4th Hypothesis), I also assigned four types of discount rates to the deals.

Table 7: Data which are needed for calculating the discounted net recoveries

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
recovery	The sum of the recoveries of the deal during the given month (in HUF).
direct_cost	The sum of the direct costs which occurred in connection with collecting the deal during the given month (in HUF).
indirect_cost	The indirect collection cost overhead in the given month (in HUF).
interest	The original lending rate of the deal.
apr	The Annual Percentage Rate of the deal at the origination.
def_rate	The central bank base rate of the original currency of the deal effective at the default of the deal.
curr_rate	The central bank base rate of the original currency of the deal effective on 30th June 2011.

(Self-made table)

After collecting the recoveries and the costs I calculated the net recoveries for each deal on monthly level, then I discounted them back to the date of the default using the following formula:

$$PV_t = \frac{Recovery_t - Direct\ costs_t - Indirect\ costs_t}{(1+r)^{t/12}} \qquad (1)$$

where: t: the length of the period from the default (year),

r: discount rate.

In case of the basic model I used the contractual lending rate of each deal as discount rate, because it reflects both the differences between the actual interest levels at the date of the origination of certain deals, and on the other hand it varies according to their currency as well. Nevertheless for the sake of investigating the deviations of the LGDs which derived from using different discount rates I quantified the present values of the net recoveries without discounting and with using the alternative discount rates as well, then I summed up the discounted monthly net recoveries on deal level.

Table 8: The nominal and the discounted net recoveries

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
disc_rec_null_lcy	The sum of the cumulative nominal (not discounted) recoveries of the deal (in HUF).
disc_rec_interest_lcy	The sum of the cumulative recoveries of the deal, discounted by the original lending rate (in HUF).
disc_rec_apr_lcy	The sum of the cumulative recoveries of the deal, discounted by the original Annual Percentage Rate (in HUF).
disc_rec_def_rate_lcy	The sum of the cumulative recoveries of the deal, discounted by the central bank base rate according to the deal's currency at the default (in HUF).
disc_rec_curr_rate_lcy	The sum of the cumulative recoveries of the deal, discounted by the central bank base rate according to the deal's currency on 30th June 2011 (in HUF).

(Self-made table)

In the next step I quantified the cumulative discounted recovery rate relating to each month, dividing the cumulative discounted recoveries by the exposure at the default event:

$$CRM_t = \frac{\sum_{i=1}^{t} PV_i}{EAD} \tag{2}$$

where: CRM_t: cumulative discounted recovery rate t months after the default,

PV_i: discounted net recovery in the i^{th} month after the default,

EAD: the exposure at the time of the default.

As the result of this procedure the monthly series of the cumulative discounted recovery rates for each deal were at my disposal,[3] on the basis of their last items the deal level LGDs have become quantifiable:

$$LGD = \begin{cases} 0, & ha \quad 1 - CRM_{t_{MAX}} \leq 0 \\ 1 - CRM_{t_{MAX}}, & ha \quad 0 < 1 - CRM_{t_{MAX}} < 1 \\ 1, & ha \quad 1 - CRM_{t_{MAX}} \geq 1 \end{cases} \tag{3}$$

where: t_{MAX}: the total length of the recovery period considered.

In the course of my analyses t_{MAX} is the duration from the default of the given deal to its "recurring" or its closing.

It is conspicuous from the above formula that I truncated the deal level LGD values at 0% and 100% in accordance with the procedure which is frequently mentioned by the literature, so I considered that the bank can not lose larger amount than the exposure at the date of the default (the LGD can not exceed 100%), and it can not realize larger cumulative recovery than the exposure at the default (the LGD can not be negative).

(c) Pooling the deals according to the closing type

Generally, the aim of pooling is to split the portfolio into homogenous groups from the point of view of the risk on the basis of the characteristics of the product, the deal, the client and the underlying collateral, which factors are expected to influence significantly the recoveries. My 1st and 2nd Hypotheses have a connection with this fact, in the framework of which I investigated the deviations of the LGD values relating to the subportfolios constructed on the ground of the purpose of the loan *(loan_purpose)* and the type of the application *(application_type)*. In case of all three of them characteristics served as a basis for the grouping, which were already known at the origination of the deal, so the certain deals could be squarely assigned to the proper group.

In this subsection I show another sort of using the categorization: in the course of my empirical research I segmented the deals according to the closing type of the collection process, and for the sake of that I defined the date of closing the deal and some connecting data referring to this date.

Table 9: Data about closing the deals

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
write_off_flag	Dummy variable which indicates whether the collection of the deal closed with writing off losses.
woe_month	The period of closing the deal (year, month).
woe_months_since_default	The duration from the origination of the deal to the closing (number of months).
woe_exposure_lcy	The exposure of the deal at the date of the default event (in HUF).
woe_defaulted_minwage	Dummy variable which indicates whether the deal has default status in the period of the closing according to the materiality threshold, which is defined by the lowest monthly minimum wage.
woe_defaulted_huf50000	Dummy variable which indicates whether the deal has default status in the period of the closing according to the materiality threshold of HUF 50000.
woe_defaulted_huf20000	Dummy variable which indicates whether the deal has default status in the period of the closing according to the materiality threshold of HUF 20000.
woe_defaulted_huf2000	Dummy variable which indicates whether the deal has default status in the period of the closing according to the materiality threshold of HUF 2000.
woe_defaulted_huf0	Dummy variable which indicates whether the deal has default status in the period of the closing according to the materiality threshold of HUF 0.
fv_crm_lcy	The cumulative nominal (not discounted) recovery rate of the deal referring to the last period of the recovery process.
real_term	The effective duration of the deal (number of months).

(Self-made table)

[3] Thereafter I always use the term "recovery rate" for the last member of this series.

Based on all these I worked up the under-mentioned categories *(deal_status)*:

- *"WorkoutEnd"*: The deals which are not in default status any more, because the client has paid back the delayed amount, the exposure has been written off or for example the property which served as underlying collateral has been sold.
- *"NoFurtherRec"*: The deals which are still in default status, since their becoming non-performing longer duration has passed than the effective recovery period, and in case of which at least 90% of the exposure at the date of default has recovered (nominally, without discounting: *fv_crm_lcy*).
- *"NotClosed"*: The deals which can be assigned to neither of the previous categories, in case of which the collection procedure is still in progress.

In the course of my analyses I considered the effective length of the collection period 36 months, because analyzing the data of the database I experienced on the basis of the discounted cumulative recovery rates that regarding the majority of the quarters considerable recoveries did not occur after the first 36 months of the collection process.

