St. Petersburg University
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Master in Corporate Finance

Modeling expected credit losses in Russian banks

Master's Thesis by the 2nd year student
Concentration – Corporate Finance
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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

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25 May 2018 (Date)

АННОТАЦИЯ

Автор	Стариков Даниил Игоревич
Название магистерской диссертации	Моделирование потенциальных кредитных потерь в российских банках
Факультет	Высшая Школа Менеджмента
Направление подготовки	38.04.02 “Менеджмент” (Профиль: Корпоративные финансы)
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Научный руководитель	Пустовалова Татьяна Александровна
Описание цели, задач и основных результатов	Стандарт МСФО 9, разработанный Советом по Международным Стандартам Финансовой Отчётности, вступил в силу с 1 января 2018 года в ряде стран, в том числе на территории России. Переход от старого стандарта (МСФО 39) к новому стандарту (МСФО 9) является наиболее проблематичным для финансовых учреждений (в особенности для банков), ввиду специфики их деятельности. В настоящее время отсутствует единая методология составления отчетности по МСФО 9. В рамках исследования, автор ставит перед собой задачу разъяснения ряда требований стандарта и демонстрацию их применения путем разработки собственной методологии моделирования ожидаемых кредитных потерь для средних российских банков. Основная цель исследования: 1) разработать единую методологию оценки потенциальных кредитных потерь по стандарту МСФО 9 для российских банков и 2) оценить, как влияет на резерв переход от МСФО 39 к МСФО 9. В рамках исследования были разработаны две группы регрессионных моделей отдельно для двух сегментов: корпоративных заемщиков и розничных заемщиков. В результате было доказано, что именно многофакторные логистические регрессионные модели должны применяться при дальнейшей оценке потенциальных кредитных потерь в соответствии с МСФО 9, а не линейные или экспертные модели. Более того, было выявлено, что резерв под обесценение кредитов изменяется в результате перехода от МСФО 39 к МСФО 9.
Ключевые слова	МСФО 9, Банковский менеджмент, Обесценение кредитов, Потенциальные кредитные потери, Вероятность дефолта, Доля потерь при дефолте

ABSTRACT

Master Student's Name	Daniil Igorevich Starikov
Master Thesis Title	Modeling Expected Credit Losses in Russian Banks
Faculty	Graduate School of Management
Main field of study	38.04.02 “Management” (specialization: Master of Corporate Finance)
Year	2018
Academic Advisor's Name	Pustovalova Tatiana Aleksandrovna
Description of the goal, tasks and main results	IFRS 9 (executed by the IASB) started to be effective for annual periods beginning after 1 January 2018, subject to endorsement in certain territories, involving Russia. Transition from the old standard (IAS 39) to the new one (IFRS 9) is especially challenging for financial institutions (involving banks). At the present moment, there exists no unified methodology regarding reporting under IFRS 9. The thesis is expected to explain properly certain requirements of the standard and to demonstrate their application through the development of own methodology for modeling expected credit losses for middle-sized Russian banks. The main goal of the research is: 1) To develop the unified methodology for estimating expected credit losses under IFRS 9 standard for Russian banks and 2) to evaluate, how the provision is affected by the transition from IAS 39 to IFRS 9. As part of the research two groups of regression models were developed separately for the two segments: corporate borrowers and retail borrowers. As a result, the research proved that multifactor logistic regression models should be implemented in further estimation of ECL under IFRS 9 requirements rather than linear models or expert ones. What is more, it was identified that the provision for loan impairment amount changes as a result of transition from IAS 39 to IFRS 9 standard. Application of proposed methodology will enable the Bank to reflect the least amount of provision charge, at the same time, complying with all of the IFRS 9 requirements.
Keywords	IFRS 9, Bank management, Loan impairment, Expected credit losses, Probability of default, Loss given default

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INTRODUCTION

Research background

During the financial crisis, the G20 tasked global accounting standard setters to work towards the objective of creating a single set of high-quality global standards. In response to this request, the IASB and FASB began to work together on the development of new financial instruments standards. The IASB decided to accelerate its project to replace IAS 39, and sub-divided it into three main phases: classification and measurement; impairment; and hedging.

These changes are likely to have a significant impact on entities that have significant financial assets and in particular financial institutions. International Financial Reporting Standard 9 (IFRS 9) started to be effective for annual periods beginning after 1 January 2018, subject to endorsement in certain territories, involving Russia. The introduction of new requirements in IFRS 9 «Financial Instruments» will be a significant change to the financial reporting of banks. It will affect many stakeholders including investors, regulators, analysts and auditors.

Given the importance of banks in the global capital markets and the wider economy, the effective implementation of the new standard has the potential to benefit many parties involved. Conversely, a low-quality implementation based on approaches that are not fit for purpose has the risk of undermining confidence in the financial results of the banks (Deloitte report, 2017). The IASB's Chairman, in a speech in January 2016 before the European Parliament, pointed out that the biggest change deriving from the replacement of the standard is a model of expected credit losses that require a timely recognition of inevitable losses in financial statements, particularly in banks (Hoogervorst, 2016).

What is more, the new classification and measurement requirements represent a big challenge, especially for financial institutions, as management will need to assess their financial assets classification in light of the new business model requirements. This new model is substantially different from the previous guidance in IAS 39 (PwC report, 2017). This created certain confusion among the management in the banking industry in Russia, as there exists no unified methodology regarding reporting under IFRS 9.

My work is expected to explain properly certain requirements of the standard and to demonstrate their application through the development of own methodology for modeling expected credit losses on the example of one particular bank. Thus, from the point of view of managerial application the work can be used by the Russian banks as a benchmark for applying IFRS 9 standard.

The topicality of the produced research is explained by the fact that no research of that kind

were ever made in application to the Russian market. Even in the perspective of the whole world, the research on this topic is very limited (as the IFRS 9 standard became effective only in early 2018). Foreign research and methodologies related to IFRS 9 are mostly available in the closed sources only. I believe that my research on this topic can be considered as a fresh vision of the Master thesis of the student of the Graduate School of Management, because of its' uniqueness, topicality and methodology implied.

Structure of the thesis

This subchapter is dedicated to informing the reader on the structure of the thesis that has been conducted by the author during the time period of 2017-2018. The current thesis comprises four major parts:

I) Introduction

II) Literature review

III) Methodology development

IV) Conclusions

In the Introduction part research background is explored, the main goal and objectives are stated. The methodology of the research is briefly described in this part in order to prove the validity of proposed methods to satisfy the research goal.

Literature review is divided into few parts in order to provide a better focus on the theoretical perspective of the researched problem. In the literature review part the author explores various methodics, which will be later used for the purposes of model development. In general, the review of literature helps in choosing and explaining the validity of the research proposed, as well as relevance of selected methodology. Literature review starts from general study of the IFRS 9, its specifics and peculiarities, followed by the analysis of applicable classifications, measurement, controls and governance under IFRS 9 standard. Afterwards, in the framework of the literature review, the author explores Expected credit losses methodology, which would be later applied in part two of the research (model development), what is more, the author studies in great details the associated terms of Default, Probability of Default, Loss Given Default, Exposure at Default, Discounting, Staging Assessment and Microeconomic forecasts.

Later on, the author proceeds with the comparative analysis between IAS 39 and IFRS 9, investigating possible reasons that caused IAS 39 to be replaced with the new standard. Exploration

of the available literature enables the author to come to valuable conclusions concerning the choice of a methodological approach. The main outcome of the second chapter is the methodology development and estimation of transition effect from IAS 39 to IFRS 9 on provision for loan impairment and the interpretation of the obtained results.

As a result of the research produced, the author provides viable managerial applications and conclusions that could potentially be adopted by Russian banks and applied in reporting and business processes planning.

Research goal and objectives

Despite abundant motives, the **main goal of the research** can be formulated as follows: *1) To develop the unified methodology for estimating expected credit losses under IFRS 9 standard for Russian banks and 2) to evaluate, how the provision is affected by the transition from IAS 39 to IFRS 9.* In addition to the formulated research goal, the author has stated the following research questions:

1) Which models could be implemented in further estimation of expected credit losses under IFRS 9 requirements?;
2) How the provision for loan impairment amount changes (in terms of expected effect) by the transition from IAS 39 to IFRS 9 in the average Russian Bank?

The research objectives involve:

1) To review the available literature on the specifics of IFRS 9 standard and its' effect on modeling expected credit losses in Russian bank:
    - To analyze the existing approaches to ECL estimation;
    - To explore the main differences between reporting under IAS 39 and IFRS 9;
    - To investigate relevant methodologies for the multi-factor logistic regression analysis.
2) To gather required data:
    - To compound the list of empirical units;
    - To identify variables to be used in regression.
3) To develop models in order to reach the stated goal:
    - To apply relevant methods of forecasting to define forward - looking information and to use it in modeling;
    - To compare the forecasted provisions for loan impairment with the existing information in banking industry;

- To analyze the applicability of chosen models.

4) To draw valuable conclusions for Russian banks:
    - To propose practical managerial implications;
    - To identify steps for further research.

1. LITERATURE REVIEW

1.1 General description of IFRS 9 standard

IFRS 9 Financial Instruments sets out the requirements for recognizing and measuring financial assets, financial liabilities and some contracts to buy or sell non-financial items. This Standard replaces IAS 39 «Financial Instruments: Recognition and Measurement». Many users of financial statements and other interested parties told the International Accounting Standards Board (IASB) that the requirements in IAS 39 were difficult to understand, apply and interpret.

They urged the IASB to develop a new Standard for the financial reporting of financial instruments that was principle-based and less complex. Although the IASB amended IAS 39 several times to clarify requirements, add guidance and eliminate internal inconsistencies, it had not previously undertaken a fundamental reconsideration of the reporting for financial instruments. In 2005, the IASB and the US national standard-setter, the Financial Accounting Standards Board (FASB), began working towards a long-term objective of improving and simplifying the reporting for financial instruments. In November 2008, the IASB added this project to its active agenda.

In April 2009, in response to the feedback received on its work responding to the global financial crisis, and following the conclusions of the G20 leaders and the recommendations of international bodies such as the Financial Stability Board, the IASB announced an accelerated timetable for replacing IAS 39 (IFRS 9 Financial Instruments International Financial Reporting Standard, 2014). IFRS 9 started to be effective for annual periods beginning after 1 January 2018, subject to endorsement in certain territories, involving Russia.

In order to have a better understanding of the IFRS 9 and its main elements the author will use a SWOT matrix for simplification of the analysis (Huian, 2012).

Strengths •reduction of complexity of classification and measurement, •accounting is aligned with business strategy, •extensive disclosures of the reasons for any changes in the business model, •addressing the issues arising from the financial crisis, •simplification of rules with measurement of derivate (Huian, 2012, p. 42), •focus on shareholders, •detecting the losses properly, •comparability and standardization of accounting and of financial reporting, •improving in consistency and transparency of reporting with global rivals, •better access to foreign capital investment (Ghasmi, 2016, pp. 28–30).	**Weaknesses** •the introduction of new concepts (business model) that require more professional judgment and can introduce subjectivity, •the detention of many options and a variety of financial solutions, •does not provide a systematic approach for financial liabilities, •does not solve questions about impairment of hedge accounting (Huian, 2012, p. 42), •adjusting or upgrading the existing accounting systems to new calculations for IFRS 9 (Ghasmi, 2016, pp. 30, 31).
Opportunities •the introduction of new concepts (business model) that require more professional judgment and can introduce subjectivity, •the detention of many options and a variety of financial solutions, •does not provide a systematic approach for financial liabilities, •does not solve questions about impairment of hedge accounting (Huian, 2012, p. 42), •adjusting or upgrading the existing accounting systems to new calculations for IFRS 9 (Ghasmi, 2016, pp. 30, 31).	**Threats** •reduces comparability due to various decisions (for example, the business model), •too much tolerance on several topics (removal of tainting rules) that may result in choosing a certain option only to meet accounting requirements, •the indicator of the cost-benefit ratio does not favor an early adoption of the standard, •the cost of implementation is relatively difficult to quantify, •earlier adoption of standard means the display of both standards in presentations and disclosures, which weakens the usefulness of financial statements, •an approach with multiple stages creates mismatches because of new requirements or other existing rules (Huian, 2012, p. 42), •IASB as the only standard-setter

Table 1: SWOT matrix

1.2 Classification, measurement, controls and governance

On 24 July 2014, the IASB published the complete version of IFRS 9, 'Financial instruments', which replaced most of the guidance in IAS 39. This includes amended guidance for the classification and measurement of financial assets by introducing a fair value through other comprehensive income category for certain debt instruments. It also contains a new impairment model, which will result in earlier recognition of losses.

No changes were introduced for the classification and measurement of financial liabilities, except for the recognition of changes in own credit risk in other comprehensive income for liabilities designated at fair value through profit or loss. It also includes the new hedging guidance that was issued in November 2013.

Making sure that the bank has effective controls over compliance with the new financial reporting requirements – and guarding against the reputational, regulatory and financial damage that may result from material control failures – will be key concerns for those charged with governance. Some banks will be subject to additional requirements for reporting on the effectiveness of internal controls and will also need to prepare for how IFRS 9 adoption will affect their compliance with those other rules. Regardless of an entity's size and complexity, the implementation of IFRS 9 will require significant upfront and ongoing senior management effort as well as substantial changes to credit risk management and financial reporting systems, processes and internal controls.

An effective governance and control framework should be in place before, during and after transition. Banks should utilize all three lines of defense to achieve this – i.e. risk and control functions in the lending business; oversight functions including finance and risk management; and internal audit. The following areas are the key:

Data quality and availability. Management will need additional credit risk information that was not previously obtained, or is available but was not previously used for financial reporting purposes. In the latter case, the data may not currently be subject to the same rigorous governance and controls normally associated with information used for financial reporting. Appropriate governance and controls will be required for these sizeable additional data sets used for the estimation of ECLs.

Methodologies and modelling. Management will need to develop new ECL methodologies and models. This will require significant expertise and judgement in order to deliver probability-weighted and unbiased estimates of ECL on an ongoing basis. In applying IFRS 9's requirements, management has to make difficult and complex decisions about modelling principles, which could have a material impact on ECL outcomes. Ensuring that models are not a 'black box' and that ECL

outcomes can be understood and articulated internally and externally – whilst at the same time respecting the complexity of ECL estimation – will be a significant challenge for management.

Effective oversight will require robust governance and controls through the organization. The use of expert credit judgement is a necessary ingredient in the application of IFRS 9 but is an indicator of potentially higher risk of misstatement. The exercise of such judgement – together with any separately calculated adjustments to model results to address limitations in the core modelling approach - will require particular attention in the governance process.

Systems, processes and internal controls. On an ongoing basis, banks will need to produce IFRS 9 measurements and related disclosures within a short timeframe. Systems and processes that banks build – and associated controls – will need to be sufficiently automated and streamlined to deliver reliable results that are subject to appropriate review and challenge in the required timeframe. Further, as portfolio composition and market conditions change, processes, methodologies and assumptions are likely to require adaptation, sometimes quickly, in order to remain compliant with the requirements of IFRS 9. Strong governance and controls will be key. The costs – before, during and after transition – associated with achieving all these objectives are likely to be significant, both in terms of direct spend as well as management time (GPPC report, 2016).

1.3 Expected credit losses (ECL)

In probability theory, the attribute expected always refers to an expectation or mean value, and this is also the case in risk management. The basic idea is as follows: The bank assigns to every customer a default probability (DP), a loss fraction called the loss given default (LGD), describing the fraction of the loan's exposure expected to be lost in case of default, and the exposure at default (EAD) subject to be lost in the considered time period. The loss of any obligor is then defined by a loss variable:

$$\tilde{L} = EAD \times LGD \times L \;\; with\, L = 1_D, P(D) = DP, \tag{1.1}$$

where D denotes the event that the obligor defaults in a certain period of time (most often one year), and P(D) denotes the probability of D.

Now, in this setting it is very natural to define the expected loss (EL) of any customer as the expectation of its corresponding loss variable (Bluhm, L.Overbeck, C.Wagner 2003).

$$EL = E[\tilde{L}] = EAD \times LGD \times P(D) = EAD \times LGD \times DP \tag{1.2}$$

Addressing banks' reporting of expected credit losses (ECLs) in accordance with IFRS 9 undoubtedly is one of the biggest challenges in 2018. Calculating ECLs requires management to forecast the credit losses that the bank would suffer as the result of defaults under different scenarios covering prescribed future periods. ECLs represent the average of these losses, discounted and weighted by the probability that they would occur. They do not purport to represent management's best estimate of the actual credit losses that a bank will incur in the future, but rather a current dollar measure of credit risk (PwC report, 2017).

For most banks, expected credit loss (ECL) estimates are likely to be material to their financial statements. ECL estimation is complex and inherently judgmental. It is dependent on a wide range of data, which may not be immediately available, including forward-looking estimates of key macro- and micro-economic factors and management's assumptions about the relationship between these forecasts and the amounts and timing of recoveries from borrowers.

Because of the size of the potential impacts, these factors mean there is a risk of material bias affecting the financial statements. This could affect key financial and regulatory metrics. Accordingly, it is important that ECLs are determined in a well-governed environment. IFRS 9 requires ECLs to reflect (GPPC report, 2016):

- an unbiased and probability-weighted amount that reflects a range of possible outcomes; and
- reasonable and supportable information that is available without undue cost or effort about past events, current conditions and forecasts of future conditions.

1.3.1 Expected credit losses methodology

IFRS 9 requires a bank to determine an expected credit loss (ECL) amount on a probability-weighted basis as the difference between the cash flows that are due to the bank in accordance with the contractual terms of a financial instrument and the cash flows that the bank expects to receive. Although IFRS 9 establishes this objective, it generally does not prescribe particular detailed methods or techniques for achieving it.

In determining the cash flows that the bank expects to receive, many banks are planning to adopt a sum of marginal losses approach whereby ECLs are calculated as the sum of the marginal losses occurring in each time period from the balance sheet date. The marginal losses are derived from individual parameters that estimate exposures and losses in the case of default and the marginal probability of default for each period (the probability of a default in time period X conditional upon an exposure having survived to time period X).

ECLs are a probability-weighted estimate of the present value of cash shortfalls (i.e., the weighted average of credit losses, with the respective risks of a default occurring in a given time period used as the weights). ECL measurements are unbiased (i.e. neutral, not conservative and not biased towards optimism or pessimism) and are determined by evaluating a range of possible outcomes.

ECLs are generally measured based on the risk of default over one of two different time horizons, depending on whether the credit risk of the borrower has increased significantly since the exposure was first recognized. The loss allowance for those exposures that have not increased significantly in credit risk ('stage 1' exposures) is based on 12-month ECLs. The allowance for those exposures that have suffered a significant increase in credit risk ('stage 2' and 'stage 3' exposures) is based on lifetime ECLs.

12-month ECLs are the portion of the lifetime ECLs that represent the ECLs that result from default events on a financial instrument that are possible within 12 months after the reporting date (or a shorter period if the expected life of the financial instrument is less than 12 months). 12-month ECLs are weighted by the probability of such a default occurring. Lifetime ECLs are the losses that result from all possible default events over the expected life of the financial instrument (GPPC report, 2016).

1.3.2 Default

The concept of "default" is critical to the implementation of IFRS 9. IFRS 9 requires that when making the assessment of whether there has been a significant increase in credit risk since initial recognition, an entity uses the change in the risk of default occurring over the expected life of the financial instrument. For financial instruments for which there has not been a significant increase in credit risk, ECLs are recognized only in respect of default events that are possible within the next 12 months. Furthermore, IFRSs require that assets meeting the definition of credit impaired ('stage 3 assets') should be disclosed and the definition of credit impaired includes references to defaults, as well as other events that have a detrimental impact on estimated future cash flows.

IFRS 9 does not define the term "default" but instead requires each entity to do so. The definition used should be consistent with the definition used for internal credit risk management purposes and consider qualitative indicators (for example, financial covenants) when appropriate. There is a rebuttable presumption that default takes place no later than 90 days past due. However, IFRS 9 contains no further guidance on how to define default.

Regulatory literature, such as the Basel Capital Accord rules, provides examples in addition to the 90 days past due backstop which are known as unlikeliness to pay indicators ("UTP"). These

UTPs form part of the regulatory definition of default. UTPs are similar, but not identical to, the events described in the definition of 'credit-impaired financial asset' under IFRS 9. In addition, the Basel Committee has recommended that the definition of default adopted for IFRS 9 accounting purposes is guided by the definition used for regulatory purposes.

The definition of default used – e.g. using the IFRS 9 definition of credit-impaired indicators as the definition of default or using the definition of default from Basel Committee rules – affects the calculation of PDs, LGDs and EADs. Different definitions can lead to different ECL results. Accordingly, amending the definition of default used in a bank's models as part of the transition to IFRS 9 requires a recalibration of those models (GPPC report, 2016).

1.3.3 Probability of Default (PD)

Many banks plan to use PDs as a key component both in calculating ECLs and in assessing whether a significant increase in credit risk has occurred. A PD used for IFRS 9 should reflect management's current view of the future and should be unbiased (i.e. it should not include any conservatism or optimism). Two types of PDs are used for calculating ECLs:

- 12-month PDs – This is the estimated probability of default occurring within the next 12 months (or over the remaining life of the financial instrument if that is less than 12 months). This is used to calculate 12-month ECLs.
- Lifetime PDs – This is the estimated probability of a default occurring over the remaining life of the financialinstrument. This is used to calculate lifetime ECLs for 'stage 2' and 'stage 3' exposures.

PDs may be broken down further into marginal probabilities for sub-periods within the remaining life. If the bank is able to incorporate detailed forecasts of future conditions in developing PD estimates only for a period that is shorter than the entire expected life, it applies a documented policy for determining the longer-term trend in rates of default based on historical and other available reasonable and supportable information.

If the bank develops a new model to produce lifetime PDs, it will be necessary to ensure all key risk drivers and their predictive power are identified and calibrated based on historical data over a suitable time period. This could take the form of a scorecard approach (GPPC report, 2016).

1.3.4 Loss Given Default (LGD)

A key component of the sum of marginal losses approach is loss given default (LGD). For banks that are directly calculating expected cash flows, a combination of PD and LGD is used in order to calculate the expected cash flows from the projection of contractual cash flows. Estimates

of LGD should consider forward-looking information.

The modelling approach for LGD (but not necessarily the actual LGD estimates) generally does not vary depending on which stage the exposure is in, i.e. there is a common LGD methodology that is applied consistently. However, if the bank has more specific data to model the LGD for a loan in default it uses that data. The modelling methodology for LGD is designed, where appropriate, at a component level, whereby the calculation of LGD is broken down into a series of drivers. For secured exposures, the approach considers at a minimum the following components:

- forecasts of future collateral valuations, including expected sale discounts;
- time to realization of collateral (and other recoveries);
- allocation of collateral across exposures where there are a number of exposures to the same counterparty (cross- collateralization);
- cure rates (including consideration of how the bank has looked at re-defaults within the lifetime calculation);
- external costs of realization of collateral.

For unsecured exposures, the approach considers at a minimum the following components:

- time to recovery;
- recovery rates;
- cure rates (including consideration of how the bank has looked at re-defaults within the lifetime calculation).

The estimation of the components considers the range of relevant drivers, including: geography (location of the counterparty and the collateral) and seniority of the credit exposure. The estimation of LGD reflects expected changes in the exposure, so that it is not biased (for example, a conservative estimate may arise if the expected exposure amount dropsover time but this is not taken into account in estimating LGD).