The unclosed deals in case of which the length of the collection period (the time from the default event) exceeded the 36 months, were classified into the *"NoFurtherRec"* category, increasing the quantity of the deals which can be involved in the analysis, since in case of the basic model I carried out the calculations on the basis of those deals only, which are relating to the first two groups *("WorkoutEnd", "NoFurtherRec")*, I disregarded the deals which were assigned to the third category in the course of quantifying the LGD.

It can be considered as natural that the proportion of the latter category rises highly, since the later the given deal has become non-performing, the shorter time was disposable for it to get into another group. According to the historic experiences a large part of these deals gets into the *"WorkoutEnd"* category, because the client will settle his/her arrears, or for example the property which served as underlying collateral will be sold. Otherwise the deal will be assigned to the *"NoFurtherRec"* category maximum 36 months later than becoming non-performing, because the effective recovery period ends at this time, so following that no further considerable recoveries can be expected from it.

To sum it up: sooner or later (in maximum 36 months from the default event) all the deals will be entered into one of the first two categories. Considering that it can be stated according to the results of my analysis that significant difference can be observed between the LGD values of these two groups (1st Hypothesis), I also investigated in my empirical analysis whether any factors can be explored on the basis of which it becomes predictable which category the certain deals will get into (5th Hypothesis), since if we succeed in finding such factors, the deals assigned to the actual *"NotClosed"* category can be involved in the LGD calculation as well.

(d) Calculating the pool level LGD

Considering that in accordance with the Basel regulation a long-term average has to be applied for measuring the LGD on portfolio level, I arranged the deals into so-called cohorts[4] according to the date of non-performing event. I used monthly division, so those deals have been categorized into the same cohort which became non-performing in the same month, then I averaged the deal level LGD values on cohort level for each deal categories (*"WorkoutEnd"*, *"NoFurtherRec"*).

For the sake of carrying out the most possible accurate estimating procedure, I considered the number of the default events as weights in the course of calculating the long run average, because this method takes into consideration the fact that the recovery and cost data of more deals were used for quantifying the LGD values of the cohorts which contain larger quantity of deals, so these are statistically more grounded, thus this methodology will result in larger degree of accuracy of the model.

[4] *"Cohort: Group whose members share a significant experience at a certain period of time or have one or more similar characteristics"* (Source: http://www.businessdictionary.com/definition/cohort.html). According to this definition I refer to the group of deals whose default date falls into the same period (month) as cohort.

In the course of the empirical research I quantified the deal category level long run average weighted by number of the non-performing deals according to the under-mentioned formula:

$$LGD_{category} = \frac{\sum_{i=1}^{M} \left[LGD_i * N_i \right]}{\sum_{i=1}^{M} N_i} \tag{4}$$

where: LGD_i: average LGD value of the i^{th} cohort,

M: number of cohorts,

N_i: number of non-performing deals in the i^{th} cohort.

Throughout calculating the LGD I treated the deal categories separately, so it enabled to investigate and compare the LGD values of the certain categories, however, in the final step I averaged the category level LGD values as quantification of the aggregated LGD of the total portfolio which I studied. Being attentive to the requirement of the consistent procedure, the quantity of the deals in the certain categories served as a basis of the weighting in this case as well:

$$LGD = \frac{LGD_{WorkoutEnd} * N_{WorkoutEnd} + LGD_{NoFurther\,\mathrm{Re}c} * N_{NoFurther\,\mathrm{Re}c}}{N_{WorkoutEnd} + N_{NoFurther\,\mathrm{Re}c}} \tag{5}$$

(e) Data used for investigating the influencing factors

In the framework of my empirical research I also probed what kind of characteristics influence significantly the run of the LGD. For the sake of establishing these analyses first I constructed a table from the available data about the underlying collaterals of the deals, which contains the following data for each deal and each default event:

Table 10: The secondary data about the collaterals

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
deal_id	Deal identification number.
start_month	The period of the origination of the deal (year, month).
default_month	The period of the default event of the deal (year, month).
start_value_month	The period of defining the collateral value effective at the origination of the deal (year, month).
default_value_month	The period of defining the collateral value effective at the default of the deal (year, month).
priorcharge_rate	The quotient of the sum of the prior charges on the collateral and the realization value at the origination of the deal.
start_collvalue	The realization value of the collateral at the origination of the deal.
default_collvalue	The realization value of the collateral at the default of the deal.
start_marketvalue	The market value of the collateral at the origination of the deal.
default_marketvalue	The market value of the collateral at the default of the deal.
start_LTV	The proportion of the loan amount and the market value of the collateral at the origination.
current_LTV	The proportion of the exposure at the default and the market value of the collateral at the default.
zipcode	The zip code of the real estate which serves as collateral.
settlement	The name of the settlement of the real estate which serves as collateral.
region	The region of the real estate which serves as collateral.
county	The county of the real estate which serves as collateral.
settlement_type	The type of the settlement of the real estate which serves as collateral.
realestate_type	The type of the real estate which serves as collateral.
material	The building type of the real estate which serves as collateral.

(Self-made table)

In the course of that I considered the latter from the date of the original appraisal *(appraisaldate)* and the last revaluation date *(revaluedate)* effective at the origination and the default of the deal, as the date of defining the collateral values at the origination and the default of the deal. The cases were exceptions to that, when the values at the default differed from the values of the origination of the deal, in such cases I considered the date of the default event as the defining date of the values at the default.

In those cases when the date of the original appraisal was not disposable, then I imputed them with the date of the origination of the deal, in case of lack of the values at the default I filled them up with the values at the origination of the deal *(start_collvalue, start_marketvalue)*.

Considering that more than one real estate can lie under certain deals, and the same real estate can serve as collateral for several deals as well, I had to carry out the allocation of the collateral values and the market values of the collaterals. For the sake of that I summed up the values of the collaterals on deal level, and I linked the characteristics of the real estate with the highest value to each deal in all cases. If the same collateral referred to more than one deal, then I linked the values to the single deals allocated according to the proportion of the exposure at the default. Following that there was only one record for each deal in the data table, to which I was already able to join the region, county and type of the settlement according to the location of the real estate, so the data shown in Table 10 occurred at last.

The formerly illustrated data structures enabled me to join the secondary data referring to the collaterals to the data about the clients and the deals, and to develop the data table which grounds the analysis of the influencing factors of the LGD. In the table below (Table 11) I make known the data fields with which in this latest step I supplemented the final data table, which served as a basis for regression building.

Table 11: Macroeconomic secondary data

NAME OF THE DATA FIELD	CONTENT OF THE DATA FIELD
start_fx_rate	The exchange rate of the deal's currency at the origination.
start_unempl_rate	Unemployment rate at the origination of the deal.
start_min_wage	The lowest monthly minimum wage at the origination of the deal.
start_avg_netincome	Average monthly net income at the origination of the deal.
start_realwage_index	Yearly real wage index at the origination of the deal.
start_CPI	Yearly consumer price index at the origination of the deal.
start_GDP_growth	Yearly GDP-growth index at the origination of the deal.
fx_index_ds	The index of the exchange rate of the currency at the default and the origination (ratio).
collvalue_index_ds	The index of the realization value of the collateral at the default and the origination (ratio).
marketvalue _index_ds	The index of the market value of the collateral at the default and the origination (ratio).
unempl_rate_index_ds	The index of the unemployment rate at the default and the origination (ratio).
min_wage_index_ds	The index of the lowest monthly minimum wage at the default and the origination (ratio).
avg_netincome_index_ds	The index of the average monthly net income at the default and the origination (ratio).
cum_realwage_index_ds	The ratio of the real wages at the default and the origination.
cum_CPI_ds	The index of the consumer prices at the default and the origination (the quotient of the cumulative consumer price indices).
GDP_growth_index_ds	The index of the GDP at the default and the origination (the quotient of the cumulative GDP-growth indices).

(Self-made table)

After the review of the features of the examined portfolio, the data used as well as the definitions and assumptions applied in the basic model I enter upon the presentation of the concrete examinations.

2.4. Statistical examinations

In the framework of my 1st and 2nd Hypothesis I investigated whether the LGD values of the categories, worked up from the deals in the database examined by me, significantly differ from each other on the basis of the loan purpose and the type of the application. In the first step I compared the distributions on the basis of the descriptive statistics (mean values, indices of dispersion, kurtosis and skewness) and graphically illustrating with bar-chart, then in the next step I carried out Homogeneity Analysis regarding the equivalence of the LGD distributions.

The null hypothesis of the Homogeneity Analysis formalizes that the distribution of a variate is the same in the two populations (***Y***-population, ***X***-population), and its alternative hypothesis states that the two distributions differ from each other. Issuing from the special feature of the test function this test can be carried out with critical region only on the right side.

To carry out the Homogeneity Analysis of large samples, both the samples have to be divided up to the same classes on the basis of certain variable in the manner which can be seen in the following table:

Table 12: The work table of the hypothesis testing

CLASS	FREQUENCIES IN THE SAMPLE OF THE Y-POPULATION	FREQUENCIES IN THE SAMPLE OF THE X-POPULATION	TOTAL
C_1	n_{Y1}	n_{X1}	$n_{Y1}+n_{X1}$
C_2	n_{Y2}	n_{X2}	$n_{Y2}+n_{X2}$
…	…	…	…
C_i	n_{Yi}	n_{Xi}	$n_{Yi}+n_{Xi}$
…	…	…	…
C_k	n_{Yk}	n_{Xk}	$n_{Yk}+n_{Xk}$
Σ	n_Y	n_X	n_Y+n_X

(Self-made table on the basis of *Hunyadi – Vita [2004] pp. 475.*)

In course my dissertation I created 16 LGD bands (classes) for the purpose of the Homogeneity Analysis, but I did not define their broadness equally, instead I considered narrow intervals on the segments near 0% and 100%, and broader intervals on the middle section as separate LGD bands, moreover I worked up distinct classes for the LGD values of 0% and 100% with respect to the large quantity of the extreme values.

If the distribution of the given variable is the same in the two distributions (H_0 is true), and both samples are large enough, the χ^2 test function follows approximately χ^2-distribution with $\nu = k - 1$ degree of freedom:

$$\chi^2 = n_Y n_X \sum_{i=1}^{k} \frac{1}{n_{Yi} + n_{Xi}} \left(\frac{n_{Yi}}{n_Y} - \frac{n_{Xi}}{n_X} \right)^2 \qquad (6)$$

The null hypothesis states only the equivalence of the distributions, but it does not say anything about the type and certain characteristics of the distributions, thus in some respect it can be applied as a completion of the two-sample tests. For that very reason during my empirical analyses I also used the tests regarding the equality of the expected values and the Homogeneity Analysis simultaneously.

Despite the fact that the distributions notably differed from the normal distribution, regarding the considerably large quantity of elements I carried out asymptotic z-tests to examine the equality of the average LGD values. Here and during the execution of the statistical tests of the further hypotheses (asymptotic z-tests, t- and F-tests, Homogeneity Analyses) alike I applied a significance level of 5% and p-value approach.

My 3rd Hypothesis was directed towards evaluating to what extent certain alternative discount rates divert the LGD values from the ones of the basic model, namely I compared the LGD values, which were calculated with the alternative discount rates, to the LGD values of the basic model in all cases. Following the investigation of the descriptive statistics and the graphical illustrations of the distributions I carried out Homogeneity Analysis pair-wise referring to the equivalence of the distributions using the 16 LGD bands worked up previously, and with regard to the considerably large quantity of elements I examined the equality of the LGD values calculated with the different discount rates with paired two-sample t-tests.

In the framework of my 4th Hypothesis I investigated the effect of using four alternative thresholds, in addition to the materiality threshold in the basic model, on the results of the LGD calculation. I separated the "technical defaults", namely those which are not considered as non-performing according to the definition of the basic model, but they did according to the materiality threshold of 0 HUF. In the course of the examinations I compared the LGD values of this subportfolio with the LGD values in the basic model, using the same methodologies as during testing the 1st and the 2nd Hypothesis.

The subject of my 5th Hypothesis was the search for the features of the categories defined on the basis of the closing type of the deals, since according to my anticipative expectations the characteristics of the cases which compose the categories of the different closing types are insomuch diverse, that they are properly classifiable with using statistical methods.

The logistic regression model does not have any assumptions regarding the distribution of the explanatory variables, so it is particularly suitable for classifying the result variables whose distribution is discrete, since in this case the discriminant analysis is not applicable because of the unfulfilment of the multivariate normality of the explanatory variables.

The dichotomous logistic regression model carries out the categorisation of the observations based on the $\boldsymbol{\beta}$ parameters in a way that it defines the critical value (cut-off) of the certain event's emergence, and it classes the observations, in case of which the conditional probability exceeds this value, into the given category, and the other observations into the complementary one *(Hajdu [2004])*.