The bank considers whether component values are dependent on macro-economic factors and reflects any such dependency in its modelling considering relevant forward-looking information. In particular, for exposures secured against real estate, the bank considers the interdependency between real estate prices and macro-economic variables. Similarly, the bank considers whether there is any correlation or interdependency between components of LGD and then reflects that correlation in the estimation of LGD.

The data history that supports the modelling of LGD and its components covers a suitable period to support the relevance and reliability of the modelling (e.g. over a full economic cycle).

The estimation of the component values within LGD reflects available historical data and considers whether there have been or are expected to be any changes in economic conditions, or changes to internal policies or procedures, that should impact the calculation of LGD but which are not otherwise reflected in the modelling.

The LGD approach reflects discounting of cash shortfalls considering their expected timing using the EIR. If regulatory LGD values are used as a starting point,then the effect of the different discount rates inherent in the regulatory LGD value is adjusted for. Furthermore, if regulatory LGD values used as a starting point contain floors that would lead to a biased result, these floors are removed for IFRS 9 purposes.

The IFRS 9 LGD only reflects credit enhancements that are integral to the terms of the exposure and that are not accounted for separately. If regulatory LGD values are used as a starting point and reflect credit enhancements that should not be included for IFRS 9 purposes (e.g. credit default swaps), then the impact is removed (GPPC report, 2016).

1.3.5 Discounting

ECLs are measured in a way that reflects the time value of money. This means that cash shortfalls associated with default are required to be discounted back to the balance sheet date. For a financial asset, a bank uses the effective interest rate (EIR) (i.e. the same rate used to recognize interest income) or an approximation. The effect of discounting may be significant because default events and/or associated cash shortfalls may occur a long time into the future.

ECLs are calculated by estimating the timing of the expected cash shortfalls (taking into consideration realization of collateral) associated with defaults and discounting them. The discount rate is the EIR. For a financial guarantee contract, the discount rate reflects the current market assessment of the time value of money and the risks specific to the cash flows. Discount rates may be based on portfolio averages if this represents a reasonable approximation of the EIR.

Assumptions about prepayments, extensions and utilization during the period of exposure (and within contractual credit limits) used in the ECL calculation are updated to reflect currently available information and are consistent with those used in estimating interest income. The unwind of the time value of money (as the ECL is recalculated from period-to-period) is separately tracked, such that appropriate adjustments can be made to the interest income amount for credit-impaired assets if this is otherwise calculated on the gross carrying amount of the financial asset.

For variable rate assets, the benchmark interest rate used to calculate the EIR might be either the current benchmark interest rate or a projected rate based on forward yield curves. There is

consistency between the rate used to recognize interest revenue and the rate used to project and discount cash flows (GPPC report, 2016).

1.3.6 Staging Assessment

The staging assessment is a critical area for almost all banks. If an exposure's credit risk has not increased significantly since initial recognition ('stage 1'), then the bank recognizes only 12-month ECLs as a loss allowance. However, if the exposure has suffered a significant increase in credit risk ('stage 2'), then the bank recognizes a loss allowance equal to lifetime ECLs.

Therefore, the assessment – especially for longer dated portfolios – can have a significant impact on reported earnings and equity. The staging assessment also drives how exposures will be disclosed in the notes to the financial statements. The bank's process to assess changes in credit risk is multi-factor and has three main elements (or 'pillars'):

- a quantitative element (i.e. reflecting a quantitative comparison of PD at the reporting date and PD at initial recognition);
- a qualitative element; and
- "backstop" indicators.

For larger exposures such as corporate and commercial, the assessment is usually driven by the internal credit rating of the exposure and a combination of forward-looking information that is specific to the individual borrower and forward-looking information on the macroeconomy, commercial sector and geographical region (to the extent such information has not been already reflected in the rating process).

For retail exposures, significant increases in credit risk cannot usually be assessed without undue cost and effort using forward-looking information at an individual instrument level, so the assessment is made on a collective basis that incorporates all relevant credit information, including forward-looking macroeconomic information. For this purpose, the bank groups its exposures based on shared credit risk characteristics. Approaches are consistent across portfolios within a banking group, subject to considerations of what is material for individual businesses, products or geographical locations. All exposures are subject to a forward-looking credit assessment at original recognition, so as to establish the baseline for determining if there is subsequently a significant increase in credit risk.

The staging assessment uses all relevant information from processes used by the bank to measure and monitor credit risk. These processes require regular credit reviews or other monitoring and that all exposures are allocated to a credit quality rating or risk grade based on the most recent

review or other information. The credit risk rating process includes an independent review function. The bank determines how these risk grades are predictive of the risk of default. The assessment of a significant increase in credit risk for a particular product is informed by information available to the bank from other products (GPPC report, 2016).

1.3.7 Exposure at Default (EAD)

Many banks plan to use exposure at default ("EAD") as a key component of their ECL calculations. Although IFRS 9 does not explicitly require banks to model EAD, understanding how loan exposures are expected to change over time is crucial to an unbiased measurement of ECLs. This is particularly important for 'stage 2' loans, where the point of default may be several years in the future.

Ignoring an expected fall in exposure (e.g. on a loan repayable in instalments) could lead to measurements of ECLs being too high. Ignoring an expected increase in exposure (e.g. drawdowns within an agreed limit on a revolving facility) could lead to measurements of ECLs being too low. It is also necessary to determine the period of exposure that is considered for IFRS 9 purposes. The period of exposure limits the period over which possible defaults are considered and thus affects the determination of PDs and measurement of ECLs.

Except for some revolving credit facilities, the maximum period over which expected credit losses are measured is the maximum contractual period over which the entity is exposed to credit risk. This maximum contractual period is determined in accordance with the substantive terms of the contract, including the bank's ability to demand repayment or cancellation, and the customer's ability to require extension.

Where the period of exposure is taken to be the full contractual period, historical behavioral information (e.g. on prepayments) is reflected in the EAD model. Where the period of exposure is calculated based on historical behavioral information, the bank considers appropriate segmentation to reflect different behavioral lives for different portfolio segments. Furthermore, the bank gives consideration to whether historical behavioral information captures current conditions and forward-looking information or needs to be adjusted.

For revolving credit facilities within the scope of IFRS 9.5.5.20 (i.e. that include both a loan and an undrawn commitment component, and the bank's contractual ability to demand repayment and cancel the undrawn commitment does not limit the bank's exposure to credit losses to the contractual notice period), the period of exposure is determined by considering the bank's expected credit risk management actions that serve to mitigate credit risk, including terminating or limiting credit exposure. In doing this, the bank:

- Considers its normal credit risk mitigation process, past practice and future intentions and expected credit risk mitigation actions;
- Analyses what actually happens in practice as a result of each of these types of actions and demonstrates that there is sufficient historical evidence that such actions are executed and impact the lifetime of the exposure. The analysis considers historical information and experience about the period over which the bank was exposed to credit risk on similar instruments and the length of time for defaults to occur on similar instruments following a significant increase in credit risk.

The modelling approach for EAD reflects expected changes in the balance outstanding over the lifetime of the loan exposure that are permitted by the current contractual terms, including:

- Required repayments/amortisation schedule;
- Full early repayment (e.g. early refinancing);
- Monthly overpayments (i.e. payments over and above required repayments but not for the full amount of the loan);
- Changes in utilization of an undrawn commitment within agreed credit limits in advance of default;
- Credit mitigation actions taken prior to default.

The bank uses a cash-flow model to calculate the estimated exposure at each future month-end. This model is consistent with any similar model used for EIR or macro fair-value hedging purposes. This cash-flow model further reflects movements in the EAD in the months before default. For example, three months of interest payments might be included in the EAD to reflect an expectation that these interest payments would be missed in advance of a default.

The inputs into the EAD model are reviewed to assess their suitability for IFRS 9 and adjusted, where required, to ensure an unbiased, probability-weighted ECL calculation reflecting current expectations and forward-looking information. EAD models are differentiated to reflect the different risk characteristics of different portfolios. The bank considers these different underlying drivers in determining the different inputs to EAD models (GPPC report, 2016).

1.3.8 Macro-economic forecasts and forward-looking information

A measure of ECL is an unbiased probability-weighted amount that is determined by evaluating a range of possible outcomes and using reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions.

When there is a non-linear relationship between the different forward-looking scenarios and their associated credit losses, more than one forward-looking scenario would need to be incorporated into the measurement of expected credit losses to meet the above objective. In order to achieve the objective set out above, the overall approach to calculating ECL involves either to:

- Take the weighted average of the credit loss determined for each of the multiple scenarios selected, weighted by the likelihood of occurrence of each scenario *plus/minus* a separate adjustment for 'additional' factors; or
- Take the credit loss determined for the base scenario *plus/minus* a separate modelled adjustment to reflect the impact of other less likely scenarios and the resulting non- linear impacts (as a proxy for the above method*) plus/minus* a separate adjustment for 'additional' factors.

"Additional" factors are alternative economic scenarios or events not taken into account in the scenarios used in the main calculation (e.g. more extreme or idiosyncratic events not otherwise reflected in historical or forecast information such as a vote for a member state to exit from the EU or significantly increased political and military tension between nations in a particular region). The following principles are applied within the approach adopted.

Number of economic scenarios: representative scenarios that capture material non-linearities are modelled (e.g. a base scenario, an upside scenario and a downside scenario). Different numbers of scenarios may be appropriate depending on the facts and circumstances - e.g. in periods of expected increased volatility.

Determining alternative economic scenarios: whether a bank produces its own forward economic estimates or uses third party estimates, it considers all reasonable and supportable information available without undue cost or effort, unless the marginal effect of using additional data would be insignificant. In certain economies, extensive data will be available, but in other territories, less information may be available. When developing and using internal forecasts, a bank considers third party data and views and justifies differences from external forecasts, but this does not mean it must replicate them.

Representative scenarios: upside and downside scenarios used are not biased to extreme scenarios such that the range and weighting of scenarios used is not representative. In particular, as noted by the Basel Committee, "stressed scenarios developed for industry-wide supervisory purposes are not intended to be used directly for accounting purposes.

Base scenario: the base scenario is consistent with relevant inputs to other estimates in the financial statements (e.g. deferred tax recoverability and goodwill impairment assessments),

budgets, strategic and capital plans, and other information used in managing and reporting by the bank. However, these inputs should not be lagging or biased. Even if the inputs used are timely and unbiased, if the group budget is developed in September but macro-economic conditions have changed by the December year-end, or if the budget contains inherent optimism or pessimism, then appropriate adjustments are made to these inputs when using them to determine the base scenario for the purposes of the year-end ECL calculation.

Sensitivities and asymmetries: scenarios selected are representative and take account of key drivers of ECL, particularly non-linear and asymmetric sensitivities within portfolios. For example, if a bank has significant property exposures and hence significant ECL sensitivity to future property values, then different changes in property prices are modelled. The sensitivity of ECL to each individual forward economic parameter is monitored to identify key drivers and to estimate effects of changes in parameters on ECL.

Parameter coherence: in developing the detail of a specific economic scenario (e.g. a scenario with individual point estimates of future GDP, unemployment, interest rates, etc.), any expected correlation or other interrelationship between parameters (e.g. an increase in unemployment is expected to result in a decrease in interest rates) is considered in the development of the scenario so that it is realistic.

Granularity of adjustments: the calculation of a separate modelled adjustment to reflect the impact of less likely scenarios and the resulting non-linear impacts is performed at an appropriately low level of granularity, which takes account of qualitatively different risk characteristics and sensitivities. Additionally, this separately modelled adjustment is calculated using specific portfolio-level sensitivities and minimizes the use of qualitative expert credit judgement that is not supported by quantitative analysis.

"Additional" factors: a list of significant scenarios or events not explicitly incorporated within the modelling of ECL, but which are nevertheless considered possible future outcomes and could have a significant effect on ECLs, is compiled and evaluated. The bank assesses whether any adjustment to recognized ECLs should be made in respect of these 'additional' factors at the reporting date including: whether allowance for such events is already reflected in historical or forecast data and the need to avoid double-counting of the possible effects of extreme events; and whether the entity would have a reasonable and supportable basis on which to estimate an expected impact on credit risk and credit losses at the reporting date, such as whether reasonable and supportable information is available as to the likelihood of the event, its effect on PDs and, if the event does occur, its effect on credit losses.

The bank makes an adjustment to recognized ECLs to reflect an additional factor if the bank can do so on the basis of reasonable and supportable information that is available without undue cost and effort, even if the adjustment reflects a relatively high level of measurement uncertainty. The bank does not make an adjustment to recognized ECLs to reflect an additional factor if the bank does not have a reasonable and supportable basis on which to estimate the event's impact. There are robust governance and controls around the process of identification, evaluation and inclusion or exclusion of additional factors (GPPC report, 2016).

1.4 Comparison of IFRS 9 and IAS 39

The financial crisis had an impact on international financial reporting standards. The International Accounting Standards Board (IASB) prepared a new standard for financial instruments. The replacement changes the view to accounting data in financial statements and changes the view to data in organizations, especially banks, and financial institutions. Historical prices are replaced with expectation in the future, which is not anymore a decision of the managers but has its basis on business operations. All organizations that have financial instruments in the statement of financial position have to replace the existing IAS 39 with IFRS 9 in early January of 2018 (Gornjak, 2017).

IFRS 9 introduces accounting on the basis of principles, while IAS 39 is based on rules, despite the fact that these rules allow the decision makers to take more stable and predictable decisions in an unstable environment (Scapens, 1994, p. 310). Criticism to the rules-based approach includes the fact that rules do not adapt and are useless in an environment with innovative transactions, while criticism to the standards based on the principles approach include the lack of operational guidance (Benston, Bromwich, & Wagenhofer, 2006, p. 169).

With the introduction of standards based on principles, a comparison across organizations is no longer possible, because standards require from the organizations the determination of the assumptions and judgments that are confirmed and verified by the regulators and auditors (Benston et al., 2006, p. 169).

Huain (2012, p. 28) summarizes that the IAS 39 is one of the causes of the financial crisis in 2008, so the G20, the Ecofin Council, and the Committee proposed the improvement of the standard for financial instruments with the view to increase financial stability, taking into account:

- the complexity of the existing standard for financial instruments,
- the extent to which the financial instrument is subject to fair value, and
- the procedure of recognition and measurement of financial instruments.

In sharp contrast to IAS 39, IFRS 9 improves the financial reporting, notably in the field of debt instruments. Impairment of financial assets brings different but significant changes in accounting policies, which are based on the model of future losses, while stakeholders have an insight into instruments with increased credit risk (Marshall, 2015). As a weakness, we can point out the costs incurred at the time of implementation, but Marshall (2015, p. 1) estimates that the benefits outweigh the costs of implementation.

IFRS 9 introduces a new accounting within the selected business model and where assets are managed in order to generate cash flows – by collecting contractual cash flows, selling financial assets, or both (Marshall, 2015, p. 13). The business model for managing basic debt instruments is set up by the operations in an organization that has to consider into the nature of business (Marshall, 2015, p. 13):

- the way the presentation of performance within business model and management of financial assets and the presentation to the key management personnel,
- risks that affect the performance of the business model and the way in which those risks are managed, and
- the determination of the compensation for executives.

The table below (Table 2) demonstrates comparison between IAS 39 and IFRS 9 in the light of the purpose of the standard, the initial recognition, the measurement of the initial categories of the instruments, reclassification of instruments, profit or loss and impairment.

We can conclude that in purpose, in initial recognition and in initial measurement, there are no differences between the standards. The classification of financial instruments and its subsequent measurement are the biggest changes in the replacement. IAS 39 has four categories of classification and three categories of measurement, while IFRS 9 has only three categories of measurement, which are also the categories of classification. IFRS 9 simplifies the classification of financial instruments. The replacement also decreases several models of impairment in IAS 39 to a less complex and unified model of impairment in IFRS 9. By replacing the standard, some elements of accounting for financial instruments will change (Gornjak 2017).

Category	IAS 39	IFRS 9
The purpose of the standard	Applies to all financial assets, with a few exceptions.	The same.
The initial recognition of assets	When an organization becomes a party to the contractual provisions.	The same.
Initial measurement	The fair value including transactions costs (for financial assets that are not intended for trading purposes).	The same.
Subsequent measurement	The fair value. Amortized cost. Cost (for the share-based instruments, which do not have a reliable fair value measurement).	Fair value through profit or loss (FVTPL). Amortized cost (AC). Fair value through other comprehensive income (FVOCI).
Types of classification	Available for sale (AFS). Held to maturity (HTM). Loans and receivables. Fair value through profit or loss (FVTPL).	Fair value through profit or loss (FVTPL). Amortized cost (AC). Fair value through other comprehensive income (FVOCI).
Reclassification	Reclassification is prohibited through profit or loss after initial recognition.	Change of business model.
Equity instruments	All equity instruments available for sale are measured at a fair value in another comprehensive income.	Irrevocable choice to designate as fair value through other comprehensive income, fair value through profit and loss if held for trading.
Gains and losses	Usually through profit or loss.	Usually through profit or loss.
Impairment	Several models of impairment, model of incurred losses.	A unified model of impairment for all financial instruments – the expected loss model.

Table 2. Comparison of Key Categories between IAS 39 and IFRS 9 (Huian, 2012)

Impairment is considered being one of the key changes between IFRS 9 and IAS 39. IFRS 9 applies a single impairment model to all financial instruments subject to impairment testing while IAS 39 has different models for different financial instruments. Impairment losses are recognized on initial recognition, and at each subsequent reporting period, even if the loss has not yet been incurred.

In addition to past events and current conditions, reasonable and supportable forecasts affecting collectability are also considered when determining the amount of impairment in accordance with IFRS 9 (Deloitte, 2017).

2. METHODOLOGY DEVELOPMENT

2.1 General description of data and parameters

In order to fulfill the objectives of the present research, internal information is required from the banks. However, the required information is highly confidential (no particular bank allows this type of information to be publicly disclosed), so the decision was made to create a model “Bank”. For the purposes of this research the model of a middle-sized Russian bank (the “Bank”) was developed.

The construction of this model is based on the principles of artificial intelligence (AI) and machine learning: Azure Machine learning packages and extensions in "R" were used. Real data for five Russian banks (IFRS and RAS reports, management reports, loan portfolios, technical reports, data collection reports, etc.) was taken as a basis. Then, based on these reports, the model was developed. The model considered the following specified parameters (that were estimated by the author based on taking the averages for the five Russian middle-sized banks):

- Total Assets – 120 bln. RUB, Total Equity – 15 bln. RUB, Interest Income – 12 bln. RUB, Net Income – 1,5 bln. RUB. Approximate position in National rating of Russian banks – 50-70.
- Total Loan portfolio is 80,5 bln. RUB, Total Provision under IAS 39 is 4,35 bln. RUB, Total PLI rate is 5,4%.

As a result, artificially generated data was obtained. The summary tables for the generated loan portfolios are presented below:

Segment	Amount	Number of clients	Provision IAS 39	PLI rate IAS 39
Large corporate borrowers	17 000 000	300	1 190 000	7,0%
Sub-Sovereign borrowers	5 000 000	10	15 000	0,3%
Leasing companies	3 000 000	10	60 000	2,0%
Small borrowers	1 500 000	500	375 000	25,0%
Medium borrowers	500 000	50	10 000	2,0%
Total	**27 000 000**	**870**	**1 650 000**	**6,11%**

Table 3: Corporate portfolio of the Bank

Segment	Amount	Number of clients	Provision IAS 39	PLI rate IAS 39
Mortgage	35 000 000	22 000	800 000	2,3%
Consumer	15 000 000	60 000	1 500 000	10,0%
Credit cards	3 000 000	51 000	250 000	8,3%
Car	500 000	1 000	150 000	30,0%
Total	**53 500 000**	**134 000**	**2 700 000**	**5,05%**

Table 4. Retail portfolio of the Bank

For the purposes of the study, we assume that all of the segments under IAS 39 are applicable under IFRS 9 requirements, although, in a real bank there are some circumstances, which lead to changing the segmentation. Moreover, various parameters were modelled for each segment. The

detailed description would be provided in the following sections of the research. All the tables presented in the present chapter and appendices are prepared by the author, without any borrowings from outside sources.

2.2 Breaking down the ECL

ECL is a probability-weighted estimate of credit losses. A credit loss is the difference between the cash flows that are due to an entity in accordance with the contract and the cash flows that the entity expects to receive discounted at the original effective interest rate. Because ECL considers the amount and timing of payments, a credit loss arises even if the entity expects to be paid in full but later than when contractually due.

ECL calculation is the complex process, because ECL depend on various components. The diagrams below represent the complete process of calculation from two perspectives:

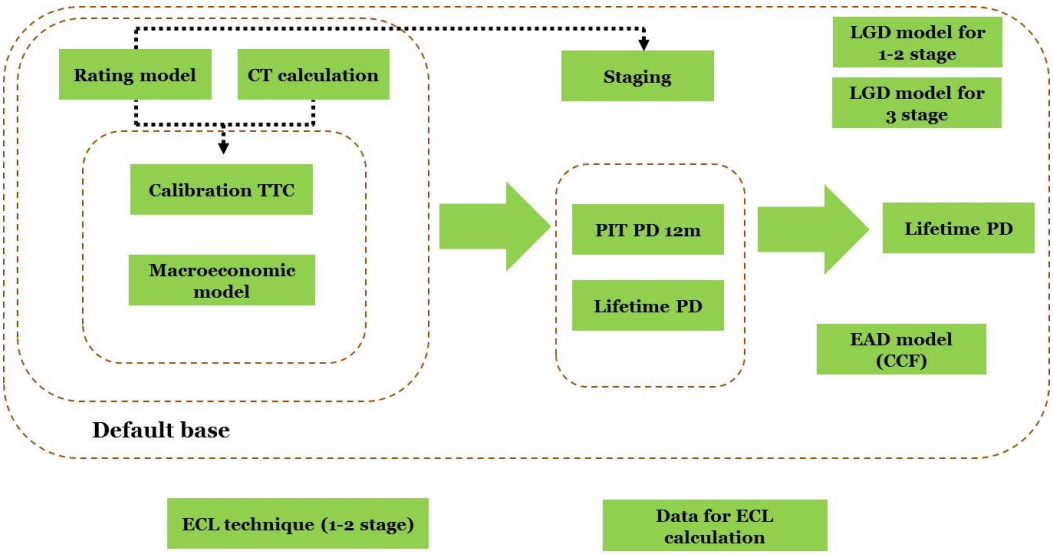

Diagram 1. ECL components view

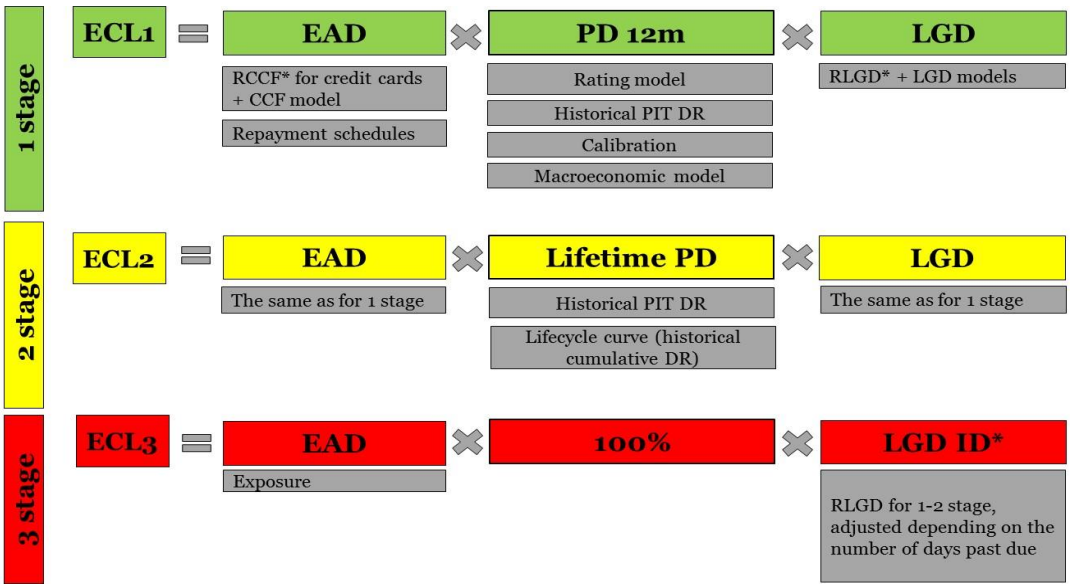

Diagram 2. ECL staging view

As part of the thesis, we would cover all of the components mentioned above and analyze the obtained results.