The types of the models differ from each other in that respect, what kind of transformation they apply and what kind of assumptions they have relating to the distribution of the $\boldsymbol{u}$ error factor. The best-known types are the probit and the logit models: in case of the probit model the standard normal distribution describes the estimated probability, whereas the logit model uses the logistic cumulative distribution function for characterising the estimated probability *(Maddala [2003]; Ramanathan [2003]; Greene [2003])*:

Proceeding from the theorem that a significant relation exists between some explanatory variable and the result variable, if the partial coefficient of the regression is not 0 at a given confidence level, the testing of the significance of the parameters can be done inversely by two types of methods, similarly to the classical linear regression *(Hajdu [2004])*:

- The z-test statistic is suitable for both one-tailed and two-tailed testing, whose distribution is asymptotically standard normal for large samples in case of the validity of the $\boldsymbol{H_0}$: $\boldsymbol{\beta_j}$=0 null hypothesis.
- The testing against the two-tailed $\boldsymbol{H_1}$: $\boldsymbol{\beta_j}$<>0 alternative hypothesis also can be carried out by using the Wald statistic, which also follows roughly $\boldsymbol{\chi^2}$-distribution with the degree of freedom $\boldsymbol{df=1}$ for large samples *(Wooldridge [2009])*.

The logistic model is actually a special case of the generalised linear model (GLIM: Generalized Linear Interactive Modelling) worked out by *Nelder and Wedderburn [1972]*, which enables the linear modelling of explanatory variables whose measuring scale is different.

In the course of my empirical research I built the logistic regression with SAS Enterprise Miner™ 5.2 applying stepwise model selecting procedure. Testing numerous model types and transformation procedures I compared the performances of the regressions on the basis of fit statistics, and considering them I decided upon the model which applies logit link without any transformation. Following that I analyzed the results of the Maximum Likelihood estimation referring to the variables of the model also from the viewpoint of interpretability.

In the course of examining my 6th Hypothesis my goal was to make a survey of the factors which are able to predict statistically confidently the length of the period which is needed for the recoveries from selling the collateral or the debt, and to predict the recovery rate itself. For the purpose of justifying my hypothesis I built separately linear regressions referring to the expected length of the recovery period and to the recovery rate deriving from the selling on the basis of the Hungarian Interbank LGD Database.

Following that in the framework of my 7th Hypothesis I investigated whether the influencing factors of the LGD values of the deals with different closing types differ considerably from each other. In this case I also created linear regressions separately for the categories according to the closing types of the deals, and on the basis of them I searched the factors which proved to be significant.

I built the models, which served as a basis for the examination of my 6th and 7th Hypotheses, with stepwise procedure using SAS Enterprise Miner™ 5.2, then in case of the models whose adjusted coefficients of determination were rather low I made modifications on expert base for the sake of improving the explanatory power. During the model selection I considered the adjusted coefficients of determination and the results of the global Wald test, and I verified the relevance of each variable with using $\boldsymbol{t}$-test.

3. The results of the dissertation

In the framework of this dissertation I studied the specialities of the LGD parameter of the retail mortgage loans, and I took steps to prepare a model with which more exact and more accurate LGD calculation will be possible. In the following I summarize the most important results of my research.

3.1. 1st Hypothesis: The LGD values of the loans with home purpose are lower than the LGD values of the mortgage equity withdrawals.

The object of my 1st Hypothesis was the connection between the purpose of the loan and the LGD. According to my anticipative expectations in the case of the deals, where the purpose of the loan is the construction or purchase of the real estate which serves as collateral, larger recoveries can be expected in comparison with the mortgage equity withdrawals. In addition to the preceding empirical results (for example *Grippa et al. [2005]*) the belief lies behind this that the clients presume less to take the risk of losing their home in the case, if they had decided to take up the loan exactly for the sake of its obtainment.

According to the examinations, which were carried out, my 1st Hypothesis did not prove to be true, the LGD values of the loans with home purpose seemed lower than the LGD values of the mortgage equity withdrawals at none of the popular significance levels, the results of the tests show just the opposite of that. The analyses also clarified that the LGD distributions of the two groups defined within the loans with home purpose (home building and home purchase) differ much less from each other than the LGD distributions of the mortgage loans with home purpose and the mortgage equity withdrawals, thus the separate treating has relevance only in the case of the two latter groups in the course of the categorization, the application of more detailed parcelling does not have any notable added value.

3.2. 2nd Hypothesis: The purely collateral-based loans without income verification are characterized by higher LGDs than the loans based on income verification.

In the framework of my 2nd Hypothesis I investigated whether the LGD values of the purely collateral-based loans without income verification and the mortgage loans based on income verification differ from each other significantly. According to my presumption only lower recoveries can be expected from the deals which belong to the former group, following the occasional default event, because the income of the clients who have resort to this kind of loan is supposedly lower and less steady in comparison with the ones who are prepared to give free run of their income certificate to the bank at the application.

The tests, which were carried out, uniformly seem to verify my 2nd Hypothesis, since they show that the LGD values of the purely collateral-based loans without income verification and of the deals based on income verification differ from each other significantly, the graphical illustration of the distributions and the descriptive statistics clearly show that the LGD values of the latter category are lower in the examined portfolio.

Considering that the LGD values of the deals based on income verification proved to be significantly lower than the LGD values of the purely collateral-based loans without income verification, if the deals pertaining to the latter category dominate among the loans with home purpose, then this can partly explain why the statement which is composed in the 1st Hypothesis did not prove to be watertight. However, since the average LGD values of the loans with home purpose are higher in case of both deal categories which are defined on the basis of the type of the application, in comparison with the ones of the mortgage equity withdrawals, it does not give any explanation why the statement composed in the 1st Hypothesis did not pass the test. Moreover the fact that in the examined portfolio the purely collateral-based loans without income verification represent larger proportion within the group of the mortgage equity withdrawals, than within the category of the loans with home purpose, would reason intuitively exactly the fact that the mortgage equity withdrawals should be featured by higher LGD values.

3.3. 3rd Hypothesis: The type of the applied discount rate influences the calculated LGD value considerably.

In case of the basic model I used the contractual lending rate of each deal as discount rate, and in the course of investigating my 3rd Hypothesis I analyzed the effects of using the four following alternative discount rates: discount rate of 0%, the contractual Annual Percentage Rate of the given deals, the central bank base rate of the currency of the deal effective at the default, and the central bank base rate of the currency of the deal effective on 30th June 2011.

My examinations showed that, though in the high LGD range large differences did not appear between the proportions of the LGD values, which are calculated with the given alternative discount rates, considerable deviations can be experienced by 0% and in the LGD bands which are near that. The use of the 0% discount rate and the contractual Annual Percentage Rate diverted the LGD values the most considerably from the ones of the basic model. Although the differences seemed to be smaller in the case of the two other discount rates, even in case of them the presumption of both the equivalence of the distributions and the equality of the averages had to be rejected at all the popular significance levels. From all these results it may be concluded that the used discount rate has an important LGD influencing role, so they support the statement composed in my 3rd Hypothesis.

3.4. 4th Hypothesis: The lowering of the materiality threshold used in the basic model does not affect the result of the LGD calculation considerably in case of the retail mortgage loans.

Considering that the credit institutions are also allowed to use criteria for materiality threshold which are different from the prescriptions *(Hkr. 68. § (5)-(7) Paragraph)*, if they are able to justify its necessity, reasonability, my 4th Hypothesis was directed towards investigating whether a considerable role can be put down to the use of the lower materiality thresholds from the viewpoint of the result of the LGD calculation. According to my anticipative expectations the low-amount arrears are quite rare in case of the mortgage loans, so it has a relatively small probability that the clients delay with an amount which is smaller than the materiality threshold described by the Hkr.

For the sake of testing my hypothesis I compared the LGD values of the "technical defaults" with the LGD values in the basic model, and the results showed that the statement composed in my 4th Hypothesis, according to which using the lower materiality thresholds does not cause considerable affect on the result of the LGD calculation, can be accepted only at quite low significance levels.

3.5. 5th Hypothesis: The LGD values of the categories according to the closing type of the deals differ strongly from each other, and the elements of the two groups which have closed recovery process ("NoFurtherRec", "WorkoutEnd") can be properly separated with using logistic regression.

In the course of my 5th Hypothesis I investigated whether my anticipative expectation can be justified that the LGD values of the categories defined according to the closing type of the deals differ strongly from each other, and the logistic regression methodology can be successfully applied for carrying out the classification. As the result of the modelling I managed to configure two fairly strong models.

In the model which applies the logit link the reasons of the default (whether the deal is considered as non-performing because of death; whether the delay is the reason of the default status), the settlement type of the real estate which serves as collateral, some macroeconomic factors (the yearly average growth of the GDP and of the real wages from the origination of the deal to the default; the yearly real wage index at the default event), the ratio of the loan amount and the market value of the collateral at the origination as well as the paying history (the length of the period from the origination of the deal to the default event) proved to be key factors regarding the categorization of the default events.

Table 13: The variables of the logistic regression with logit link

Parameter	*Estimate*	*Standard Error*	*Wald χ^2*	*$Pr > \chi^2$ (p-value)*	*Exp(Estimate)*
Intercept	2.4906	0.1940	164.76	<.0001	12.069
REASON_DEATH = 0	1.0071	0.1595	39.88	<.0001	2.738
REASON_PASTDUE = 0	0.9365	0.2344	15.96	<.0001	2.551
SETTLEMENT_TYPE = Budapest & environs	0.3630	0.1383	6.89	0.0087	1.438
SETTLEMENT_TYPE = County town & environs	0.4630	0.1228	14.22	0.0002	1.589
SETTLEMENT_TYPE = Other city & environs	-0.0689	0.1024	0.45	0.5010	0.933
SETTLEMENT_TYPE = Small village	-0.4707	0.1395	11.38	0.0007	0.625
STD_CUM_REALWAGE_INDEX_DS_Y	0.4041	0.0531	57.82	<.0001	1.498
STD_DEFAULT_REALWAGE_INDEX	-0.2433	0.0616	15.58	<.0001	0.784
STD_GDP_GROWTH_INDEX_DS_Y	-1.3934	0.0983	200.95	<.0001	0.248
STD_MONTHS_TO_DEFAULT	1.1343	0.1064	113.74	<.0001	3.109
STD_START_LTV	-0.3588	0.0671	28.55	<.0001	0.699

(Self-made table: own calculation results)

In the model which applies the probit link the variables in connection with the rate of growth of the real wage do not appear, but as a quasi compensation the indices which measure the changing of the consumer prices proved to be significant. Similarly, the model which applies the probit link does not contain the ratio of the loan amount and the market value of the collateral at the origination, but the product type which is in tight connection with this variable, was qualified as significant. The industry of the client's employer, the region of the property and the amount of the first instalment occurred as further variables.

It is an important lesson that the reasons of the default, the settlement type of the real estate which serves as collateral, the yearly average rate of the GDP-growth in the period from the disbursement of the loan to the default, and the length of the period to the default proved to be significant in case of this model as well, and regarding these variables the direction of the connections are the same as the ones in the model with the logit link. Roughly speaking it can be stated that the two models show considerable cognateness concerning both the scale of the influencing factors and the direction of the connections.

On the basis of all these results my 5th Hypothesis can be considered as justified.

3.6. 6th Hypothesis: With the linear regression models on the basis of the Hungarian Interbank LGD Database, the deals of the "NotClosed" category can also be involved in the calculation, and a more exact and more accurate deal level LGD estimation becomes possible.

My 6th Hypothesis was directed towards the examination of the Hungarian Interbank LGD Database: my goal was to make a survey of the factors which are able to predict statistically confidently the length of the period which is needed for the recoveries from selling the collateral or the debt, and to predict the recovery rate itself. I took steps with using the data of the Hungarian Interbank LGD Database to develop a complex model, with which the deals can also be involved in the calculations whose collection process has not been closed yet. However, it is its very important condition to prepare regressions, with which a precise prediction can be made referring to the expected length of the recovery period of the deals and the recovery rate deriving from the selling, on the basis of the data which are available at the default.

In the first step I built a linear regression referring to the expected length of the recovery period. A part of the variables of the model prepared on the basis of the Maximum Likelihood estimation is in connection with the deal itself (the purpose of the loan; the proportion of the exposure at the default and the disbursement amount) or with the underlying collateral (the county; the ratio of the exposure at the default and the value of the collateral at the same time), whereas the other part of them consists of the macroeconomic changes in the period from the origination of the deal (the yearly average growth of the consumer prices and the unemployment rate from the origination of the deal to the default event) and the characteristics of the macroeconomic situation at the default (the consumer price index; the minimal wage).