2.3 Defining default

Default definition should be reviewed to be consistent with IFRS 9 requirements. In the framework of the research is it assumed, that borrower's default is recognized when any of the following events occur:

1) Delay of credit obligations to the Bank for a continuous period of more than 90 calendar days;

2) Forced restructuring of the credit commitment;

3) In respect of a legal entity, there are circumstances that indicate the inability of the counterparty to repay its obligations, including:

- realization of a credit claim with substantial economic losses as a result of deterioration of the credit quality (at a price less than 70% of the credit claim book value);
- borrower's bankruptcy;

Forced restructuring – the restructuring transactions, carried out due to the significant increase in credit risk from the moment of recognition, despite the fact that the Bank's denial of such a restructuring would have led to the overdue debt. Criteria of forced restructuring for corporate

borrowers are:

1) Lowering the interest rate to 0%;

2) Postponed interest payment period;

3) Distinctive restructuring, in respect to which the Bank recognized the fact of insufficient sources of repayment for the full and timely repayment of debts.

If the credit commitment is defaulted and from a certain date no longer corresponds to the conditions specified above, hereof, it is counted as a credit commitment without default from this date. The criterion for restoring default for retail borrowers is the simultaneous fulfillment of the following conditions:

4) Delay on the reporting date is less than 3 days;

5) The loan rate is kept at 9% per annum or higher.

2.4 ECL components determination for Corporate borrowers

2.4.1 PD models

As was stated above, we have the following segments: Large corporate borrowers (LCB), Sub-Sovereign borrowers (SSB), Leasing companies (LC), Small borrowers (SB) and Medium borrowers (MB). These segments were outlined in accordance with the requirement that products with similar portion of credit risk should be combined into homogeneous groups.

For LCB, MB and LC internal ranking models based on financial ratios and PD through-the-cycle models (PD TTC) would be proposed. For SSB external ranking model based on ratings of S&P, Moody's and Fitch (shadow bond approach) and PD TTC model would be proposed. For SB I would use behavioral model based on different behavioral factors.

Usually, small and medium sized banks use expert models to determine the probability of default because of the difficulty of implementation of statistical software packages in the internal environment of the Bank in order to ensure the proper level of information security. However, such models are often very volatile, and they consist specific expert judgment from the side of management, that, consequently, affects models' quality. Therefore, the present study will use only models built using statistical methods to minimize the human factor.

For **LCB segment** AI model has randomly selected 300 Russian companies, which were included in the portfolio. The list of financial indexes analyzed includes 141 indexes. The period of modelling is from 2008 to 2016. As a result, the number of observations included in analysis is 276 568.

The VIF tests were applied to exclude the multicollinear effect. In addition, F-test was run to exclude insignificant variables. As a result, a list of variables that could be involved in building the model and actually explain the change in portfolio default was obtained (see Appendix 1).

For modelling logistic regression was chosen. Logit regression analysis is the multivariate technique, which allows to estimate the probability that the event will occur by predicting a binary dependent outcome from a set of independent variables. The response yi is equal to 0 if default occurs (with probability Pi) and to 1 if default does not occur (with probability 1 – Pi). In regression model, we model the probability Pi (default will occur) by specifying the following model:

$$P_i = f(\alpha + \beta' x_i) \tag{2.1}$$

where xi is a particular financial indicator and α, β are estimated parameters.

There are many ways to specify Pi, but in this paper we will focus on the logit transformation, thus, logit model will be applied. In logit model, we use the, so-called, logistic transformation (Gurny, 2013):

$$P_i = \frac{1}{1+e^{(-\alpha-\beta' x_i)}} \tag{2.2}$$

Further, in the process of modelling, different combinations of variables (from 2 to 21) were tested. As a result, the following model with 5 variables was recognized as the most successful:

$$P_i = \frac{1}{1+e^{(2{,}986-0{,}513*EBITDA-0{,}558*\frac{Debt}{Net\ Assets}-0{,}535*AP\ turnover-0{,}494*EBITDA\ dynamics-0{,}779*Quick\ ratio)}} \tag{2.3}$$

Lateron, the model's discriminatory power should be tested. There are various statistical methodologies for the assessment of discriminatory power. The following methodologies can be most frequently found in the literature or are commonly applied on practice in the financial industry:

- Cumulative Accuracy Profile (CAP) and its summary index, the Accuracy Ratio (AR);
- Receiver Operating Characteristic (ROC) and its summary indices, the ROC measure and the Pietra coefficient;
- Bayesian error rate;
- Conditional entropy, Kullback-Leibler distance, and Conditional Information Entropy Ratio (CIER);
- Information value (divergence, stability index);
- Kendall's τ and Somers' D (for shadow ratings);

- Brier score.

Most banks prefer to use the first method because of its simplicity, consistency and clarity. The Cumulative Accuracy Profile is also known as the Gini curve, Power curve or Lorenz curve. It is a visual tool whose graph can easily be drawn if two representative samples of scores for defaulted and non-defaulted borrowers are available. Concavity of the CAP is equivalent to the property that the conditional probabilities of default given the underlying scores form a decreasing function of the scores. Moreover, non-concavity indicates suboptimal use of information in the specification of the score function (Basel Committee on Banking Supervision, 2005).

The most common summary index of the CAP is the Accuracy Ratio (or Gini coefficient). It is equivalent to the ROC measure so that its statistical properties can be discussed together with those of the ROC measure below. The shape of the CAP depends on the proportion of solvent and insolvent borrowers in the sample. Hence, a visual comparison of CAPs across different portfolios may be misleading.

Practical experience shows that the Accuracy Ratio mostly lays in the range between 50% and 80%. However, observations should be interpreted with caution as they seem to strongly depend on the composition of the portfolio and the numbers of defaulters in the samples. The consequent steps for calculating Gini are presented in BCBS report (Basel Committee on Banking Supervision, 2005).

In the research, Gini was calculated and its value was 68,36%. Final ROC curve is presented in Appendix 2. Gini coefficient of 68,36% was the best from the models built and is acceptable for PD modelling in banking industry.

Next step was to perform timely validation of the model. The model should be validated at each reporting date, in our case – each year. Initially, the sample was divided into 2 subsamples - testing and validation. The model was developed for the testing sample (given in the appendix 1). Validation sampling is used to confirm the ability of the model to predict the probability of default in the current period. In other words, we check whether the model built for the data from 2008 to 2016 is able to calculate correctly the probability of default for 2017.

After new data is introduced into the model, the Gini coefficient is calculated. If the values of this coefficient (in case of validation and testing samples) are comparable, the model does not require revision or refinement. Validation of the proposed model has shown that model is acceptable. Gini coefficient is 66,89%, which is consistent with the results of the model. ROC curve is presented in Appendix 2. It was confirmed that the model was effective and could be used in the current period to determine the probability of default of a borrower. The following table summarizes

the results of the model:

Score range	Default rate	Number of Good	Number of Bad	Total	Share of sample	Share of Good	Share of Bad	WOE	IV
more than 80	0,45%	223	1	224	14,10%	14,82%	1,19%	252,14	34,36%
(65;80]	0,79%	503	4	507	31,91%	33,42%	4,76%	194,86	55,85%
(55;65]	3,18%	304	10	314	19,76%	20,20%	11,90%	52,87	4,39%
(40;55]	6,32%	341	23	364	22,91%	22,66%	27,38%	- 18,93	0,89%
(25;40]	22,05%	99	28	127	7,99%	6,58%	33,33%	- 162,28	43,42%
less than 20	33,96%	35	18	53	3,34%	2,33%	21,43%	- 222,08	42,42%

Table 5. Modeled DR for LCB segment

Probability of default of borrowers is determined by the score of each borrower. Then the breakdown of score by range is carried out. The weight of effect (WOE) approach, which is based on the analysis of the number of “good” and “bad” borrowers in each interval, is used to determine the boundaries of the ranges. The WOE of each range must be significantly different from the two adjacent intervals. To determine the significance of each interval information value is used (IV). These procedures are necessary to present the model in a simple and understandable form and for the purpose of subsequent calibration.

The same approach was used for **MB segment**. The results are given below (details in Appendix 1 and 2):

Model used

$$P_i = \frac{1}{1+e^{(1{,}488-0{,}232*Industry-0{,}123*\frac{ST\ Debt}{Expenses}-0{,}095*AGR-0{,}087*\frac{LT\ Debt}{Revenue}-0{,}023*Age\ of\ borrower)}} \tag{2.4}$$

Gini - 41,32%

Score range	Default rate	Number of Good	Number of Bad	Total	Share of sample	Share of Good	Share of Bad	WOE	IV
more than 60	2,44%	40	1	41	22,78%	25,64%	4,17%	181,71	39,02%
(43;60]	4,17%	23	1	24	13,33%	14,74%	4,17%	126,37	13,37%
(37;43]	6,67%	28	2	30	16,67%	17,95%	8,33%	76,73	7,38%
(32;37]	8,33%	33	3	36	20,00%	21,15%	12,50%	52,61	4,55%
(19;32]	24,14%	22	7	29	16,11%	14,10%	29,17%	-72,67	10,95%
less than 19	50,00%	10	10	20	11,11%	6,41%	41,67%	-187,18	65,99%

Table 6. Modeled DR for MB segment

A similar approach was used for the **LC segment**, but it was adjusted to the specifics of the segment. Historically, leasing companies rarely default, so it is quite difficult to find small or medium sized bank that would have defaults on the portfolio of leasing companies in default history. In this regard, market defaults are usually used rather than internal ones. Therefore, we consider all Russian leasing companies on the market, taking into account their historical default when building the model.

This model is then applied directly to leasing companies in the Bank's portfolio. Indicators from 1613 financial statements of the largest Russian leasing companies from 2009 to 2016 were

analyzed. As a result of the analysis, 91 defaults were revealed. The results of the model are given below (details in Appendix 1 and 2):

Model used

$$P_i = \frac{1}{1+e^{(2,717-0,049*Equity-0,637*\frac{Debt}{Assets}-0,375*\frac{EBIT}{Interest\ payable}-0,103*\frac{AP}{AR})}} \tag{2.5}$$

Gini - 72,65%

Score range	Default rate	Number of Good	Number of Bad	Total	Share of sample	Share of Good	Share of Bad	WOE	IV
more than 93	1,64%	180	3	183	10,78%	11,19%	3,37%	120,02	9,39%
(78;93]	3,17%	732	24	756	44,55%	45,52%	26,97%	52,36	9,72%
(53;78]	4,58%	542	26	568	33,47%	33,71%	29,21%	14,31	0,64%
(38;53]	14,42%	89	15	104	6,13%	5,53%	16,85%	-111,35	12,60%
(20;38]	19,15%	38	9	47	2,77%	2,36%	10,11%	-145,37	11,27%
less than 20	30,77%	27	12	39	2,30%	1,68%	13,48%	-208,32	24,59%

Table 7. Modeled DR for LC segment

To determine PD for **SSB segment** it is necessary to understand the methodology applied for low-default portfolios. Low-default portfolios (LDP) are one of the most knowledge-intensive areas in the field of risk modeling in the corporate portfolio. Their high importance for the credit institution, based on the volume of accepted risk, is combined with the lack of sufficient statistics for the construction of "standard" models and, therefore, requires deep study in terms of mathematical apparatus and economic hypotheses underlying the model.

At the same time, the principle of conservatism, often recommended when assessing risks in LDP portfolios, should be as limited as possible in accordance with the requirements of new international standard (IFRS 9), preventing unjustified reduction of the credit institution's presence in truly low-risk segments.

In the classic ("frequency") approach to determining the desired parameters, it is assumed that there is a certain true value of the parameter, for example, the average frequency of defaults in the portfolio. The more data we accumulate, the more accurate we will be able to determine this true value. Bayesian methods are based on the concept of a priori distribution of the desired parameter.

Therefore, the parameter that determines the average frequency of defaults in the portfolio itself is a random variable with a certain distribution function. The final (a posteriori) distribution function, by which we can predict the values of the parameter, is formed on the basis of a priori knowledge about the distribution of the parameter and the actual data that we observed. Using the Bayes ' formula, designated by $p(pd|\mathcal{D})$ posterior distribution function of our unknown parameter pd, we can determine the following:

$$p(pd|\mathcal{D}) = \frac{p(\mathcal{D}|pd)p(pd)}{p(\mathcal{D})}, \tag{2.6}$$

where $p(pd)$ is our a priori assumption of the parameter distribution, $p(\mathcal{D}|pd)$ is the probability of seeing our historical sample at a fixed value of the parameter (i.e. the value of the function of maximum likelihood), $p(\mathcal{D})$ is the probability of our sample.

As shown in (Murphy, 2012), in the limited cases of infinitely large data volumes, the methods will converge to the maximum likelihood function, i.e. the "classical" frequency approach. However, the less statistics we have accumulated, the higher the difference may be in the application of these concepts.

The Bayesian approach allows us to supplement insufficient factual information in low-default portfolios by using the knowledge (assumption) about the a priori distribution of the default frequency in the portfolio. Thus, based on the convergence properties of the method of maximum likelihood, the estimates will automatically move in the direction of their own statistics of the portfolio as of its accumulation.

However, in order to apply the approach, one of the most important issues of the Bayesian method should be solved – to determine the a priori distribution of the parameter $p(pd)$. The following can be the key criteria when choosing the form and parameters of a priori distribution:

1) The stages and results of the calculations should be intuitive and transparent from an economic point of view.
2) The model must be computationally efficient.
3) A priori distribution should not lead to underestimation of risks, i.e. to be more "optimistic" than the actual statistics on the segment (portfolio), but the degree of conservatism should be as low as possible to obtain estimates with minimal bias.

To fulfill the first two requirements, as shown below, the optimal take conjugate a priori distribution, for binomial distribution (binomial distribution describes the number of defaults in the portfolio) conjugate is the beta distribution. The area of definition of beta distribution coincides with the probabilistic boundaries [0;1] and has a very flexible structure, depending on the two parameters (a,b). Due to the conjugacy property, as shown in (Murphy, 2012), the posteriori distribution of the sought PD parameter will also have a beta distribution:

$$p(pd|\mathcal{D}) \propto p(\mathcal{D}|pd)p(pd) \propto Bin(D|pd,N)Beta(pd|a,b) \propto Beta(pd|a+D,N-D+b) \quad (2.7)$$

According to the properties of the Beta distribution, the desired parameter can be perceived as a mathematical expectation of the a posteriori distribution:

$$\overline{pd} = \frac{a+D}{a+b+N} \quad (2.8)$$

It can be shown that $\overline{pd}$ is a convex combination of the mathematical expectation of a priori distribution and the estimation obtained by the maximum likelihood method:

$$\mathbb{E}(pd|\mathcal{D}) = \frac{\alpha m+D}{N+\alpha} = \frac{\alpha}{N+\alpha}m + \frac{N}{N+\alpha}\frac{D}{N} = \lambda m + (1-\lambda)\frac{D}{N} \tag{2.9}$$

where $\alpha = a + b$ is equivalent to the sample size of the prior, $m = a/\alpha$ is expectation of the prior, $\lambda = \frac{\alpha}{N+\alpha} = \frac{a+b}{N+a+b}$ is weight of the prior.

The "weight of prior" λ allows us to clearly see the contribution of internal statistics and prior to the final assessment of the Central trend. It is obvious that at $N \to \infty$, the"weight of prior" λ will tend to be 0. Thus, the requirement to automatically reallocate the contribution of internal statistics to the final estimate is met, as historical data is accumulated.

The implementation of the third criterion depends on the approach to determining the parameters of the a priori distribution. According to the author, the most rational solution to this problem is the application of empirical Bayes approach, it will allow us to assess the level of conservatism of the model and is economically intuitive.

The essence of the empirical base approach is the following: the parameters of a priori distribution are determined by statistical methods on the basis of a wider, representative set of data. In order to simplify the approach of empirical Bayes as much as possible, it is proposed to calibrate the parameters of a priori distribution by the maximum likelihood method on the portfolio meeting the following requirements (MLP – maximum likelihood portfolio):

- The statistics of defaults on the MLP portfolio should be sufficient to build statistically reliable estimates of the probability of default (for example, in terms of the requirements of the regulator or internal standards of validation models).
- From an economic point of view, risk drivers operating on a low-grade portfolio should coincide with the MLP portfolio (for example, the portfolio of banks Top 1000 is an unsuccessful choice of MLP portfolio for LCB).
- From an expert point of view and based on actual statistics, the MLP portfolio should be more conservative than the low-default portfolio.

Briefly, MLP - this is the least conservative and close from the point of view, the risk drivers of the portfolio, with sufficient statistics for a reliable determination of the average frequency of defaults in the portfolio with given historical horizon. As a result, the Bayesian approach algorithm for determining the Central tendency in a low-default portfolio is formalized as follows:

1) The selection of the MLP portfolio;
2) Calibration by maximum likelihood parameters of the beta distribution to the historical frequencies of defaults in the portfolio of MLP;
3) Usage of the formula above to calculate the final estimate of the Central tendency and to identify the weights of internal and external statistics.

This approach was used in our particular case in relation to SSB segment:

- External ratings are assigned, the average historical frequency of defaults according to statistics from 2000 to 2016;
- Annual portfolios of SSB segment with external ratings are formed, for each year the average frequency of defaults in the portfolio is calculated based on the assigned external ratings and default probabilities obtained at the previous step (as a proxy of the actual frequency of defaults);
- The parameters of the beta distribution are evaluated;
- Formula is used, combining internal and external statistics.

The results of the model application according to the data of the rating agencies, dependent on the number of observations in the portfolio (it is assumed that defaults in this segment were not observed), is shown in the table below:

№	S&P	Moody's	Fitch	PD SSB
1	AAA	Aaa	AAA	0,00%
2	AA+	Aa1	AA+	0,00%
3	AA	Aa2	AA	0,01%
4	AA-	Aa3	AA-	0,01%
5	A+	A1	A+	0,02%
6	A	A2	A	0,02%
7	A-	A3	A-	0,04%
8	BBB+	Baa1	BBB+	0,07%
9	BBB	Baa2	BBB	0,11%
10	BBB-	Baa3	BBB-	0,19%
11	BB+	Ba1	BB+	0,32%
12	BB	Ba2	BB	0,54%
13	BB-	Ba3	BB-	0,93%
14	B+	B1	B+	1,59%
15	B	B2	B	2,75%
16	B-	B3	B-	4,76%
17	CCC+	Caa1	CCC+	8,20%
18	CCC	Caa2	CCC	13,89%
19	CCC-	Caa3	CCC-	22,66%
20	CC	Ca	CC	34,67%

Table 8. Modeled DR for SSB segment

The resulting default probabilities are applied to the respective ratings of the segment borrowers. These probabilities of default do not require additional calibration.

Various behavioral factors were analyzed to construct a model for the **SB segment:** the

number of days overdue, the initial loan amount, the number of months from the date of last issue, the presence of restructuring (yes/no), the number of restructurings, the number of facts of delay. These factors were analyzed from 2012 to 2016 (6736 observations). As a result, only the model with 2 factors was determined to be significant:

Model used

$$P_i = \frac{1}{1+e^{(3,317-0,449*Days\ overdue-0,172*Number\ of\ delays)}} \tag{2.10}$$

Gini (testing) - 60,63% (see Appendix 2), Gini (validation) - 72,15% (see Appendix 2)

Score range	Default rate	Number of Good	Number of Bad	Total	Share of sample	Share of Good	Share of Bad	WOE	IV
more than 45	3,24%	1 853	62	1 915	74,54%	77,53%	34,64%	80,58	34,56%
(40;45]	10,80%	322	39	361	14,05%	13,47%	21,79%	-48,07	4,00%
(32;45]	14,63%	140	24	164	6,38%	5,86%	13,41%	-82,81	6,25%
(18;32]	22,58%	24	7	31	1,21%	1,00%	3,91%	-135,95	3,95%
(8;18]	40,28%	43	29	72	2,80%	1,80%	16,20%	-219,78	31,65%
less than 8	69,23%	8	18	26	1,01%	0,33%	10,06%	-340,26	33,08%

Table 9. Modeled DR for SB segment

2.4.2 QMM Calibration

The main purpose of calibration is to make a transition from DR to one-year PD. The essence of the QMM (Quasi-Moment-Matching) approach is to simultaneously meet the two calibration criteria:

1) Weighted average of the number of observations in the rating, the calibrated PD, is equal to the CT to which the calibration was performed;
2) The change in PD rating classes is proportional to the Gini coefficient (AR) of the behavioral model calculated for the period of the economic cycle. This means that in the absence of predictive ability of the model (AR= 0), PD become the same in all rating classes (since the model cannot distinguish "bad" borrowers from "good"). With the growth of AR, higher PD is assigned to "bad" rating classes, and PD in "good" rating classes is reduced. This is reflected in the fair redistribution of the model of "bad" loans from "good" rating classes to "bad".

Indicators CT (central tendency) and AR are calculated. CT is calculated separately for each segment. AR is calculated for ranking models separately for each segment. The calculation of AR was described in previous section, but we need to define the method to calculate CT.

The calculation is based on the data of loan portfolios of legal entities in the context of borrowers at the beginning of each year for the economic cycle (but not less than the last 5 years). All counterparties that have credit exposures in accordance with IFRS for the respective dates that

do not have default status for these dates are included in the calculation set. The default frequency is calculated for each year of the analyzed period according to the formula:

$$DR_i = \frac{Q_{(will\ be\ in\ default)i}}{Q_{(non-defaults)i}} \tag{2.11}$$

CT is calculated as the average frequency of defaults in accordance with the formula:

$$CT = \frac{\sum_{i=t}^{n} DR_i}{N} \tag{2.12}$$

where t is the month of the loan portfolio used,

n – the last year of the current economic cycle,

N - number of full years in the current economic cycle.

The rules of selection of observations on which AR is calculated coincide with the rules for generating data for CT calculation. The data is aggregated by rating category in aggregate for all reporting dates of the beginning of the year for the period of the current economic cycle. The target data structure for the AR calculation is a table with columns $Q_{(non-defaults)i}$ and $Q_{(will\ be\ in\ default)i}$ for the ratings generated during the economic cycle. The CT and AR input parameters must be inserted into the equations below:

$$CT = \sum_{x=1}^{k} \Pr[D|X = x]\Pr[X = x]$$

$$AR = \frac{1}{CT(1-CT)}\Big(2\sum_{x=1}^{k}(1 - \Pr[D|X = x])\Pr[X = x]\sum_{x=1}^{x-1}\Pr[D|X = t]\Pr[X = t] + \sum_{x=1}^{k}\Pr[D|X = x](1 - \Pr[D|X = x])\Pr[X = x]^2\Big) - 1 \tag{2.13}$$

Where X: $x_1 \dots x_k$ – rating, D – borrowers defaulted within one year, N – non-defaulted borrowers for each date. Let us represent Pr [D | X = x] using a logistic curve:

$\Pr[D|X = x] \approx \frac{1}{1+e^{(\alpha+\beta\Phi^{-1}(F_N))}}$, where $F_N(x) = \frac{\Pr[X < x|N]+\Pr[X \le x|N]]}{2}$ and $\Phi(x) = \frac{1}{\sqrt{2\pi}\int_{-\infty}^{x} e^{-1/2 y^2} dy}$

We solve numerically the system of equations for α and β. The resulting numerical values of $\hat{\alpha}$ and $\hat{\beta}$ must be substituted in the expression for the logistic curve:

$$\Pr[D|X = x] \approx \frac{1}{1+e^{(\hat{\alpha}+\hat{\beta}\Phi^{-1}(\frac{\Pr[X < x|N]+\Pr[X \le x|N]]}{2}))}} \tag{2.14}$$

Thus, each ranking is expressed by the corresponding value of PD. All of the PD lay on a

positive and monotonic curve. The table below shows the results of the calculated CT and AR for each segment:

Segment	CT	AR
LCB	3,86%	66,89%
SSB	not applicable	not applicable
LC	3,22%	72,65%
SB	7,86%	72,15%
MB	11,38%	41,32%

Table 10. CT and AR for each segment

Then QMM calibration was performed. The results in the context of the ratings and the segments are presented in the table below:

Rating	LCB PD TTC	LC PD TTC	MB PD TTC	SB PD TTC
1	0,24%	0,28%	2,18%	1,58%
2	0,79%	0,58%	6,71%	15,39%
3	1,92%	2,18%	10,09%	20,09%
4	4,32%	7,90%	12,08%	43,81%
5	11,37%	21,23%	17,08%	67,29%
6	38,86%	49,22%	28,25%	80,99%

Table 11. Results of QMM calibration for each segment

The movement from DR to PD TTC is presented in the charts in Appendix 3.

2.4.3 Macroeconomic model

For the purpose of accounting for forward-looking information, a macroeconomic model was built. The architecture of this model is based on logistic multi-factor regression, which studies the dependence of the actual default of the portfolio on changes in macroeconomic factors. During the initial analysis, 30 variables were tested, as well as various combinations of these variables.

The macroeconomic component in the calculation of the ECL is taken into account by adjusting the PD TTC to the macro factor, which is calculated separately for legal entities and individuals. Stages of calculation of the macro factor:

1) Formation of statistics on the level of default in the format of quarterly data on the share of transactions at the beginning of the quarter in the loan portfolio and defaulted on the horizon of 12 months, in the non-debt loan portfolio at the beginning of the quarter. The period should cover at least 5 years.
2) Formation of series of macroeconomic indicators, for which there is an expert assumption about the impact on the overall level of default on loans.
3) Identification of macroeconomic indicators, for which the correlation analysis confirms the hypothesis of the impact on the overall level of default on corporate and/or retail loans of the Bank, and selection of indicators with the highest predictive power.

4) Construction of models of approximation of the dependence of the General level of default on each of the macro indicators.
5) Calculation of the General level of default by macro model for all scenarios approved (very positive, positive, negative, crisis).
6) Calculation of the probability of each scenario being implemented for a period of 12 months after the reporting date based on expert judgement.
7) Calculation of the forecasted value of the General level of default for the period of 12 months after the reporting date, taking into account the probability of scenarios.
8) Calculate the coefficient of macro factor (Km) according to the formula:

$$\text{Км} = \frac{EDF_{forecast}}{CT} \tag{2.15}$$

where $EDF_{forecast}$ is forecasted value of the General level of default for the period of 12 months after the reporting date; CT – central tendency for all of the statistics. The final model is presented below:

$$P_i = \frac{1}{1+e^{(-0{,}465+0{,}688*\text{LN(Oil)}-1{,}151*\text{WA interest rate}+2{,}740*\text{LN(GDP growth rate)})}}, \tag{2.16}$$

where LN (Oil) - natural logarithm of the volume of oil production in Russia multiplied by its selling price; WA interest rate - weighted average interest rates on deposits of legal entities attracted by credit institutions; LN (GDP growth rate) – natural logarithm of GDP quarterly growth rate.

Resulted forecasted DR is 6,27% and adjusted macrofactor is 85%. Detailed information is presented in Appendix 4. Then we apply this macrofactor to all of the PDs of loans in 1 stage, converting them into PD PIT (point-in-time). This indicator can be used only for the first stage loans, as the model determines the impact of macroeconomics on the 12-month horizon.

2.4.4. Staging assessment

The determination of the threshold increase in credit risk should be supported by the economic rationale (for example, the growth of PD on the amount exceeding the initial cost of risk, laid down in the loan agreement). Transition criteria is determined solely on the basis of existing business processes in the field of risk-management and credit monitoring of the Bank.

There are two approaches to develop a stage model: sophisticated and simplified. Within the framework of this research, it was decided to use a simplified approach, as sophisticated approach involves a deep analysis of the internal processes of a particular Bank. In our case, modeling of

internal processes seems to be quite a difficult task, the solution of which requires performing a separate research.

As for a sophisticated implementation, there are three elements of a simpler approach: quantitative, qualitative, and backstops. However, it is likely that the qualitative assessment will play a more significant role. This also may suggest a need for greater consideration as to what recalibration of PDs may be required when measuring ECLs to reflect qualitative indicators of increases in credit risk that have not been reflected in quantitative PD measures.

Even though the bank may not be able to assess changes in an exposure's lifetime PD, lifetime ECLs are generally expected to be recognized before a financial instrument becomes past due. Therefore, the assessment of whether there has been a significant increase in credit risk should be made based not only on whether the instrument is past due, or other lagging borrower-specific behavioral factors such as credit-bureau scores, but also using forward-looking information that is available without undue cost or effort (IFRS 9.B5.5.2).

For the quantitative element of the assessment, it may be possible to use changes in 12-month PDs, rather than lifetime PDs, if the bank evidences that use of changes in 12-month PDs is a reasonable approximation. This is likely to be more difficult for loans with a maturity beyond 12 months where the most significant cash flows, and hence risk of default, arise at or near maturity, such as 'bullet' loans (IFRS 9.B5.5.13-14). Criteria of reference to stage 2 were formulated for corporate borrowers with a significant deterioration in credit quality:

- 30-89 days per due at the reporting date (maximum delay in all borrower's transactions);
- Significant deterioration of the internal rating from the date of recognition (see table below);
- Professional judgment of the Bank;
- Recovery criteria: termination of the criteria on the basis of which the transaction was transferred to stage 2, as well as professional judgment of the Bank's management.

The table below shows the relative deterioration of the rating required for the transition to stage 2:

№	Rating on the date of recognition	Rating at the reporting date	Number of notches
1	AAA	A+	4
2	AA+	A	4
3	AA	A-	4
4	AA-	BBB+	4
5	A+	BBB	4
6	A	BBB-	4
7	A-	BB+	4
8	BBB+	BB+	3
9	BBB	BB	3
10	BBB-	BB-	3
11	BB+	B+	3
12	BB	B	3
13	BB-	B-	3
14	B+	CCC+	3
15	B	CCC	3
16	B-	CCC-	3
17	CCC+	CCC-	2
18	CCC	CC	2
19	CCC-	CC	1
20	CC	CC	0

Table 12. Notches for staging assessment of Corporate borrowers

The table below shows the results of the stage distribution for corporate borrowers:

Segment	Exposure	1 stage	%	2 stage	%	3 stage	%
Large corporate borrowers	17 000 000	13 730 907	80,8%	1 928 024	11,3%	1 341 068	7,9%
Sub-Sovereign borrowers	5 000 000	5 000 000	100,0%	-	0,0%	-	0,0%
Leasing companies	3 000 000	2 947 804	98,3%	-	0,0%	52 196	1,7%
Small borrowers	1 500 000	1 021 134	68,1%	103 826	6,9%	375 039	25,0%
Medium borrowers	500 000	442 777	88,6%	57 223	11,4%	-	0,0%
Total	**27 000 000**	**23 142 623**	**85,7%**	**2 089 073**	**7,7%**	**1 768 304**	**6,55%**

Table 13. Stage distribution for Corporate borrowers

The second stage includes 7,7% of corporate loans (global benchmark 5-10%).

2.4.5. Lifetime PD

To determine lifetime PDs, the bank either uses the 12-month PD model or develops a lifetime PD model separately. If the bank uses the 12-month PD model, it develops lifetime PD curves or term structures to reflect expected movements in default risk over the lifetime of the exposure. This involves:

- Sourcing historical default data for the portfolio.
- Performing vintage analysis to understand how default rates change over time.
- Extrapolating trends to longer periods where default data is not available for the maximum period of exposure.

- Performing analysis at an appropriately segmented level, such that groups of loans with historically different lifetime default profiles are modelled using different lifetime default curves.

If the bank is able to incorporate detailed forecasts of future conditions in developing PD estimates only for a period that is shorter than the entire expected life, it applies a documented policy for determining the longer-term trend in rates of default based on historical and other available reasonable and supportable information (IFRS 9.B.5.50, 52).

If the bank develops a new model to produce lifetime PDs, it will be necessary to ensure all key risk drivers and their predictive power are identified and calibrated based on historical data over a suitable time period. This could take the form of a scorecard approach.

A bank may apply simpler extrapolation techniques to the 12-month PD. For example, the bank may assume that the default rate does not change during the lifetime of the loan or use less segmentation than under a more sophisticated approach. This may be more common for shorter-term products. The bank should justify this approach with analysis evidencing that the PD profiles are appropriately similar.

If a bank uses an extrapolation approach to determine lifetime PDs, then it may combine different risk segments if they are considered to have similar lifetime PD profiles. This will simplify the modelling required and reduce the number of explicit PD profiles to be calculated at each reporting date. The bank should justify this approach with analysis supporting the assertion that the underlying PD profiles are appropriately similar.

I suggest using a simplified approach to define lifetime PD. This approach is easy to implement and is used not only by medium and small banks, but also by industry leaders. There are several methods of extrapolation:

- Survival function and hazard rate;
- Convergence to the CT;
- Transition matrices;
- Growth rate;
- Conditional probability.

The transition matrix approach is a widely used method. It can be applied and for longer periods. This approach is simple: the transition matrix is multiplied by itself in one year for obtaining a multi-year time horizon. The number of times the matrix is multiplied by itself reflects the number of years time horizon. Key deficiency is that for longer time horizons PDs are becoming less reliable,

i.e. the ranking order of the rating can no longer be maintained.

As practice shows, the most appropriate both from the point of view of economic logic and from the point of view of the obtained results is the method of conditional probability. This method is the most balanced. When using it, the probability of default in good ratings grows slowly, while in bad ratings it increases rapidly. That is, if the Bank has a good portfolio and most of the loans are in good ratings, it is recommended to use this method. The formula used is presented below:

$$PD_n = 1 - (1 - PD_{TTC})^n \tag{2.17}$$

The results of lifetime PD calculation for every segment are presented in Appendix 5.

2.4.6. Loss given default

Loss given default (LGD) is defined as:

$$LGD = 1 - Recovery\ rate,$$
$$Recovery\ rate = \frac{Amount\ recovered}{Amount\ outstanding\ at\ default}, \tag{2.18}$$

where amount recovered sums up all discounted cash flows received during the recovery process after default, less the total cost incurred.

There are major differences between PD and LGD modelling. While LGD is a continuous variable and usually follows a beta distribution, default events (PD) are binomial. LGD depends on the recovered amount, which may take several years after default to resolve, whereas PD describes the likelihood of a default event occurring within a specified period (usually 1 year). Information about events occurring after default has no effect on PD (Yang and Tkachenko, 2012).

Usually there is a lack of reliable historical data for LGD. Interest in LGD data collection started in years 1996 - 2001 when specific mandatory BASEL requirements were imposed on financial institutions in order to become AIRB (advanced internal rating bands) compliant. According to the requirements of IFRS 9 and Basel recommendations for the calculation of implemented LGD, the following assumptions were formulated:

- *Collateral.* Analysis is made in respect of 3 collateral types (cash, real estate, other);
- *Discounting.* Payments are discounted for relevant loan rate at the date of default;
- *Write-offs.* Write-offs are excluded from calculation;
- *Realized collateral.* Historical coefficient of collateral realization was calculated and adjustment to collateral on a balance was performed;
- *Payments.* Payments are analyzed in relation to year when they were received. Extra commitments should be also taken into account;

- *Extra sources of cash.* Cash from cessions and amicable agreements;
- *Horizon.* 5 years. Loans defaulted less than 2 years ago from current reporting date should be excluded.

The calculation is made only for defaulted loans. LGD calculation for LCB and MB segments is made in the context of the types of collateral, as the risk profiles vary depending on the collateral. Write-offs are excluded from the calculation, as they are not sources of repayment of the loans. The calculation of the historical coefficient of sale of the collateral taken on balance for usage in the reporting period was made (87%). Horizon for the calculation of the LGD was chosen in accordance with the average duration of collection in the industry.

In the case of the segments of the LCB and MB, calculation is made at the level of each transaction and then averaged within the framework of particular collateral type. In the SB segment, it is quite difficult to track the repayment at the level of each transaction, so the calculation is made by generations of issue and averaged over the years (see Appendix 6). Such loans are not usually analyzed by type of collateral. The results of the calculations are presented below, as well as a breakdown by type of collateral:

Segment	Exposure	RR	LGD	№ of defaults	Type of LGD calculation
SB	700 000	29,0%	71,0%	324	By generation of issue
LCB and MB	8 000 000	49,1%	50,9%	108	By transaction
Total	**8 700 000**	**47,4%**	**52,6%**	**432**	

Table 14. LGD for SB, LCB and MB segments

Type of collateral	Exposure	RR	LGD
Cash collateral	215 340	80,0%	20,0%
Real estate	5 046 915	52,3%	47,7%
Other	1 340 774	31,8%	68,2%
Total	**6 603 029**	**49,1%**	**50,9%**

Table 15. LGD in breakdown by collateral type

Since there were no defaults in the SSB and LC segments, we will use the calculation by type of collateral.

2.4.7. Credit conversion factor

For revolving credit products (e.g. credit lines), the probability of conversion of off-balance sheet amount of liabilities in the carrying amount of the asset is a setting in the CCF. CCF shows how much of the off-balance will be converted to the balance from the reporting date to the default date.

Use of segmented credit conversion factor (CCF) models may be appropriate if the bank can justify this approach with analysis showing that exposures within each CCF segment are expected to behave similarly. A CCF is a modelled assumption which represents the proportion of any undrawn exposure that is expected to be drawn prior to a default event occurring. For calculation of CCF we used the following appumptions:

- CCF (Credit conversion factor) – probability of conversion from off-balance items to balance ones at the moment of default;
- For CCF calculation the following formula is used:

$$CCF_t = \frac{Balance_d - Balance_{-t}}{Off\ balance_{-t}} \tag{2.19}$$

$Off\ balance_{-t}$ – amount of undrawn limits before t months from default

$Balance_d$ – amount of withdrawn limits at the date of default

$Balance_{-t}$– amount of withdrawn limits before t months from default

- CCF is defined on a horizon of 12 months with a breakdown of products;
- Exposure at default (EAD) is defined as CCF multiply undrawn limits at the reporting date.

The table below shows the results of CCF calculation on different horizons for credit lines and overdrafts:

Product	CCF	12m	9m	6m	3m
Credit lines	**37,23%**	37,23%	21,12%	17,63%	10,15%
Overdrafts	**85,12%**	85,12%	81,00%	82,96%	94,21%

Table 16. CCF for revolving credit products

There are different approaches to averaging CCF on several horizons, but CCF on the horizon of 12 months is most often used and the most conservative approach.

2.5 ECL components determination for Retail borrowers

2.5.1 Behavioral models

In credit scoring the main interest is in developing a scoring system which can correctly rank the customers in terms of their relative default risk so that the customers above some cut-off score are more or less riskier than those who are below. Credit scoring models can broadly be classified into two types, application scoring and behavioral scoring. The objective of both is to classify whether a customer will default (Bad) or not default (Good) in a given time period, which leads to

estimates of probability of default (PD) of the customer in that period.

Application scores are used to predict customers' default risk, say 12 months in future, at the time of application made for the loan. In application scoring, past customers are classified as Good or Bad based on whether they defaulted, which usually means 90+ days delinquent, during the first 12 months of the starting of the loan. The information available at the time of application in the form of application variables and credit bureau records is then used to estimate the probability of being good/bad in the given time period.

Behavioral scoring is similar in principal to application scoring except that in behavioral scores we observe the recent, say last one year, payment and purchase behavior of customers who have been granted loan and use this information in addition to the information available for application scoring to predict the probability of default in next twelve months or some other fixed time horizon. As the name suggests in behavioral scoring the individuals behavior with a particular lender and on a specific product is considered in addition to the information the lender has through credit bureaus.

The above estimates of default probabilities are then transformed into scores, which are used as a basis to accept or reject a customer for credit, depending on the cut-off decided by the banks for application scorecards or to make lending decisions on current customers, like increasing/decreasing credit limit, offering new financial products, offering new interest rates, based on behavioral scores. Lenders update their behavioral scores monthly by using the most recent information on their customers. The following assumptions were used to construct the models

- The models are built on all retail products (mortgage, consumer loans, car loans) except for credit cards (separate approach). Then it was made a separate calibration for each retail product;
- Data used: 1 Jan 2013 – 31 Dec 2016;
- After statistical tests, it was decided that the sample should be divided into 2 parts (loans without delay and loans with delay of 1-90 days). These loans have different risk profiles and behave differently. Accordingly, two different models will be built;
- During the development process, more than 20 factors, often used in the construction of behavioral models, were analyzed. 7 factors for the model without delays and 6 factors for the model with delays were chosen;
- The number of rating categories is decided to be 10 in each model (WOE analysis).

Final models for retail loans are presented below:

Variable	Coefficient	P-value (Gini)
Fraction of days without delays for 12 months	-0,362	0,000
Number of delays for 6 months	-1,011	0,012
Number of days with Bank	0,217	0,047
Presence of salary card in Bank	0,008	0,019
Education	-0,411	0,037
Current exposure/initial exposure	-1,097	0,000
Age	0,019	0,009
Constant	**-1,284**	**61,40%**

Table 17. Behavioral model for loans without delays

Variable	Coefficient	P-value (Gini)
Number of days in delay	-1,519	0,023
Delayed exposure	-0,713	0,011
Current exposure/initial exposure	-1,001	0,03
Number of delays for 6 months	-0,373	0
Number of delays for 12 months	-0,226	0,039
Presence of salary card in Bank	0,014	0,015
Constant	**-2,013**	**62,30%**

Table 18. Behavioral model for loans with delays

Detailed information is provided in Appendices 7 and 8. These models allow us to determine the probability of default in a particular rating, but it is necessary to clarify the probability of default for a certain segment using QMM calibration.

2.5.2 QMM Calibration

The approach to calibrating models for retail loans and corporate loans is the same (see p. 2.4.2). The only difference is that the last available 12-months DR for each segment is used for calibration purposes. The table below shows the results of the calculated DR and AR for each segment:

Segment	DR (no delays)	AR (no delays)	DR (delays)	AR (delays)
Mortgage	1,2%	61,4%	26,4%	62,3%
Consumer	1,8%		37,9%	
Auto	3,3%		43,4%	
Total	**1,6%**		**35,5%**	

Table 19. DR and AR results for Retail loans

Then QMM calibration was performed. The results in the context of the ratings and the segments for each model are in the table below:

Rating	Mortgage	Consumer	Auto
1	0,14%	0,32%	0,50%
2	0,34%	0,69%	1,09%
3	0,62%	1,19%	1,87%
4	0,93%	1,69%	2,66%
5	1,31%	2,28%	3,57%
6	1,60%	2,72%	4,25%
7	2,09%	3,43%	5,36%
8	3,33%	5,13%	7,96%
9	5,27%	7,62%	11,68%
10	18,92%	22,61%	32,06%

Table 20. QMM calibration for Retail loans without delays

Rating	Mortgage	Consumer	Auto
1	3,73%	6,81%	6,82%
2	6,28%	10,93%	11,17%
3	9,89%	16,36%	17,00%
4	14,53%	22,86%	24,02%
5	19,95%	29,87%	31,60%
6	28,97%	40,45%	42,94%
7	44,03%	55,87%	59,05%
8	54,93%	65,72%	68,99%
9	62,86%	72,35%	75,49%
10	78,45%	84,40%	86,80%

Table 21. QMM calibration for Retail loans with delays

The movement from DR to PD TTC is presented in graphs in Appendices 9 and 10.

2.5.3 Macroeconomic model

The approach is the same as for corporate borrowers (see p. 2.4.3). The final model is presented below:

$$P_i = \frac{1}{1+e^{(-7{,}064+0{,}430*LN(Oil)+1{,}128*LN(Loans\ Ind\ rates)+0{,}050*Real\ salary\ index)}}, \qquad (2.20)$$

where LN (Oil) - natural logarithm of the volume of oil production in Russia multiplied by its selling price; LN (Loans Ind rates) – natural logarithm of weighted average interest rates on loans of individuals attracted by credit institutions.

When calculating the macro factor, the actual DR is used instead of CT. Resulted forecasted DR is 3,97% and adjusted macrofactor is 97%. Detailed information is presented in Appendix 11.

2.5.4 Staging assessment

For retail loans, it is difficult to identify qualitative indicators for the developing of the stage

model. Therefore, it is proposed to use the calculation of the difference between the actual PD and the original PD above the defined threshold, which considers the qualitative characteristics of loans.

First step is to calculate Annualized PD (APD). APD is a geometric mean of probability of default over the parts of the MPD curves, which are still remaining at the given reporting date:

$$APD^{k}{}_{t0} = 1 - \sqrt[N]{\prod_{t=t_0}^{N}(1 - MPD_t)} \tag{2.21}$$

where

k denotes individual exposure;

t_0 stands for current MOB;

MPD_t is the marginal probability of default during the next 12 months for the exposure at MOB equal t (monthly MPD over one-year horizon);

N denotes maturity as at reporting date.

Second step is to calculate the APD ratio and relative threshold. The APD ratio calculated on the basis of MPD curve at the moment of origination and MPD curve as at reporting date. The relative change in APD is calculated and its significance is assessed based on threshold defined by the user (alfa parameter), according to the formula:

$$\frac{current\ APD_{t_0}^{k}}{initial\ APD_{t_0}^{k}} > \alpha \Rightarrow transfer\ to\ stage\ 2 \tag{2.22}$$

The α threshold equals 3 for the purpose of current research. Alfa determination is based on the analysis of the APD ratio distribution against average DPD (see the chart below).