Table 14: The variables of the regression developed for the length of the recovery period

Parameter	*Estimate (non-standardised)*	*Estimate (standardised)*	*Standard Error (standardised)*	*t Value*	*Pr > |t| (p-value)*
Intercept	-100.7	14.9128	0.4085	36.51	<.0001
COUNTY=Baranya	1.1004	1.1004	1.3274	0.83	0.4072
COUNTY=Borsod-Abaúj-Zemplén	-2.4692	-2.4692	0.9468	-2.61	0.0092
COUNTY=Budapest	1.8953	1.8953	0.7837	2.42	0.0157
COUNTY=Bács-Kiskun	1.0652	1.0652	1.2701	0.84	0.4018
COUNTY=Békés	-3.7576	-3.7576	1.2714	-2.96	0.0032
COUNTY=Csongrád	3.2227	3.2227	1.1520	2.80	0.0052
COUNTY=Fejér	0.1592	0.1592	1.3159	0.12	0.9037
COUNTY=Győr-Moson-Sopron	0.4562	0.4562	1.5834	0.29	0.7733
COUNTY=Hajdu-Bihar	-0.3116	-0.3116	1.1118	-0.28	0.7793
COUNTY=Heves	-1.5188	-1.5188	0.9731	-1.56	0.1188
COUNTY=Jász-Nagykun-Szolnok	-0.2926	-0.2926	0.9262	-0.32	0.7521
COUNTY=Komárom-Esztergom	-0.4112	-0.4112	1.1715	-0.35	0.7256
COUNTY=Nógrád	0.7071	0.7071	0.9255	0.76	0.4450
COUNTY=Pest	-0.1437	-0.1437	0.6565	-0.22	0.9268
COUNTY=Somogy	-0.3566	-0.3566	0.9087	-0.39	0.6948
COUNTY=Szabolcs-Szatmár-Bereg	-1.6533	-1.6533	0.6420	-2.58	0.0101
COUNTY=Tolna	5.6115	5.6115	2.2564	2.49	0.0130
COUNTY=Vas	-2.7035	-2.7035	2.6723	-1.01	0.3118
COUNTY=Veszprém	0.7974	0.7974	1.5420	0.52	0.6052
LOAN_PURPOSE=Other	0.3749	0.3749	0.4136	0.91	0.3649
LOAN_PURPOSE=Real estate construction	1.5622	1.5622	0.6627	2.36	0.0185
LOAN_PURPOSE=Real estate purchase	-1.2811	-1.2811	0.4434	-2.89	0.0039
CUM_CPI_DS_Y	88.6327	1.2608	0.2738	4.60	<.0001
UNEMPL_RATE_INDEX_DS_Y	4.4630	0.5840	0.2930	2.01	0.0445
DEFAULT_CPI	42.6944	0.7877	0.3022	2.61	0.0092
DEFAULT_MIN_WAGE	-0.00033	-1.4144	0.2852	-4.96	<.0001
DEFAULTED_PER_START_EXPOSURE	-10.1692	-1.2241	0.3132	-3.91	<.0001
CURRENT_LTV	8.7642	1.4951	0.2613	5.72	<.0001

(Self-made table: own calculation results)

In the next step I constructed a linear regression also for the recovery rate (the proportion of the recovery deriving from the selling discounted to the date of the default and the exposure at the default). It is conspicuous that numerous ones among the explanatory variables appear also in the model created for the length of the recovery period, namely there is a large overlapping between the factors of the two models: as a matter of fact very similar factors influence the length of the recovery period and the recovery rate deriving from the selling.

In this case as well, a part of the variables of the model prepared on the basis of the Maximum Likelihood estimation is in connection with the deal itself (the purpose of the loan) or with the underlying collateral (the county; the type of the settlement; the ratio of the exposure at the default and the value of the collateral at the same time; the quotient of the prior charges on the collateral and the realization value at the origination of the deal), whereas the other part of them consists of the macroeconomic changes in the period from the origination of the deal (the yearly average growth of the consumer prices and the unemployment rate from the origination of the deal to the default event), but the role of the characteristics of the macroeconomic situation at the default did not prove to be important. My results agreed in numerous respects with the results published in the studies of *Qi and Yang [2007; 2009]*.

Table 15: The variables of the regression developed for the recovery rate deriving from the selling

Parameter	*Estimate (non-standardised)*	*Estimate (standardised)*	*Standard Error (standardised)*	*t Value*	*Pr > |t| (p-value)*
Intercept	3.7596	0.5866	0.0112	52.37	<.0001
COUNTY=Baranya	-0.0772	-0.0772	0.0334	-2.31	0.0208
COUNTY=Borsod-Abaúj-Zemplén	0.0192	0.0192	0.0237	0.81	0.4175
COUNTY=Budapest	0.1468	0.1468	0.0363	4.04	<.0001
COUNTY=Bács-Kiskun	-0.0192	-0.0192	0.0317	-0.60	0.5462
COUNTY=Békés	-0.0134	-0.0134	0.0318	-0.42	0.6737
COUNTY=Csongrád	-0.0444	-0.0444	0.0291	-1.52	0.1279
COUNTY=Fejér	0.0194	0.0194	0.0329	0.59	0.5547
COUNTY=Győr-Moson-Sopron	0.000177	0.000177	0.0395	0.00	0.9964
COUNTY=Hajdu-Bihar	0.0314	0.0314	0.0278	1.13	0.2591
COUNTY=Heves	-0.0360	-0.0360	0.0244	-1.48	0.1399
COUNTY=Jász-Nagykun-Szolnok	-0.0246	-0.0246	0.0323	-1.06	0.2885
COUNTY=Komárom-Esztergom	-0.00372	-0.00372	0.0293	-0.13	0.8988

Table 15 (continuation): The variables of the regression developed for the recovery rate deriving from the selling

Parameter	Estimate (non-standardised)	Estimate (standardised)	Standard Error (standardised)	t Value	Pr > |t| (p-value)
COUNTY=Nógrád	-0.0253	-0.0253	0.0234	-1.08	0.2810
COUNTY=Pest	0.0125	0.0125	0.0190	0.66	0.5120
COUNTY=Somogy	-0.00909	-0.00909	0.0228	-0.40	0.6902
COUNTY=Szabolcs-Szatmár-Bereg	-0.0377	-0.0377	0.0160	-2.35	0.0187
COUNTY=Tolna	0.0299	0.0299	0.0563	0.53	0.5960
COUNTY=Vas	-0.0377	-0.0377	0.0667	-0.57	0.5719
COUNTY=Veszprém	0.0735	0.0735	0.0385	1.91	0.0565
SETTLEMENT_TYPE=Budapest & environs	0.00621	0.00621	0.0266	0.23	0.8155
SETTLEMENT_TYPE=County town & environs	0.0353	0.0353	0.0144	2.45	0.0145
SETTLEMENT_TYPE=Other city & environs	-0.0117	-0.0117	0.0113	-1.03	0.3021
SETTLEMENT_TYPE=Small village	-0.0180	-0.0180	0.0136	-1.32	0.1858
CUM_CPI_DS_Y	-2.5920	-0.0369	0.00603	-6.12	<.0001
UNEMPL_RATE_INDEX_DS_Y	-0.1342	-0.0176	0.00642	-2.73	0.0063
CURRENT_LTV	-0.5953	-0.1016	0.00704	-14.42	<.0001
PRIORCHARGE_RATE	-0.3176	-0.0498	0.00688	-7.23	<.0001
LOAN_PURPOSE=Other	0.0185	0.0185	0.00998	1.85	0.0643
LOAN_PURPOSE=Real estate construction	-0.0566	-0.0566	0.0166	-3.41	0.0007
LOAN_PURPOSE=Real estate purchase	0.0257	0.0257	0.0112	2.30	0.0216