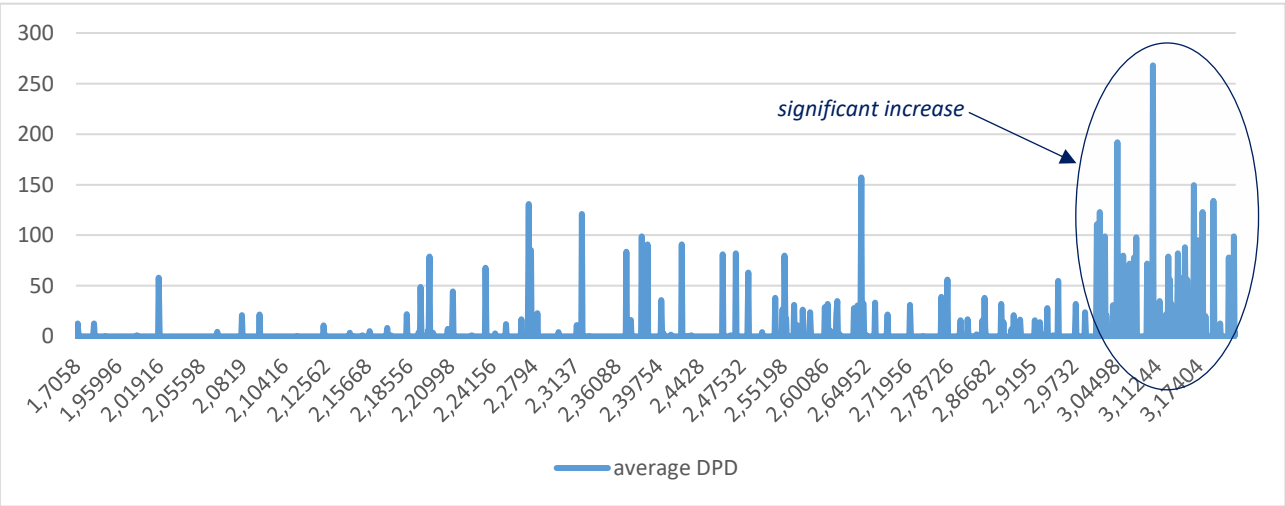

Chart 1. Average DPD vs APD ratio

The table below represents final application PDs for each segment multiplied by relative threshold:

Segment	before 2013	2013	2014	2015	2016	2017
Mortgage	11,92%	19,33%	11,47%	6,07%	9,85%	12,87%
Consumer	11,97%	15,03%	11,06%	12,76%	10,31%	10,67%
Car	6,40%	6,38%	5,95%	7,02%	5,83%	6,79%

Table 22. Indicators for transition to stage 2 for each segment by the year of recognition

This means that if the final PD value for a product in a certain segment is greater than the value in this table (according to the year of issue), then the loan is assessed to stage 2. For credit cards, the distribution by stages is made separately (see p.2.5.7). The table below shows the results of the stage distribution for retail borrowers:

Segment	Exposure	1 stage	%	2 stage	%	3 stage	%
Mortgage	35 000 000	32 505 661	92,9%	1 312 110	3,7%	1 182 229	3,4%
Consumer	15 000 000	12 833 795	85,6%	440 967	2,9%	1 725 238	11,5%
Credit cards	3 000 000	2 696 074	89,9%	28 510	1,0%	275 416	9,2%
Auto	500 000	295 318	59,1%	36 024	7,2%	168 658	33,7%
Total	**53 500 000**	**48 330 848**	**90,3%**	**1 817 611**	**3,4%**	**3 351 541**	**6,3%**

Table 23. Stage distribution for Retail borrowers

The second stage includes 3,4% of retail loans (global benchmark 2-7%).

2.5.5 Lifecycle curves

Lifecycle curves are calculated for the following segments of the loan portfolio of individuals: car, mortgage and consumer loans. For the purpose of calculation, the non-defaulted portfolio of individuals at the beginning of each month (according to available statistics) is divided into the following overdue buckets:

- without delay;
- delay from 1 to 30 days;
- delay from 31 to 60 days;
- delay from 61 to 90 days.

The calculation is made separately for each segment and delay bucket according to the following algorithm:

1) At each reporting date, the number of transactions that have defaulted n months after the reporting date is determined (n varies from 0 to the period available according to the latest statistics).
2) At each reporting date, the number of trades that have not closed n months after the reporting date is determined (n changes from 0 to the period available according to the latest statistics).

3) Time-series structure of the incremental PD TTC is calculated for each segment, each delay bucket and each horizon n according to the formula below:

$$T(PD\ TTC)_{inc\ n} = \frac{\sum(d_{ni})}{(\sum(K_{ni})+\sum(D_i))}, \tag{2.23}$$

where

d_{ni} – the number of transactions that defaulted from the i reporting date after n months,

K_{ni} – the number of trades that have not defaulted and have not closed since the i reporting date after n months,

D_i - the number of transactions that have defaulted since the i reporting date.

4) Time-series structure of cumulative PD TTC is calculated for each segment, each delay bucket and each horizon n according to the formula below:

$$T(PD\ TTC)_{cum\ n} = \sum_{j=1}^{n}(T(PD\ TTC)_{inc\ j}) \tag{2.24}$$

Then resulted lifecycle curves are used for each segment, for each delay bucket and for each term of a contract. The final lifecycle curves are presented in Appendices 12 and 13.

2.5.6 Loss given default

The approach is similar to that of corporate borrowers. LGD is calculated separately for car, mortgage and consumer loans, credit cards segments. LGD is calculated by defaults that occurred at least 5 years. The amount received as a result of recovery measures on the recovery horizon is analyzed for 60 months from the date of default on the transaction. The LGD calculation is carried out according to the formulas:

$$LGD = 1 - Recovery\ rate,$$

$$Recovery\ Rate = \frac{\sum_i X + \sum_i Z}{\sum_i Y} \tag{2.25}$$

where $\sum_i X$ is the discounted amount of principal and interest payments received on the recovery horizon after the default recognition. For mortgage loans, the amount of loan repayment is adjusted for the sales ratio from the balance sheet, calculated on the Bank's statistics on the ratio of the amounts received from the sale of property. The discounting is made at the initial rate on the loan on the date of the loan.

$\sum_i Z$ – exposure on principal and interest as of the default date, recovered in accordance with the criteria in p. 2.3.

$\sum_i Y$ – exposure on principal and interest on the date of default.

The recovery period could be set between 2 and 5 years. The LGD calculation includes only those defaults for which the calculation period equal to the horizon has passed since the moment of default. The recovery period can be set separately for segments (groups of segments) based on the sufficiency of internal statistics, taking into account its relevance.

For non-impaired loans, LGD is calculated on the established horizon. The level of losses is calculated for impaired loans depending on the period of delay at the reporting date. The calculation is made by generations of issue and averaged over the years (see Appendix 14). The results of the calculations are presented below:

Segment	Exposure	RR	LGD	Horizon	Averaging
Mortgage	35 000 000	60,0%	40,0%	48m	12m
Consumer	15 000 000	33,3%	66,7%	24m	12m
Credit cards	3 000 000	36,5%	63,5%	24m	12m
Car	500 000	39,6%	60,4%	24m	60m
Total	**53 500 000**	**51,0%**	**49,0%**		

Table 24. LGD for Retail loans

The Bank shall independently choose the horizon and averaging period for the calculation of LGD for each segment (see details in Appendix 14). The horizon should depend on the average duration of collection for each product. The averaging period should be chosen depending on the depth of available statistics and management's judgment.

Thus, for all products the horizon of 2 years was chosen, except for the mortgage, whose collection usually lasts longer, i.e. 4 years. The averaging period for all products was set to 1 year, except for car loans. For auto loans, there is less statistics than for other segments, so it was decided to average recoveries on a transaction level for all statistics.

2.5.7 Simplified approach for Credit cards

The key idea of simplified approach to the assessment of ECLs on credit cards and overdrafts is building of loss curve (PD*EAD) without calculating each of the components PD and EAD. Determining losses for stage 1 and stage 2 transactions:

$$\mathrm{ECL}_{t_0} = \sum_{i=0}^{H-1} \mathrm{PD} \times \mathrm{EAD}(\mathrm{t}_i,\ \mathrm{t}_{i+1}) \times \frac{1}{\left(1+\frac{\mathrm{EIR}}{12}\right)^i} \times \mathrm{LGD}\big(\mathrm{EAD}(\mathrm{t}_i,\ \mathrm{t}_{i+1})\big) \qquad (2.26)$$

where

t_0 – current date.

H – horizon of losses, determined by the stage. For the 1 stage it equals to 12 months, for 2 stage it equals to the lifetime of the product. The life expectancy of a credit card is 2 years (see details in Appendix 15).

$\mathrm{PD} \times \mathrm{EAD}(\mathrm{t}_i,\ \mathrm{t}_{i+1})$ – expected default losses arising between reporting dates t_i and t_{i+1}.

LGD – loss given default.

EIR – effective interest rate of current exposure at the reporting date.

The definition of losses for stage 3 is calculated by the formula:

$$\mathrm{ECL}_t = \mathrm{TotalDebt}_t \times \mathrm{LGD}_t \tag{2.27}$$

Then we need to define the stage. The portfolio is divided depending on the delay bucket:

- no delays and delays up to 30 days;
- delays from 31 to 60 days;
- delays from 61 to 90 days.

The stage assessment in accordance with simplified approach is based on delay bucket. Stage 1 corresponds to the bucket "no delays and delays up to 30 days", stage 2 corresponds to the buckets "delays from 31 to 60 days" and "delays from 61 to 90 days", stage 3 corresponds to exposures with delay more than 90 days. Next step is to define loss curve (PD*EAD).

The calculation of the formula component $\mathrm{PD} \times \mathrm{EAD}(\mathrm{t}_i,\ \mathrm{t}_{i+1})$ is carried out by constructing a loss curve model on the Bank's historical data for each delay bucket. The loss curve is the percentage of loans that have been defaulted (amount of the principal at the date of default) at the corresponding age – TTC loss curve. Loss curve, built on all available statistics is extrapolated using the most actual statistics so that loss curve crosses the forecasted loss level at the 12 month. Extrapolation is done as follows:

- PIT loss curve is built for last 6 months for each delay bucket.
- Additionally TTC loss curve is built across all available statistics. The goal is to calculate the proportion of overdue loans with delay more than 30 days after 4 months later the reporting date (amount of principal at the time of transfer to delay 30+).
- Extrapolation factor is calculated for each bucket based on all available statistics.

For bucket "no delays and delays up to 30 days" the factor is calculated by the formula:

$$K_{0-30} = \overline{\left(\frac{\mathrm{sum\_90pl\_age12\ (TTC)}_{\iota}}{\mathrm{sum\_30pl\_age4(TTC)}_{\iota}}\right)} \tag{2.28}$$

where

$\text{sum\_90pl\_age12 (TTC)}_i$ - the amount of defaulted loans after 12 months later the reporting date (amount of principal at the time of the default).

$\text{sum\_30pl\_age4(TTC)}_i$ - the amount of overdue loans with delay more than 30 days after 4 months later the reporting date (amount of principal at the time of transfer to delay 30+).

For buckets "delays from 31 to 60 days" and "delays from 61 to 90 days" the factor is calculated by the formula:

$$K_{31-60,\ 61-90} = \overline{\left(\frac{\text{sum\_90pl\_age12 (TTC)}_i}{\text{sum\_90pl\_age4(TTC)}_i}\right)} \tag{2.29}$$

where

$\text{sum\_90pl\_age12 (TTC)}_i$ - the amount of defaulted loans after 12 months later the reporting date (amount of principal at the time of the default).

$\text{sum\_90pl\_age4(TTC)}_i$ - the amount of defaulted loans after 4 months later the reporting date (amount of principal at the time of default).

PD PIT Cumulative is calculated for each delay bucket on 12 months horizon. For bucket "no delays and delays up to 30 days":

$$PD\ PIT_{12\ cum\ 0-30} = K_{0-30} * \text{TTC Loss curve}_{4\ (30+)} \tag{2.30}$$

where

$\text{TTC Loss curve}_{4\ (30+)}$ - share of loans delayed more than 30 days on 4 months horizon according to the data for the last 6 months.

For buckets "delays from 31 to 60 days" and "delays from 61 to 90 days" PD PIT Cumulative is defined by the formula:

$$PD\ PIT_{12\ cum\ 31-60,61-90} = K_{31-60,61-90} * \text{TTC Loss curve}_{4\ (90+)} \tag{2.31}$$

where $\text{TTC Loss curve}_{4\ (90+)}$ - share of loans delayed more than 90 days on 4 months horizon according to the data for the last 6 months.

For each bucket Cumulative PIT Loss Curve is calculated, where the values for months from 1 to 4 equal to factual values for the last 6 months. For months 5 and more (except 12, which is previously calculated) Cumulative PIT Loss Curve is calculated by the formula:

$$PD\ PIT_{n\ cum} = PD\ PIT_{n-1\ cum} + \frac{\text{TTC Loss curve}_n * (PD\ PIT_{12\ cum} - PD\ PIT_{4\ cum})}{\sum_{i=5}^{12} \text{TTC Loss curve}_i} \tag{2.32}$$

For each delay bucket, Marginal PIT Loss Curve is calculated by the formula:

$$PD\ PIT_{n\ marg} = PD\ PIT_{n\ cum} - PD\ PIT_{n-1\ cum} \quad (2.33)$$

Marginal and Cumulative loss curves for each delay bucket is presented in Appendix 15.

2.6 Transition effect for Corporate and Retail borrowers

After calculation of all ECL components, expected credit losses for corporate and retail borrowers were calculated using the formula (formula number) and expected transition effect was estimated. Below is presented the summarized information in regards of corporate and retail borrowers. Detailed tables with breakdown by stage are presented in Appendix 16 and 17.

Segment	Exposure	Number of borrowers	Provision IAS 39	Rate IAS 39	Provision IFRS 9	Rate IFRS 9	Effect
LCB	17 000 000	300	1 190 000	7,0%	1 459 194	8,6%	269 194
LC	3 000 000	10	60 000	2,0%	63 536	2,1%	3 536
SSB	5 000 000	10	15 000	0,3%	22 590	0,5%	7 590
SB	1 500 000	500	375 000	25,0%	343 188	22,9%	-31 812
MB	500 000	50	10 000	2,0%	20 668	4,1%	10 668
Off-balance	9 450 000	0	0	0,0%	26 479	0,3%	26 479
Grand total	**36 450 000**	**870**	**1 650 000**	**4,53%**	**1 935 654**	**5,31%**	**285 654**

Table 25. Transition effect for Corporate borrowers

Segment	Exposure	Number of contracts	Provision IAS 39	Rate IAS 39	Provision IFRS 9	Rate IFRS 9	Effect
Mortgage	35 000 000	22 000	800 000	2,3%	1 183 121	3,4%	383 121
Consumer	15 000 000	60 000	1 500 000	10,0%	1 604 355	10,7%	104 355
Credit cards	3 000 000	51 000	250 000	8,3%	325 557	10,9%	75 557
Car	500 000	1 000	150 000	30,0%	164 907	33,0%	14 907
Grand total	**53 500 000**	**134 000**	**2 700 000**	**5,05%**	**3 277 940**	**6,13%**	**577 940**

Table 26. Transition effect for Retail borrowers

The total effect of the transition from IAS 39 to IFRS 9 is 863 million RUB, which is equivalent to 5.75% of the Bank's Net Assets or 57.5% of Net Profit. This provision for impairment of loans and advances to customers should be charged in profit and loss statement, and it would reduce the Bank's profit for the current year.

The table below presents the global banking benchmark in terms of the effect of the transition to IFRS 9. As is observed, the expected effect for the Bank is in line with the industry, some banks expect even greater effect.

№	Bank	Net assets	Transition effect
1	HSBC	11 397 409	0,51%
2	Santander	7 276 635	2,06%
3	BNP Paribas	6 946 290	2,45%
4	Barclays	5 304 714	3,44%
5	RBS	4 075 179	0,14%
6	Lloyds	3 615 141	1,93%
7	Sberbank	3 436 000	2,65%
8	Toronto Dominion	3 407 585	0,05%
9	ING	2 973 916	2,06%
10	Commerzbank	2 046 160	4,10%
11	VTB	1 466 000	5,18%
12	Gazprombank	576 809	4,57%
13	Alfabank	363 745	1,27%
14	Unicredit Bank	200 233	8,00%
15	Tinkoff	41 743	23,24%
16	**Model Bank**	**15 000**	**5,75%**

Table 27. Transition effect global benchmark

CONCLUSIONS

IFRS 9 standard replaced the previous IAS 39 standard and started to be effective from the 1st January 2018 in a variety of foreign countries as well as in Russia. This transition created a lot of confusion, due to the peculiarities of the new standard, its unknown specifics and the absence of unified methodology regarding reporting under IFRS 9.

For financial institutions, the switch to the new standard was especially challenging and the process of transition faced incomprehension from the side of the management in the banking industry in Russia. The research produced had as its main goal : 1) To develop the unified methodology for estimating expected credit losses under IFRS 9 standard for Russian banks and 2) to evaluate, how the provision is affected by the transition from IAS 39 to IFRS 9. It is possible to state that the goal stated was reached in full, as well as those objectives that were formulated in the beginning of the present research.

Two groups of regression models were developed separately for the two segments: corporate borrowers and retail borrowers. As a result, the research proved that multifactor logistic regression models should be implemented in further estimation of ECL under IFRS 9 requirements rather than linear models or expert ones.

What is more, it was identified that the provision for loan impairment amount changes as a result of transition from IAS 39 to IFRS 9 standard. The main effects are described below:

- Provision for loan impairment for corporate borrowers is increased by 286 million RUB (by 1% in provision rate);
- Provision for loan impairment for retail borrowers is increased by 578 million RUB (by 1,08% in provision rate);
- Total increase is 864 million RUB (by 1,08% in provision rate) or 5,75% of Equity.

This total increase is in line with expected industry effect (5,2% in accordance with internal PwC reports).

Application of described methodology will enable the Bank to reflect the least amount of provision charge, at the same time complying with all of the IFRS 9 requirements. Usage of simplified approaches and expert models affects the provision by more than 10% of Equity (benchmarking of banks 1 year before the transition).

Overall, the research is useful for the accounting and reporting practice of the Russian banks (in other words, useful from the standpoint of managerial application) as it explains properly certain requirements of the standard and, at the same time, demonstrates their application through the

development of own methodology for modeling expected credit losses.

IFRS 9 standard is very challenging in application, in particular for financial institutions. Currently, most Russian banks do not collect the amount of credit information required by the standard. Russian banks need to significantly modify their current credit and information systems in order to gather the required information.

On the date of initial application, management is required to disclose information that would permit the reconciliation of the ending impairment allowances in accordance with IAS 39 or the provisions in accordance with IAS 37 to the opening loss allowances determined in accordance with IFRS 9. For financial assets, this disclosure should be provided by the related financial assets' measurement categories in accordance with IAS 39 and IFRS 9, and should show separately the effect of the changes in the measurement category on the loss allowance at that date.

Management need to build new models to determine both 12-month and lifetime ECL. This requires complex judgements (for example, definition of default, definition of low credit risk and behavioral life of revolving credit facilities). It is expected that the implementation process will require a significant amount of time before a bank will be in a position to comply with the requirements of the standard, therefore, it needs to start the process as soon as possible. The methodology developed in the current research should be useful for this purpose.

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APPENDICES

Appendix 1. Variables used for PD models for Corporate borrowers

LCB

Groups of variables	Variable
Debt ratios	Debt/EBITDA
	Debt/Net assets
	Debt/EBIT
	Debt/Revenue
	ST Debt/EBITDA
	Debt/Total Assets
Interest payable ratios	Operating income/Interest payable
	EBIT/Interest payable
Profitability ratios	Return on Net income
	Return on Operating income
	Return on capital employed
Liquidity ratios	Accounts receivable/Accounts payable
	Current ratio
	Quick ratio
Turnover ratios	Accounts payable turnover
	Inventory turnover
Absolute value indexes	EBITDA
	Equity
	Revenue
Dynamics ratios	EBITDA+Other income dynamics
	Equity dynamics

MB

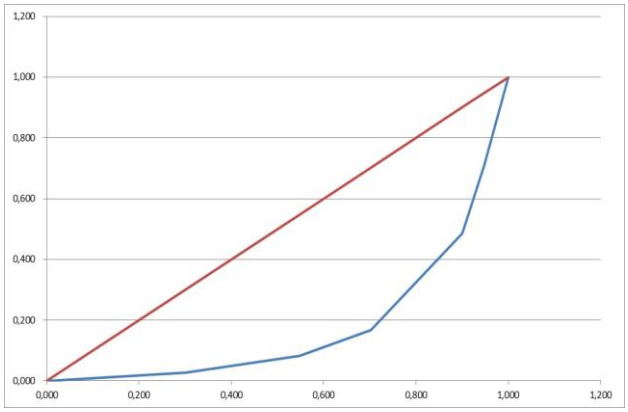
Groups of variables	Variable
Debt ratios	ST Debt/Expenses
	LT Debt/Revenue
Industry ratios	Annual growth rate of retail trade in Russia
	Industry type
Quality ratios	Age of borrower

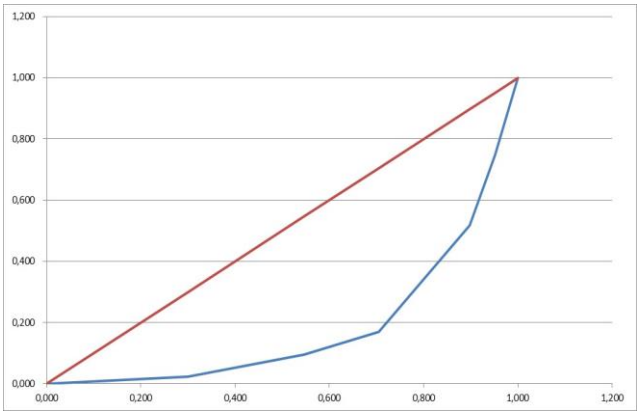
LC

Groups of variables	Variable
Debt ratios	Debt/Assets
Interest payable ratios	EBIT/Interest payable
Liquidity ratios	AR/AP
Absolute value indexes	Equity

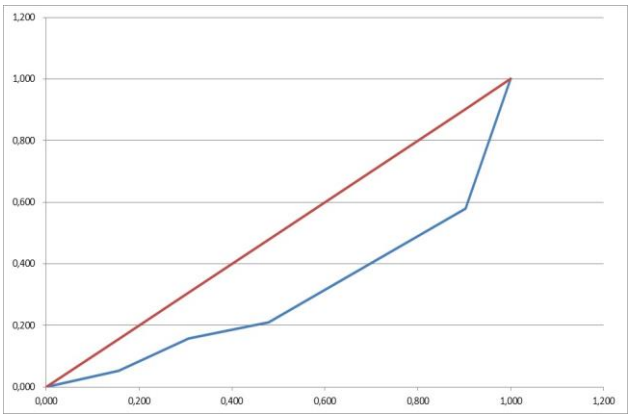
Appendix 2. ROC curves for PD models for Corporate borrowers

LCB ROC curves (test and validation samples)

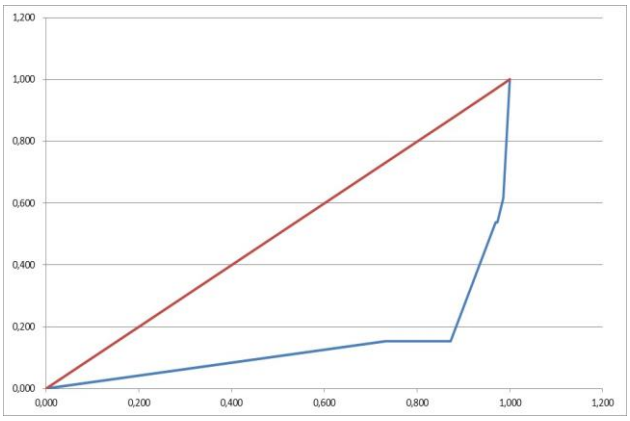




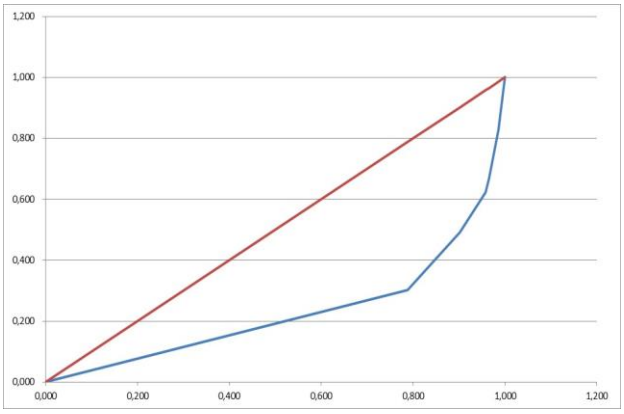
MB ROC curve

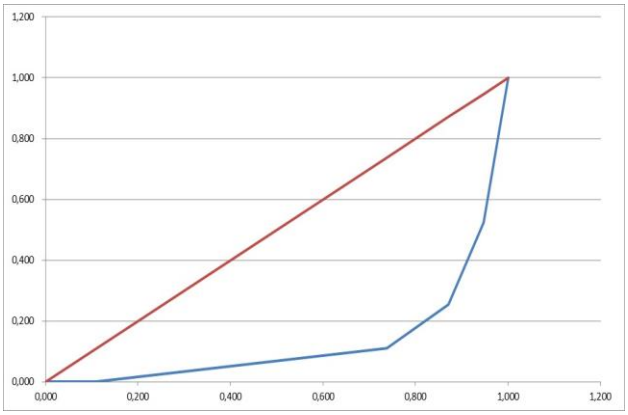


LC ROC curve

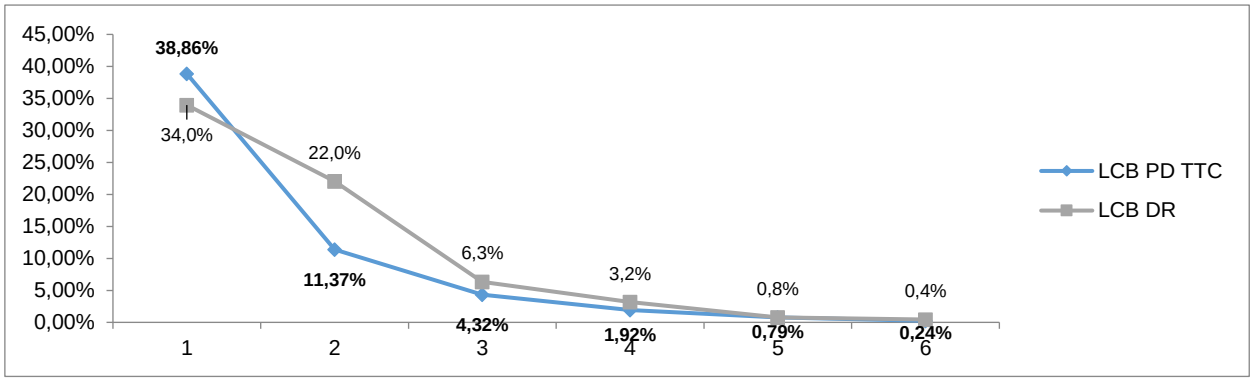


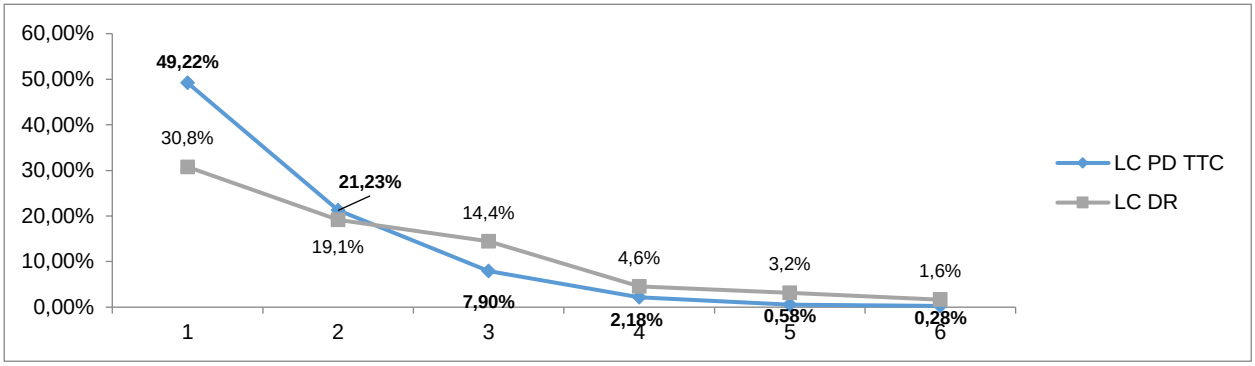
SB ROC curves (test and validation samples)

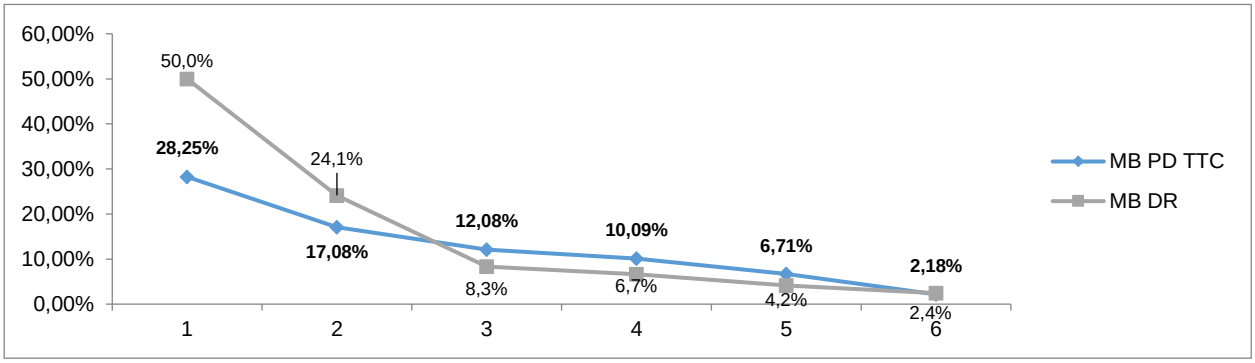


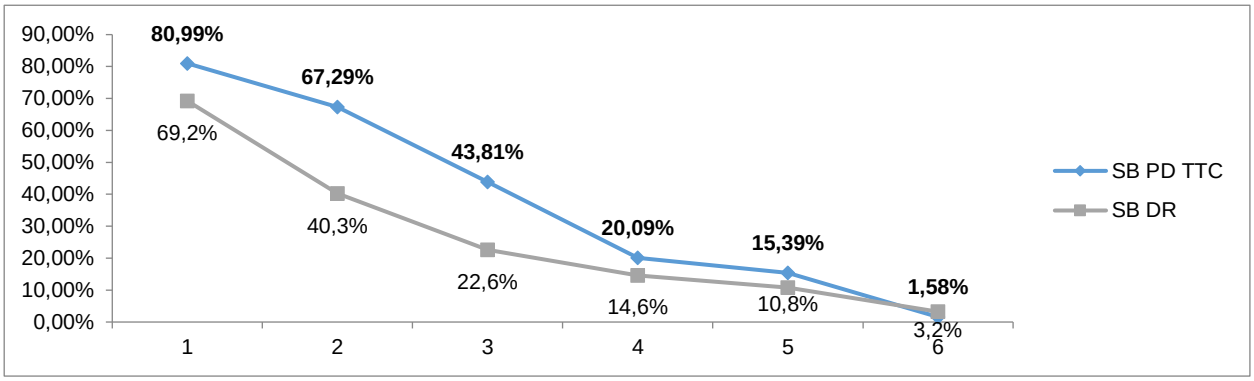


Appendix 3. Comparison between PD TTC and DR for Corporate borrowers







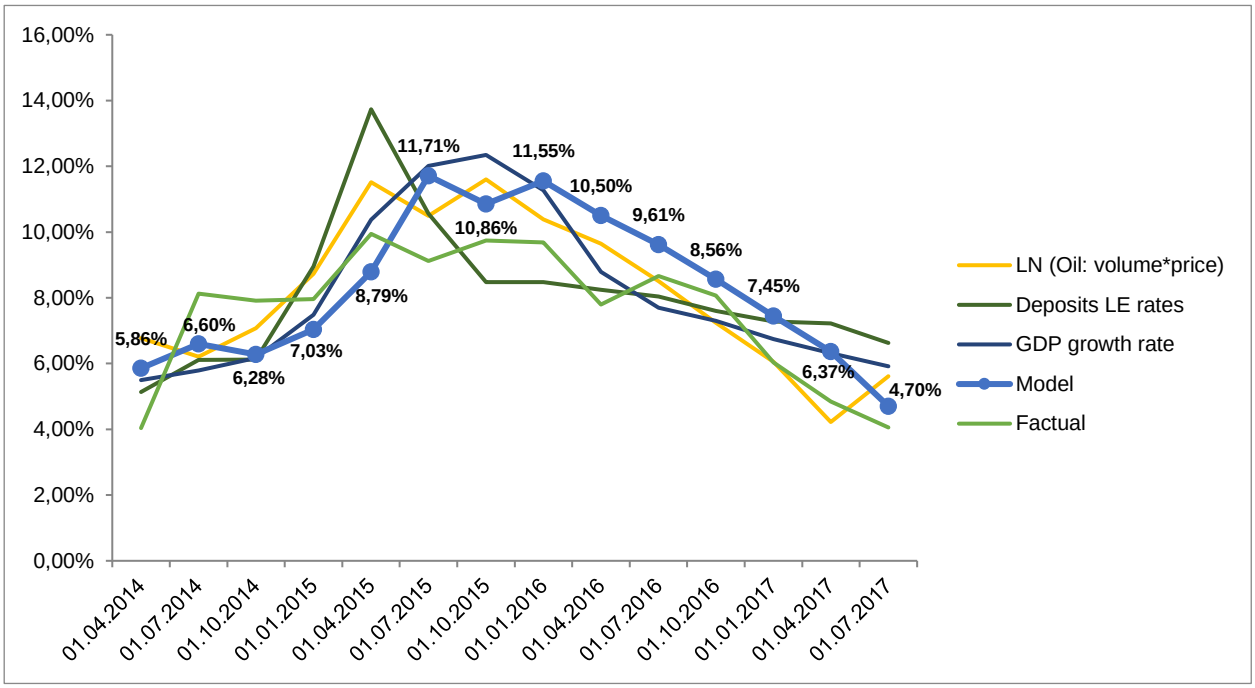


Appendix 4. Macroeconomic model for Corporate borrowers

Variable	Coefficient	P-value
LN(Oil: volume*price)	-0,69	0,002
Weighted average interest rates on deposits to legal entities	1,15	0,001
LN(GDP growth rate)	-2,74	0,014
Constant	0,47	0,000

Scenario	Probability	GDP growth rate	WA interest rates on deposits to LE	Oil production forecast in Russia (OPEC)	Oil price (USD for barrel)	DR forecast	CT	Discrepancy
Very positive	5%	101%	6,50%	100 131	55	5,47%	7,40%	-1,90%
Positive	35%	100%	8,00%		50	5,69%		-1,70%
Negative	45%	99,30%	10,50%		40	6,54%		-0,80%
Crisis	15%	98,50%	13,00%		35	7,11%		-0,30%

DR forecast	**6,27%**



Appendix 5. Lifetime PD for Corporate borrowers

LCB	1	2	3	4	5	6	7	8	9	10
Rating	PD 1	PD 2	PD 3	PD 4	PD 5	PD 6	PD 7	PD 8	PD 9	PD 10
1	0,21%	0,48%	0,73%	0,97%	1,21%	1,45%	1,69%	1,92%	2,16%	2,40%
2	0,67%	1,57%	2,34%	3,11%	3,87%	4,63%	5,38%	6,13%	6,87%	7,60%
3	1,63%	3,81%	5,66%	7,47%	9,25%	10,99%	12,71%	14,38%	16,03%	17,64%
4	3,67%	8,46%	12,41%	16,20%	19,82%	23,29%	26,60%	29,78%	32,81%	35,71%
5	9,66%	21,45%	30,38%	38,29%	45,31%	51,52%	57,04%	61,92%	66,25%	70,09%
6	33,03%	62,61%	77,14%	86,02%	91,45%	94,77%	96,80%	98,05%	98,81%	99,27%

LC	1	2	3	4	5	6	7	8	9	10
Rating	PD 1	PD 2	PD 3	PD 4	PD 5	PD 6	PD 7	PD 8	PD 9	PD 10
1	0,23%	0,55%	0,82%	1,10%	1,37%	1,64%	1,91%	2,18%	2,45%	2,72%
2	0,49%	1,15%	1,72%	2,29%	2,85%	3,41%	3,97%	4,52%	5,07%	5,62%
3	1,85%	4,32%	6,40%	8,44%	10,44%	12,40%	14,31%	16,18%	18,00%	19,79%
4	6,71%	15,18%	21,88%	28,05%	33,73%	38,97%	43,79%	48,23%	52,32%	56,09%
5	18,05%	37,96%	51,13%	61,51%	69,68%	76,12%	81,19%	85,18%	88,33%	90,81%
6	41,84%	74,21%	86,90%	93,35%	96,62%	98,29%	99,13%	99,56%	99,78%	99,89%

MB	1	2	3	4	5	6	7	8	9	10
Rating	PD 1	PD 2	PD 3	PD 4	PD 5	PD 6	PD 7	PD 8	PD 9	PD 10
1	1,85%	4,30%	6,39%	8,42%	10,42%	12,37%	14,27%	16,14%	17,96%	19,75%
2	5,70%	12,97%	18,81%	24,26%	29,34%	34,08%	38,51%	42,63%	46,48%	50,07%
3	8,58%	19,17%	27,33%	34,66%	41,26%	47,19%	52,52%	57,31%	61,62%	65,49%
4	10,27%	22,71%	32,05%	40,26%	47,48%	53,82%	59,40%	64,31%	68,62%	72,41%
5	14,52%	31,25%	42,99%	52,73%	60,80%	67,50%	73,05%	77,66%	81,47%	84,64%
6	24,01%	48,51%	63,06%	73,49%	80,98%	86,35%	90,21%	92,97%	94,96%	96,38%

SB	1	2	3	4	5	6	7	8	9	10
Rating	PD 1	PD 2	PD 3	PD 4	PD 5	PD 6	PD 7	PD 8	PD 9	PD 10
1	1,35%	3,14%	4,68%	6,18%	7,67%	9,13%	10,57%	11,99%	13,38%	14,75%
2	13,08%	28,42%	39,44%	48,76%	56,65%	63,32%	68,97%	73,74%	77,78%	81,20%
3	17,08%	36,14%	48,97%	59,22%	67,41%	73,96%	79,19%	83,37%	86,71%	89,38%
4	37,24%	68,43%	82,26%	90,03%	94,40%	96,85%	98,23%	99,01%	99,44%	99,69%
5	57,20%	89,30%	96,50%	98,86%	99,63%	99,88%	99,96%	99,99%	100,00%	100,00%
6	68,84%	96,38%	99,31%	99,87%	99,98%	100,00%	100,00%	100,00%	100,00%	100,00%

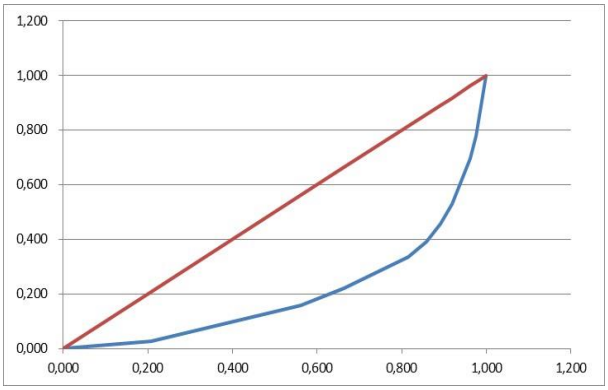
Appendix 6. LGD for SB segment

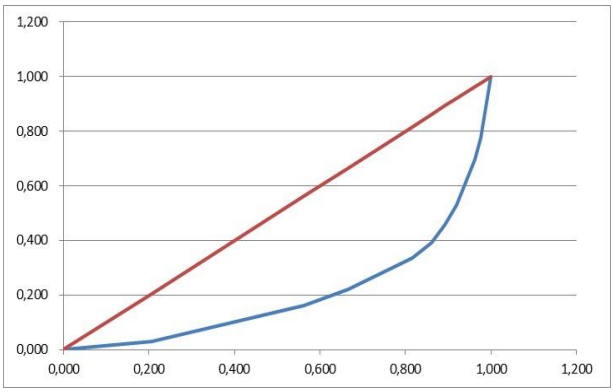
SB by generation of issue

Year of default	Exposure at default	1 year	2 year	3 year	4 year	5 year
2008	7 083	5 953	-	-	-	-
2009	8 119	7 068	-	-	-	-
2010	2 592	2 263	-	-	-	-
2011	6 492	1 082	1 359	632	-	-
2012	34 885	7 757	7 775	108	25	458
2013	108 727	16 615	16 240	865	5	-
2014	269 172	43 192	12 950	5 455	-	-
2015	188 233	28 690	16 232	-	-	-
2016	59 814	9 811	-	-	-	-
2017	14 883	-	-	-	-	-
Total	**700 000**	**122 431**	**54 557**	**7 060**	**30**	**458**
	Marginal RR	17,87%	8,72%	1,62%	0,02%	0,77%
	Cumulative RR	**29,00%**				
	Cumulative LGD	**71,00%**				

Appendix 7. Results of behavioral model without delays

Gini (test) – 61,32%; Gini (validation) – 61,78%



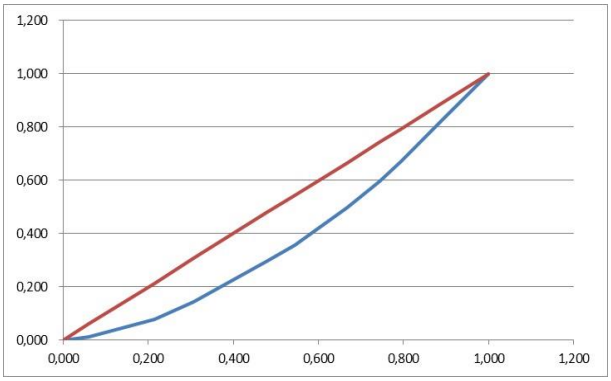


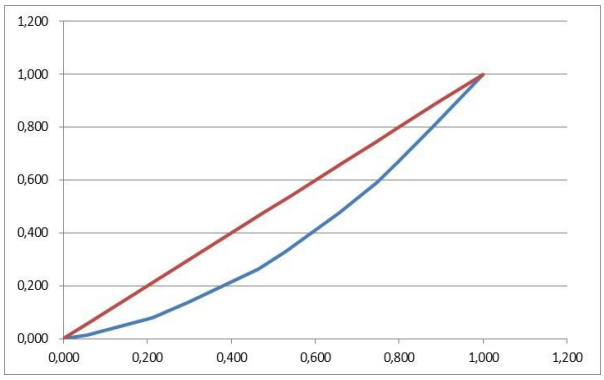
Results

Score range	Default rate	Number of Good	Number of Bad	Total	Share of sample	Share of Good	Share of Bad	WOE	IV
more than 88	0,37%	31 069	115	31 184	20,50%	20,92%	3,19%	188,10	33,34%
(74;88]	0,87%	53 924	472	54 396	35,75%	36,30%	13,09%	102,03	23,69%
(70;74]	1,29%	15 547	203	15 750	10,35%	10,47%	5,63%	62,04	3,00%
(62;70]	1,89%	22 729	438	23 167	15,23%	15,30%	12,14%	23,12	0,73%
(59;62]	2,99%	6 384	197	6 581	4,33%	4,30%	5,46%	- 23,97	0,28%
(56;59]	4,56%	4 650	222	4 872	3,20%	3,13%	6,15%	- 67,61	2,04%
(52;56]	6,84%	3 729	274	4 003	2,63%	2,51%	7,60%	- 110,73	5,63%
(42;52]	9,03%	5 987	594	6 581	4,33%	4,03%	16,47%	- 140,76	17,51%
(37;42]	14,31%	1 712	286	1 998	1,31%	1,15%	7,93%	- 192,86	13,07%
less than 37	22,25%	2 816	806	3 622	2,38%	1,90%	22,35%	- 246,70	50,45%