(Self-made table: own calculation results)

It can be generally said that all the variables of the regressions can be interpreted logically easily, after all the explanatory power of the models is insofar low that it does not justify the statement composed in the 6th Hypothesis, since using the Hungarian Interbank LGD Database I did not manage to built a linear regression model which can is applicable for the purpose of prediction.

3.7. 7th Hypothesis: Different factors influence the LGD values of the deals with different closing types ("WorkoutEnd", "NoFurtherRec"), thus it is inappropriate to handle these categories together in the course of modelling the deal level LGD.

In the framework of the 7th Hypothesis I investigated whether the influencing factors of the LGD values of the deals with different closing types differ considerably from each other.

The *"WorkoutEnd"* category contains the deals which are not in default status any more, because the client has paid back the delayed amount, the exposure has been written off or the property which served as underlying collateral has been sold. So this deal class is considerably heterogeneous, and it is not surprising that the regression, built with stepwise procedure using SAS Enterprise Miner™ 5.2, had a rather small explanatory power.

In the linear regression the factors which describe the macroeconomic situation at the default (the average default rate; the average net income; the consumer price index; the yearly growth index of the real wages; the unemployment rate) as well as some deal and collateral characteristics (the county; the exposure at the date of the default; the proportion of the exposure at the default and the disbursed amount; the quotient of the prior charges on the collateral and the realization value at the origination of the deal) gained the most dominant role, and it is conspicuous that none of the client characteristics proved to be significant influencing factor.

Table 16: The variables of the regression developed for the LGD of the "WorkoutEnd" deal category

Parameter	Estimate (non-standardised)	Estimate (standardised)	Standard Error (standardised)	t Value	Pr > |t| (p-value)
Intercept	0.7496	0.0186	0.00123	15.10	<.0001
COUNTY=Baranya	-0.00725	-0.00725	0.00551	-1.32	0.1885
COUNTY=Borsod-Abaúj-Zemplén	-0.00111	-0.00111	0.00394	-0.28	0.7776
COUNTY=Budapest	-0.00671	-0.00671	0.00283	-2.37	0.0179
COUNTY=Bács-Kiskun	-0.00444	-0.00444	0.00417	-1.06	0.2870
COUNTY=Békés	-0.00560	-0.00560	0.00452	-1.24	0.2151
COUNTY=Csongrád	-0.00802	-0.00802	0.00494	-1.62	0.1048
COUNTY=Fejér	-0.00648	-0.00648	0.00419	-1.55	0.1223
COUNTY=Győr-Moson-Sopron	-0.00099	-0.00099	0.00439	-0.22	0.8220
COUNTY=Hajdu-Bihar	-0.00417	-0.00417	0.00407	-1.02	0.3055
COUNTY=Heves	0.00716	0.00716	0.00567	1.26	0.2069
COUNTY=Jász-Nagykun-Szolnok	-0.00251	-0.00251	0.00618	-0.41	0.6854

Table 16 (continuation): The variables of the regression developed for the LGD of the "WorkoutEnd" deal category

Parameter	*Estimate (non-standardised)*	*Estimate (standardised)*	*Standard Error (standardised)*	*t Value*	*Pr > |t| (p-value)*
COUNTY=Komárom-Esztergom	-0.00220	-0.00220	0.00409	-0.54	0.5914
COUNTY=Nógrád	0.00510	0.00510	0.00584	-0.87	0.3824
COUNTY=Pest	-0.00101	-0.00101	0.00290	-0.35	0.7277
COUNTY=Somogy	-0.00658	-0.00658	0.00683	-0.96	0.3354
COUNTY=Szabolcs-Szatmár-Bereg	-0.00509	-0.00509	0.00384	-1.33	0.1847
COUNTY=Tolna	0.0169	0.0169	0.00831	2.03	0.0421
COUNTY=Vas	-0.00375	-0.00375	0.00708	-0.53	0.5965
COUNTY=Veszprém	-0.00213	-0.00213	0.00400	-0.53	0.5947
DEFAULTED_EXPOSURE_LCY	5.28E-10	0.00275	0.00101	2.72	0.0065
DEFAULTED_PER_START_EXPOSURE	0.0216	0.00399	0.00122	3.27	0.0011
PRIORCHARGE_RATE	0.0173	0.00250	0.000973	2.57	0.0103
AVG_PD	-0.6131	-0.0153	0.00307	-4.97	<.0001
DEFAULT_AVG_NETINCOME	-4.08E-7	-0.00349	0.00175	-1.99	0.0464
DEFAULT_CPI	-0.5301	-0.00774	0.00130	-5.95	<.0001
DEFAULT_REALWAGE_INDEX	-0.1616	-0.00587	0.00108	-5.42	<.0001
DEFAULT_UNEMPL_RATE	0.5051	0.00805	0.00308	2.61	0.0090

(Self-made table: own calculation results)

I consider it necessary to emphasize the negative sign of the estimated parameter of the default rate (*avg_PD*), since we can usually read in the literature about the positive correlation between the LGD and the default rate (for example *Grunert and Weber [2005]*, *Brady et al. [2007]*, *Bellotti and Crook [2008]*), or in some cases about independency respectively (*Carey – Gordy [2003]*). However, in case of the other factors the results were not surprising.

The *"NoFurtherRec"* category consists of the deals which are still in default status, since their becoming non-performing longer than 36 months duration has passed, and in case of which at least 90% of the exposure at the date of default has recovered. According to my anticipative expectations, this group is much more homogeneous in comparison with the *"WorkoutEnd"* category, and the influencing factors of the deal level LGD can be better defined. This model proved to be much stronger indeed.