Appendix 8. Results of behavioral model with delays

Gini (test) – 61,73%; Gini (validation) – 63,28%

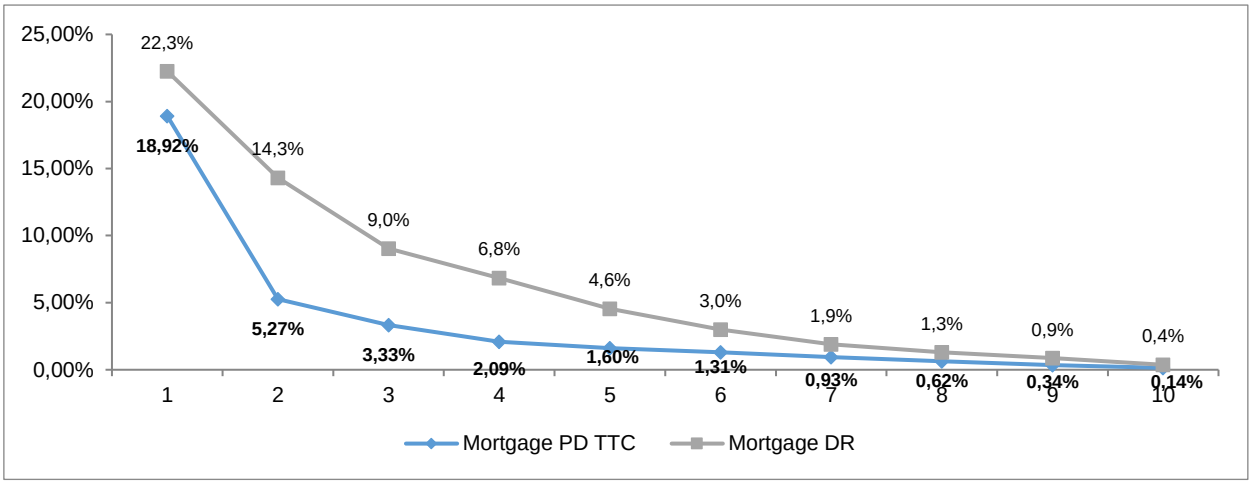


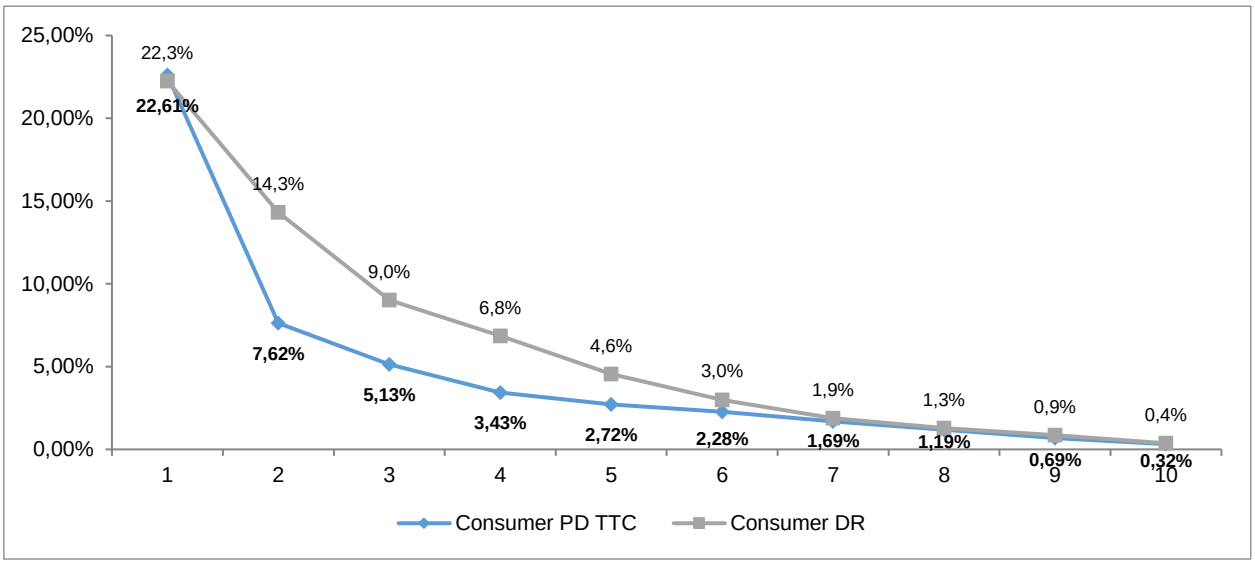


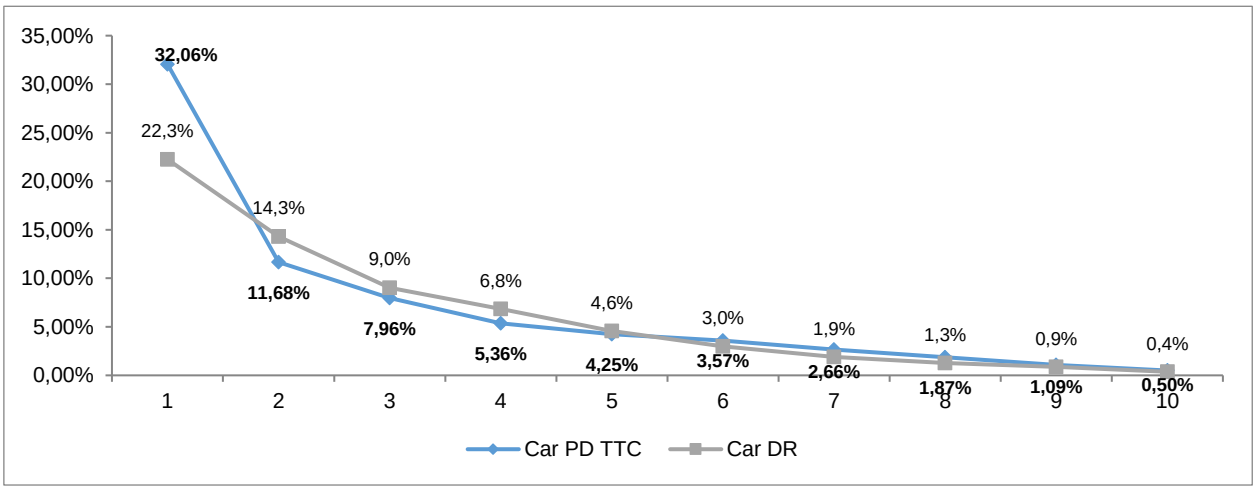
Results

Score range	Default rate	Number of Good	Number of Bad	Total	Share of sample	Share of Good	Share of Bad	WOE	IV
more than 92	12,24%	208	29	237	6,02%	13,10%	1,23%	236,26	28,03%
(80;92]	25,54%	449	154	603	15,31%	28,27%	6,55%	146,24	31,77%
(74;80]	42,74%	209	156	365	9,27%	13,16%	6,64%	68,48	4,47%
(64;74]	52,33%	327	359	686	17,42%	20,59%	15,27%	29,90	1,59%
(59;64]	55,78%	111	140	251	6,37%	6,99%	5,95%	16,03	0,17%
(47;59]	67,91%	155	328	483	12,26%	9,76%	13,95%	- 35,72	1,50%
(35;47]	78,67%	64	236	300	7,62%	4,03%	10,04%	- 91,26	5,48%
(30;35]	87,13%	26	176	202	5,13%	1,64%	7,49%	- 152,00	8,89%
(24;30]	94,65%	20	354	374	9,49%	1,26%	15,06%	- 248,12	34,24%
less than 24	95,66%	19	419	438	11,12%	1,20%	17,82%	- 270,11	44,91%

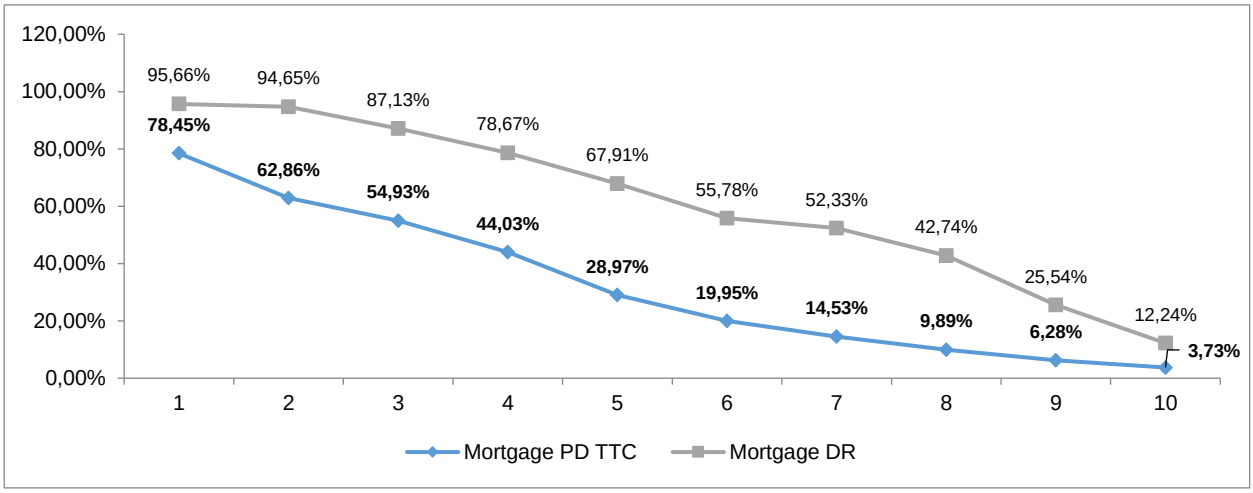
Appendix 9. Comparison between PD TTC and DR for retail loans with delays

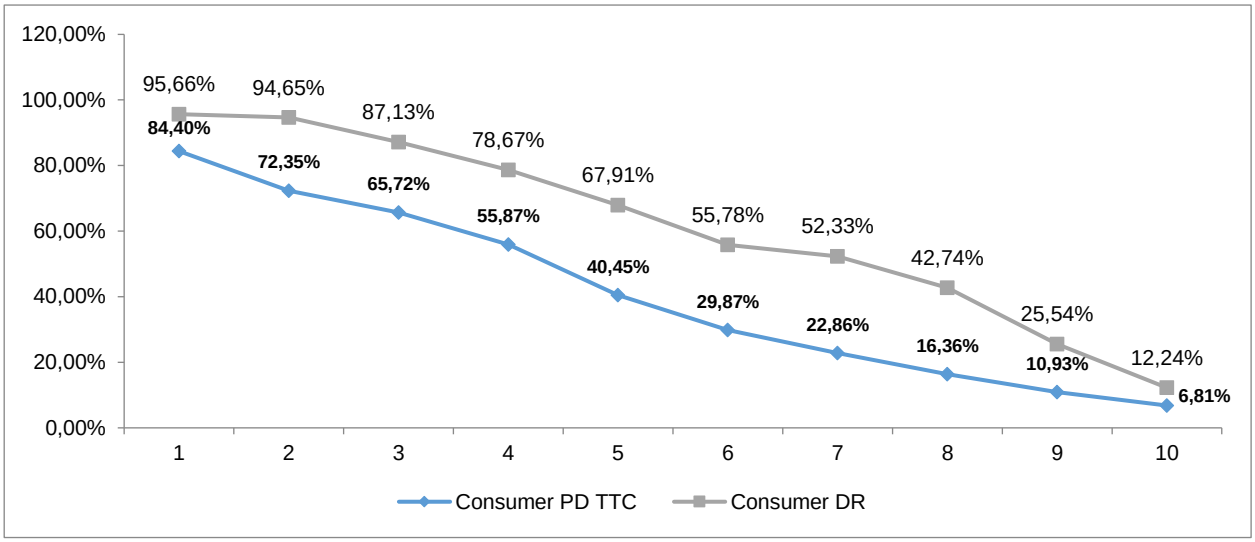


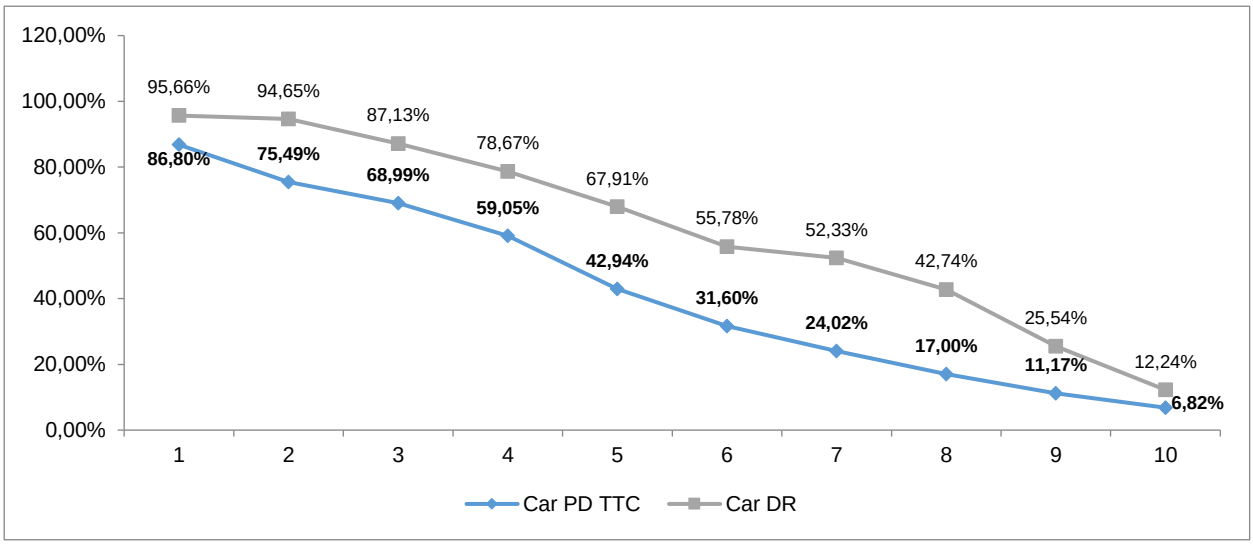




Appendix 10. Comparison between PD TTC and DR for retail loans without delays





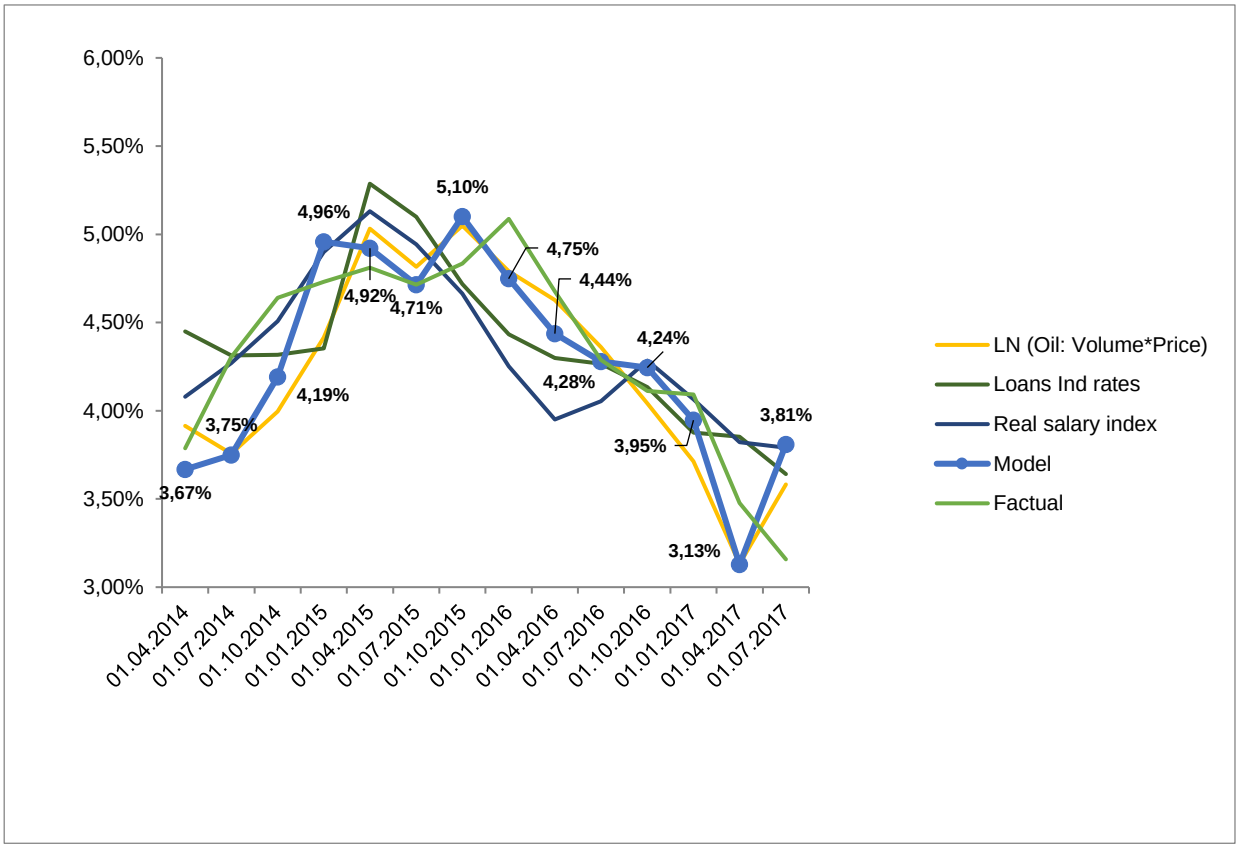


Appendix 11. Macroeconomic model for Retail borrowers

Variable	Coefficient	P-value
LN(Oil: volume*price)	0,43	0,001
LN(Loans Ind rates)	-1,13	0,027
Social income index	-0,05	0,031
Constant	7,06	0,000

Scenario	Probability	Social income index	LN(Loans Ind rates)	Oil production forecast in Russia (OPEC)	Oil price (USD for barrel)	DR forecast	CT	Discrepancy
Very positive	5%	103%	2,71%	100 131	55	4,04%	4,10%	-0,06%
Positive	35%	102%	2,83%		50	3,85%		-0,25%
Negative	45%	100,00%	2,94%		40	4,02%		-0,08%
Crisis	15%	98,50%	3,00%		35	4,10%		0,00%

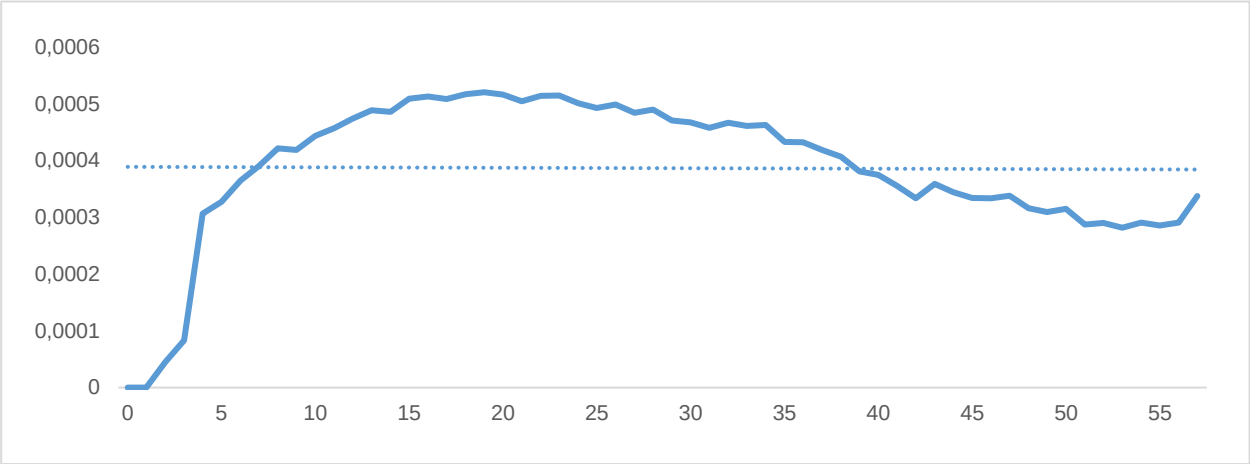
DR forecast	**3,97%**



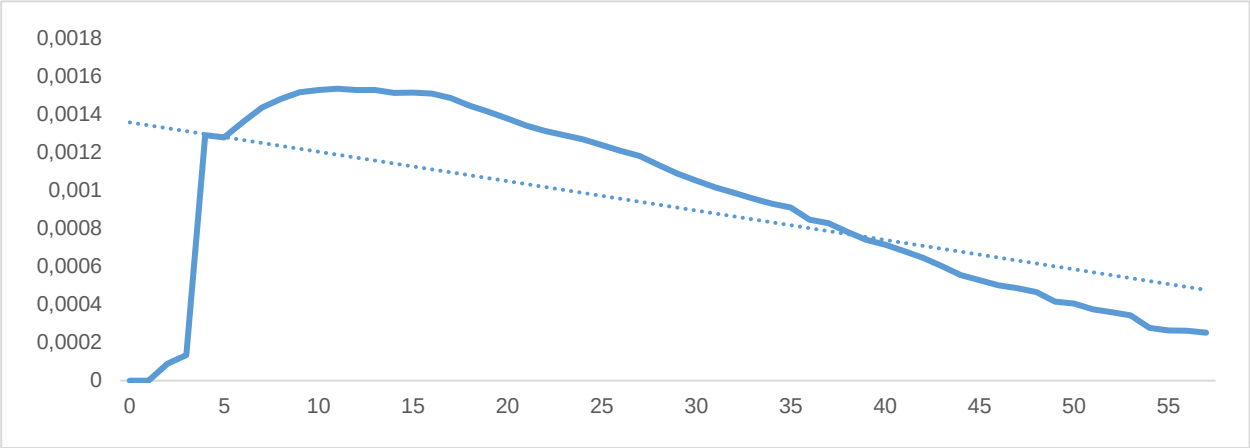
Appendix 12. Lifecycle curves (Incremental)

Without delays

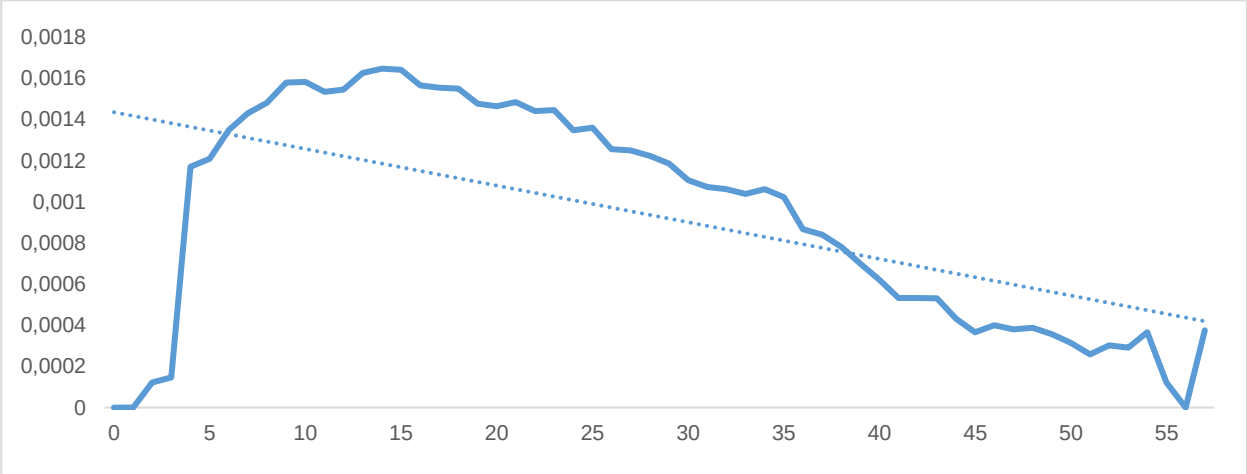
Mortgage



Consumer

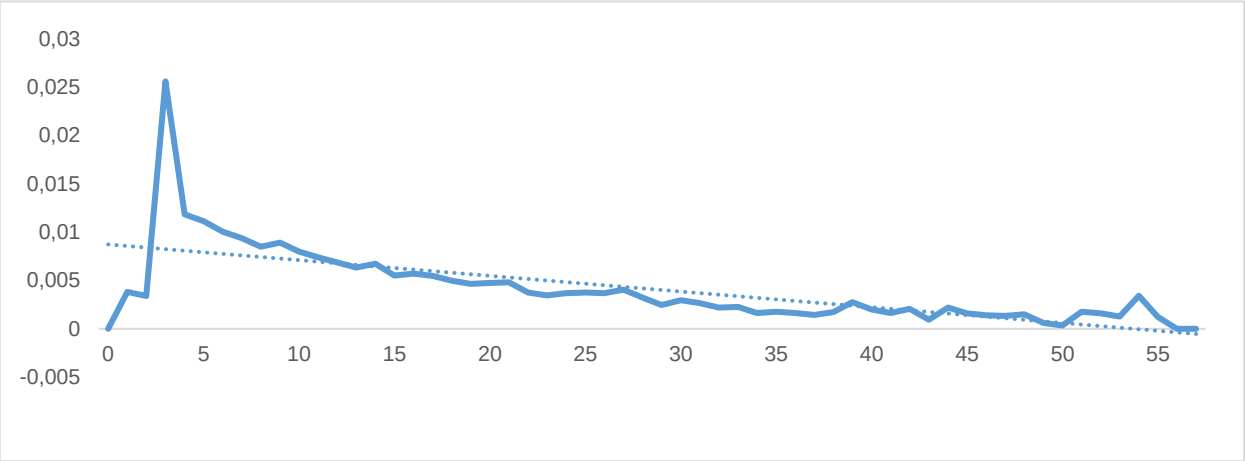


Car



Delay up to 1 month

Mortgage



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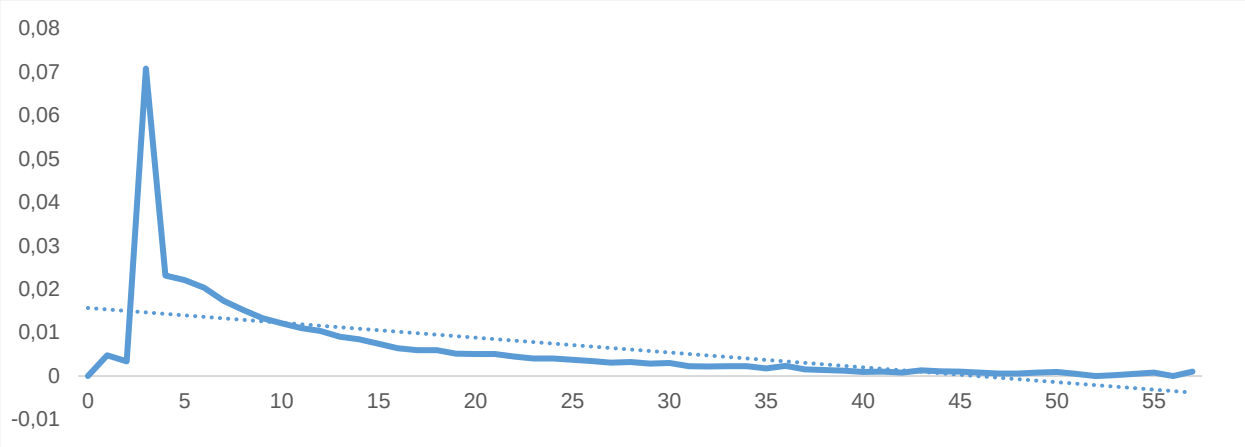