In this linear regression the client characteristics (the age of the client at the default; the landline phone) also played an important role in addition to the deal and collateral characteristics (the length of the period from the origination of the deal to the default event; whether the deal became non-performing because of delay; the region; the type of the settlement) as well as the macroeconomic factors (the growth of the real wages, of the consumer prices and of the GDP in the period from the origination of the deal to the default; the average default rate at the default date), contrary to the regression prepared for the *"WorkoutEnd"* deal category.

Table 17: The variables of the regression developed for the LGD of the "NoFurtherRec" deal category

Parameter	*Estimate (non-standardised)*	*Estimate (standardised)*	*Standard Error (standardised)*	*t Value*	*Pr > |t| (p-value)*
Intercept	-7.9544	0.7094	0.0323	21.96	<.0001
DEFAULT_AGE_MONTHS	-0.00018	-0.0251	0.0106	-2.35	0.0190
LINE_PHONE_FLAG=0	0.0209	0.0209	0.0103	2.04	0.0421
REASON_PASTDUE=0	-0.1702	-0.1702	0.0297	-5.72	<.0001
MONTHS_TO_DEFAULT	-0.0304	-0.2216	0.0358	-6.20	<.0001
REGION=Budapest & environs	-0.0347	-0.0347	0.0388	-0.89	0.3714
REGION=Central-Western	-0.0308	-0.0308	0.0283	-1.09	0.2766
REGION=Eastern	0.0284	0.0284	0.0263	1.08	0.2811
REGION=North-Eastern	0.0488	0.0488	0.0198	2.46	0.0142
REGION=North-Western	-0.0580	-0.0580	0.0305	-1.90	0.0577
REGION=South-Central	0.0361	0.0361	0.0407	0.89	0.3751
REGION=South-Eastern	-0.0347	-0.0347	0.0326	-1.06	0.2878
REGION=South-Western	0.000328	0.000328	0.0422	0.01	0.9938
SETTLEMENT_TYPE=Budapest & environs	0.0253	0.0253	0.0383	0.66	0.5091
SETTLEMENT_TYPE=County town & environs	-0.0721	-0.0721	0.0227	-3.17	0.0016
SETTLEMENT_TYPE=Other city & environs	0.00688	0.00688	0.0180	0.38	0.7034
SETTLEMENT_TYPE=Small village	0.0298	0.0298	0.0234	1.27	0.2030
CUM_REALWAGE_INDEX_DS	-2.7167	-0.0573	0.0122	-4.70	<.0001
CUM_CPI_DS	2.3466	0.0884	0.0390	2.27	0.0239

Table 17 (continuation): The variables of the regression developed for the LGD of the "NoFurtherRec" deal category

Parameter	*Estimate (non-standardised)*	*Estimate (standardised)*	*Standard Error (standardised)*	*t Value*	*Pr > |t| (p-value)*
GDP_GROWTH_INDEX_DS	9.0760	0.1762	0.0148	11.93	<.0001
AVG_PD	3.6371	0.0417	0.0137	3.04	0.0025

(Self-made table: own calculation results)

On the basis of the linear regression models developed for the *"WorkoutEnd"* and the *"NoFurtherRec"* deal categories, it can be said summing up that the results support the statement composed in my 7th Hypothesis according to which different factors influence the LGD values of the deals with different closing types, thus it is inappropriate to handle them together in the course of modelling the deal level LGD.

4. Summary: the applicability of the results in practice

In the past period the questions in connection with the capital adequacy received high priority for the credit institutions. All the ingravescent economic problems, the increasing risks and the aggravation of the capital adequacy prescriptions have the affect that the capital available for the institutions is tighter and tighter. Under such conditions the proper capital management and portfolio management are essential, thus the exact quantification of the credit risk parameters also has an increasing importance.

Taking into consideration this aspect as well, the notability of prudential definition of the pooling criteria is undoubted, since the divergence of the risk parameters results in different capital requirements withal, thus the credit risk parameters serve as important input factors for the decisions in connection with the portfolio management as well. In case of the portfolio examined by me I experienced significant differences between the LGD values of the certain subportfolios in the course of the categorization according to both the purpose of the loan and the type of the application. Naturally the appropriate pooling criteria can differ from each other institute by institute, moreover they can change in time as well, thus the dynamic approach and the systematic revisions are essential in the course of their use. For that matter the CRD prescribes as well that concerning the statistical models comprehensive supervision has to be made at least annually, which has to include the monitoring of the predictive power, the freeness of distortion and the stability, the review of specifications, the comparison of predicted and real realized results (Back Testing). For the objectivity and exploration of the model's deficiencies the requirement of a review by professional evaluation is a further prescription *(EC [2011c] Article 170; Hkr. 63. §)*.

The result that the applied discount rate has significant LGD-influencing role is important because actually neither the CRD nor the national regulation contains particular prescriptions regarding what kind of method the rate should be defined with. In my opinion the contractual lending rate of the deals can be considered as the most appropriate one, since it reflects both the differences between the actual interest levels at the date of the origination of certain deals, and on the other hand it varies according to their currency as well. However, the empirical results indicate that the definition significantly influences the calculated LGD values.

The appropriate choice of the materiality threshold is generally important, because it promotes the elimination of numerous technical default events, since therefore the delay of "insignificant amounts" does not result automatically in getting into non-performing status. On the other hand according to my empirical researches the decision about the materiality threshold takes notable effect on the calculated value of the risk parameters in case of the mortgage loans as well, so the opportunity composed in *Hkr. 68. § (5)-(7) Paragraph* according to which the credit institutions are allowed to use criteria which are different from the prescriptions has great importance.

In the course of my researches I did not manage to build regression models having so large explanatory power on the basis of the data of the Hungarian Interbank LGD Database that this way the deals can also be involved in the calculations whose collection process has not been closed yet, but according to my expectations this will also be possible later when the quantity of the deals in the database increases. Considering that the use of the data deriving from the common database can provide advantages for all the credit institutions, it would be expediential that more institutions join it and create a relatively large and variegated database by historic uploading their data, which also enables the consideration of the individual characteristics of their portfolios applying the proper filters.

Keeping it in view I focused in the framework of my dissertation on the analysis of the categories according to the closing type of the deals: I examined the differences between the LGD values of the individual groups, the opportunities of the classification as well as the influencing factors of the LGD values of the certain categories, and all of my results confirmed my anticipative expectations according to which the separate handling of these groups is reasonable. I managed to build a logistic regression with which the futural closing type of the deals with not yet closed collection process can also be predicted with quite great reliability, thus I count great potential to the data of the Hungarian Interbank LGD Database concerning its futural use in the predictions regarding the recovery rates from collateral selling.

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