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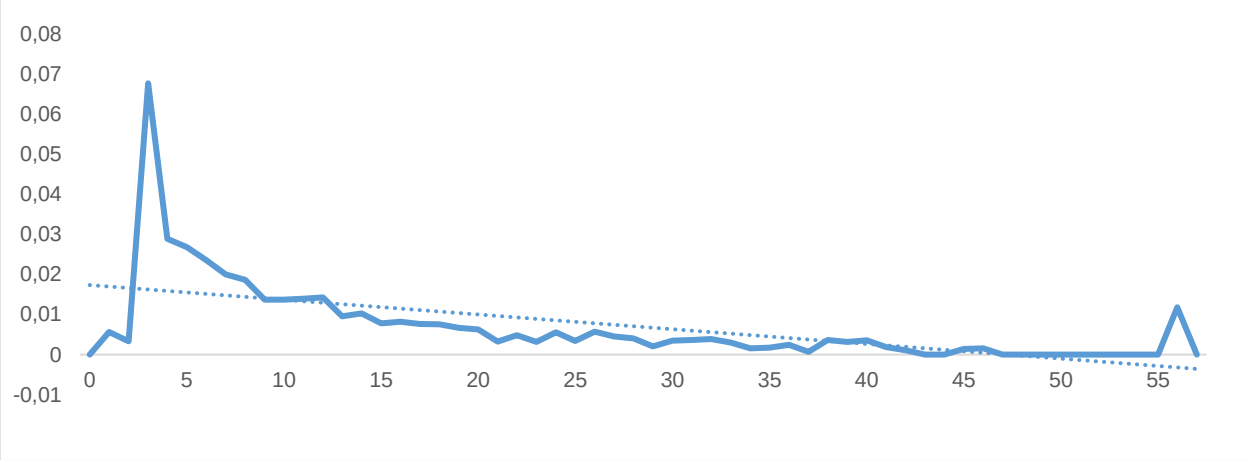
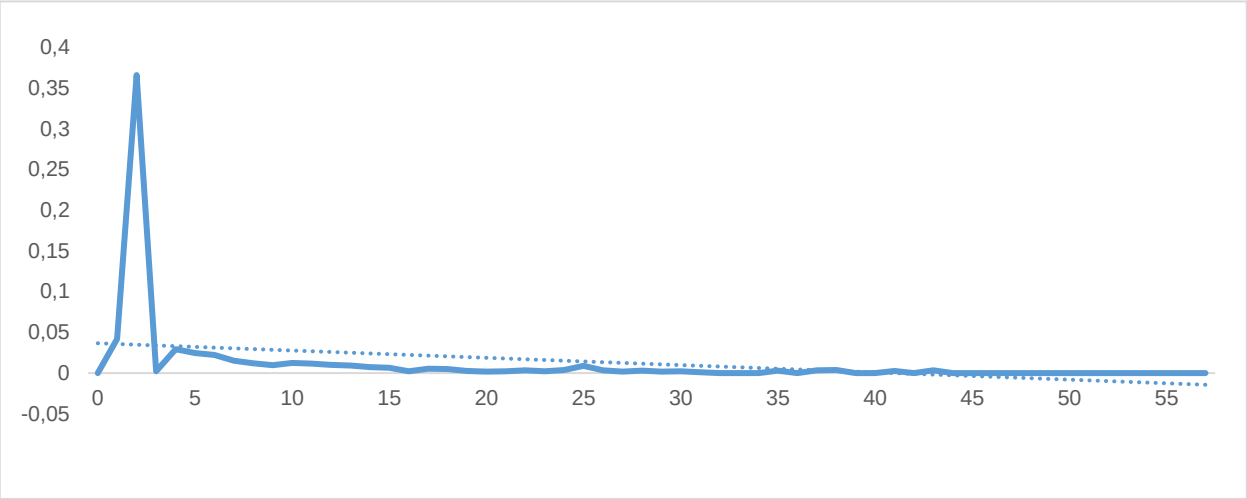
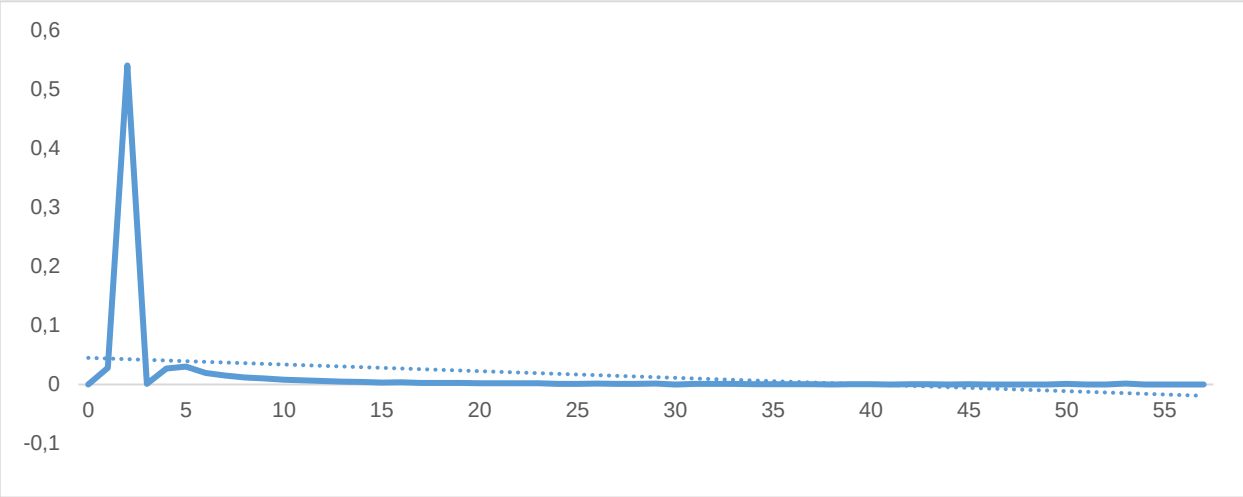


Delay from 1 to 2 months

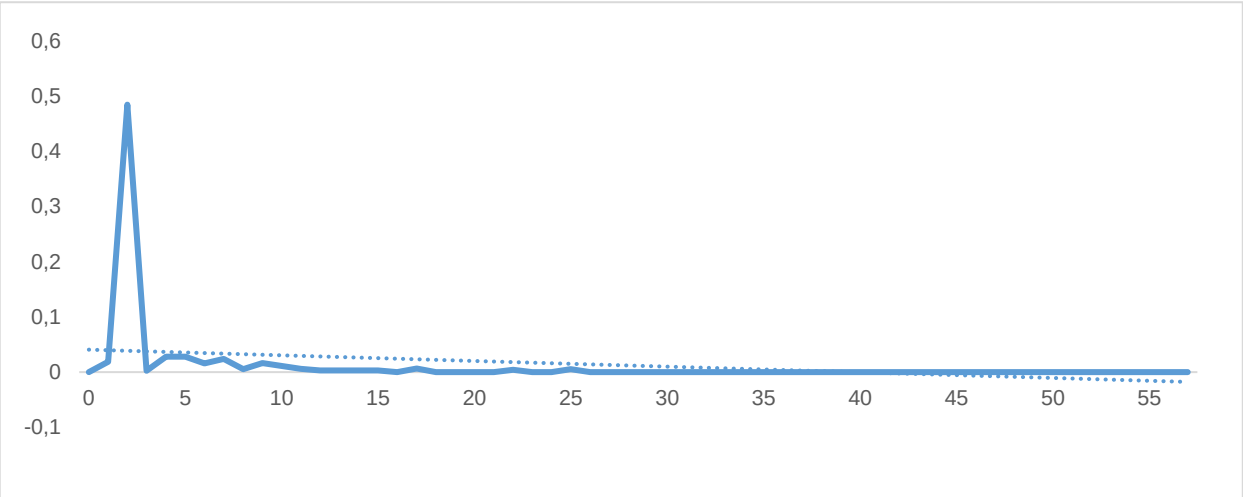
Mortgage



Consumer

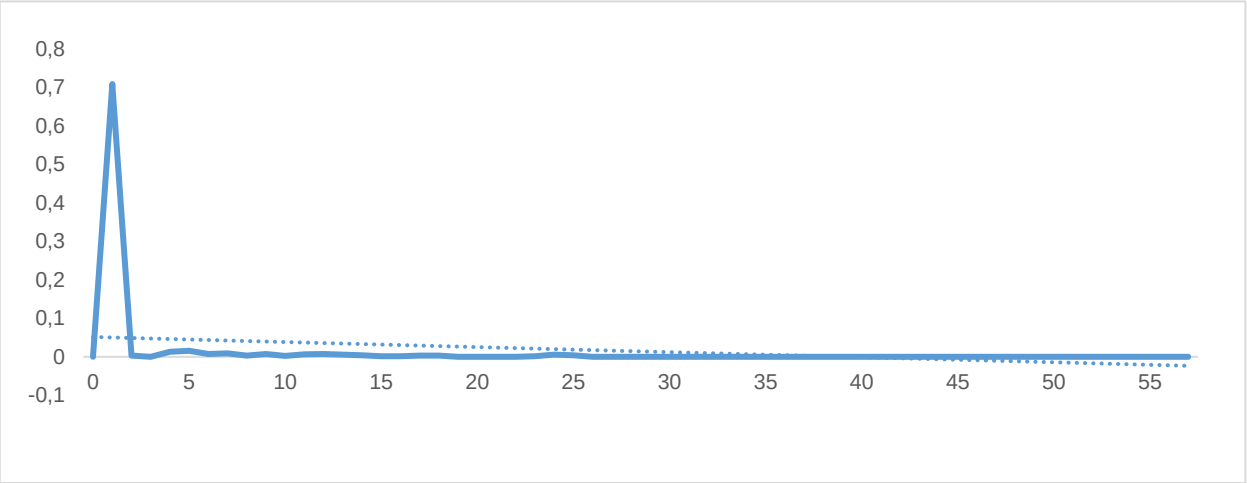


Car

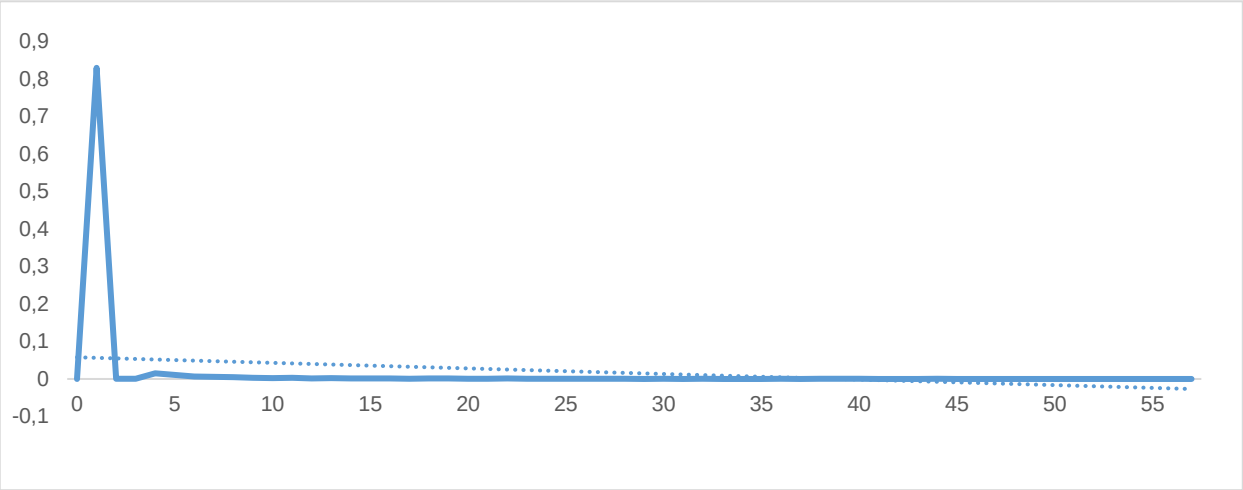


Delay from 2 to 3 months

Mortgage



Consumer



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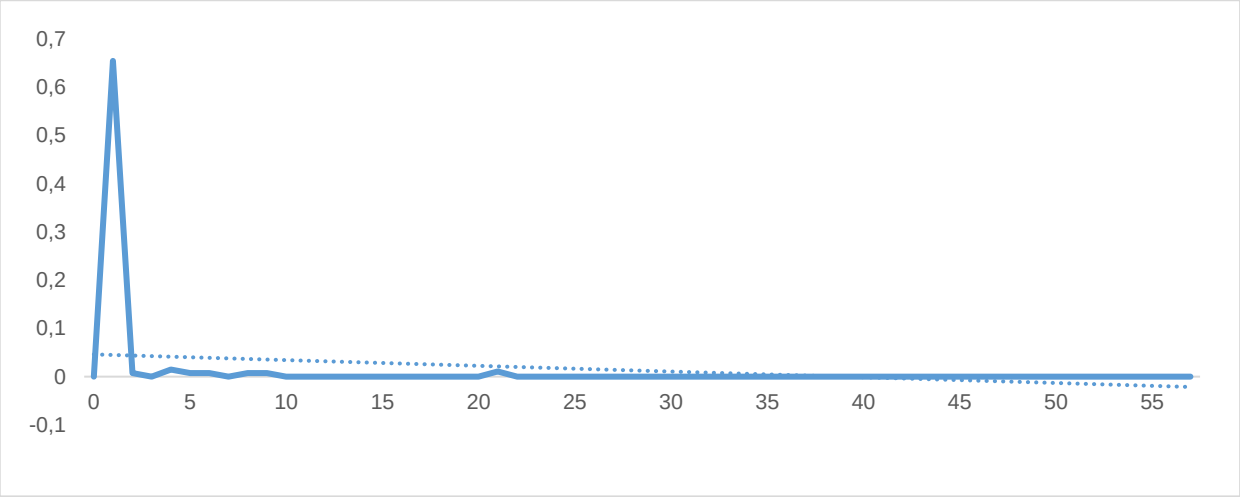
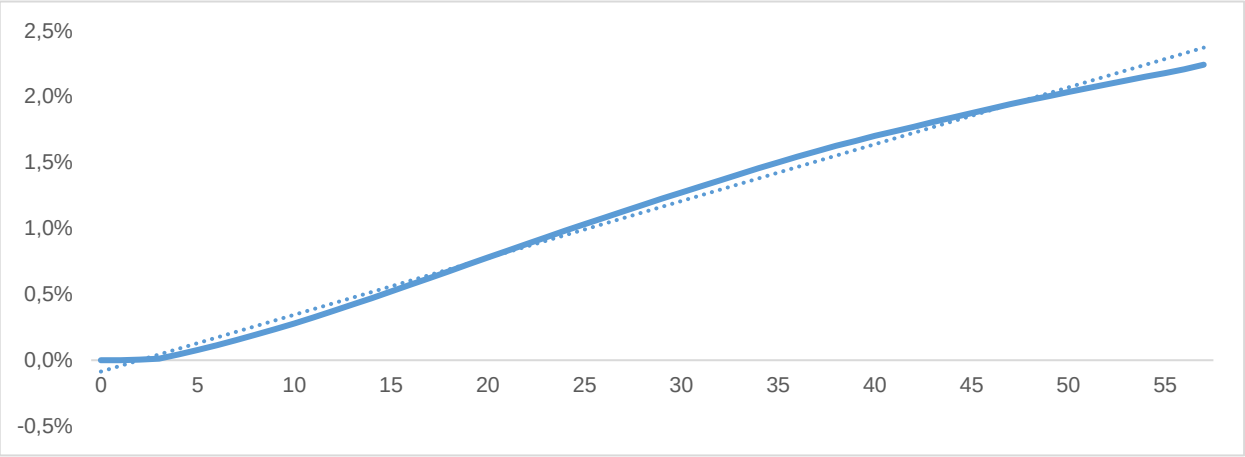


Appendix 13. Lifecycle curves (Cumulative)

Without delays

Mortgage



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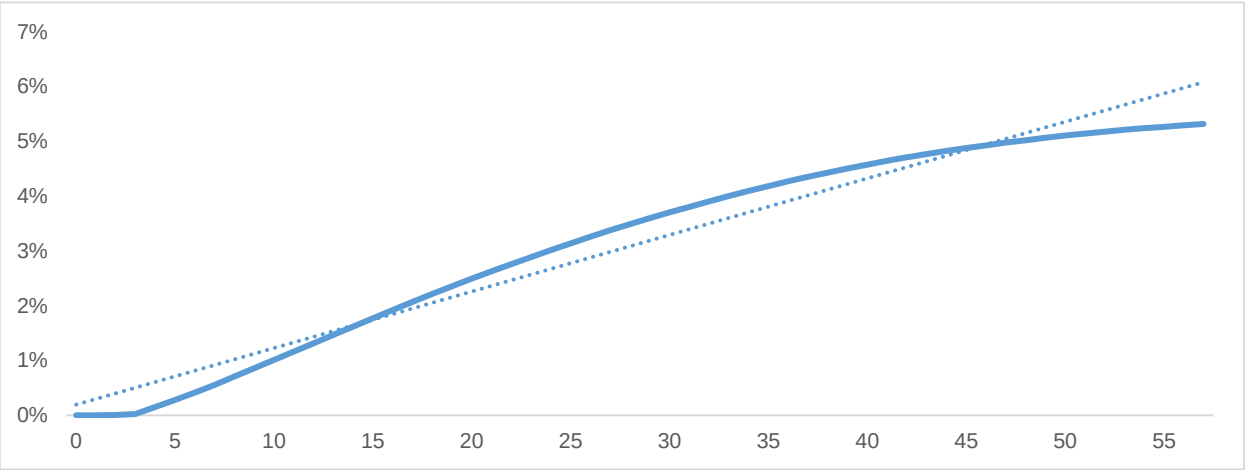

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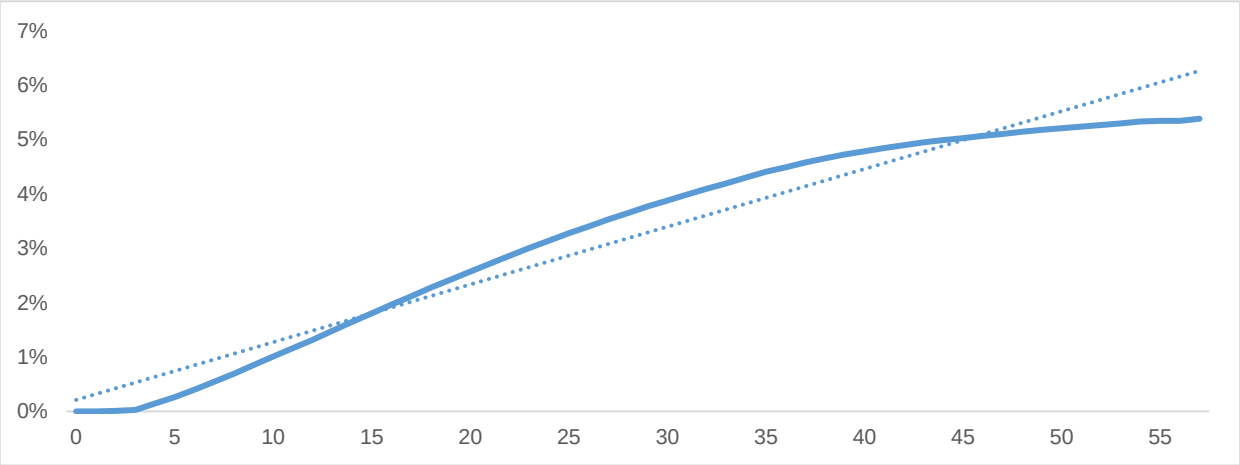
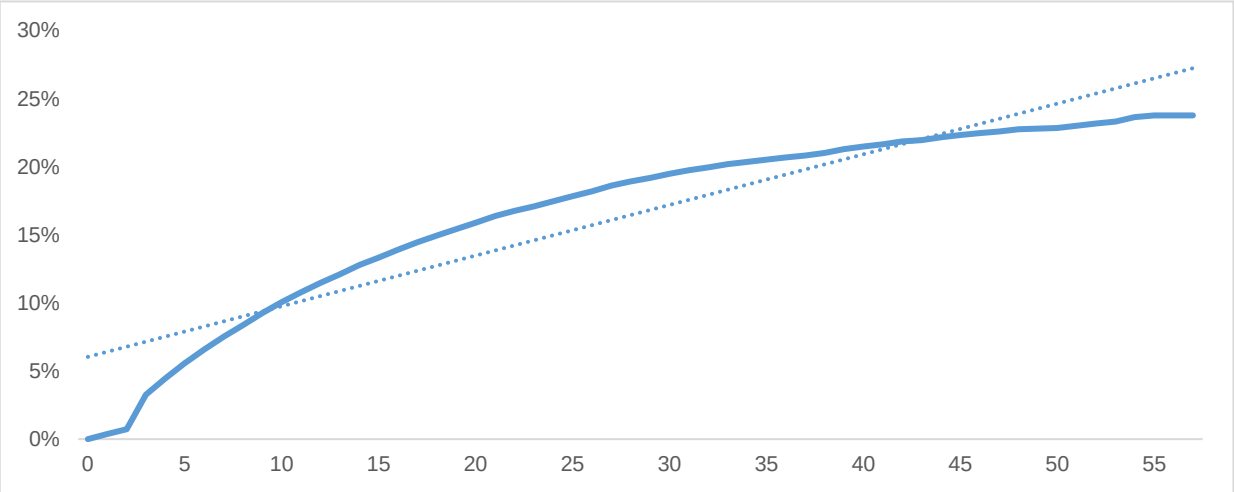


Delay up to 1 month

Mortgage



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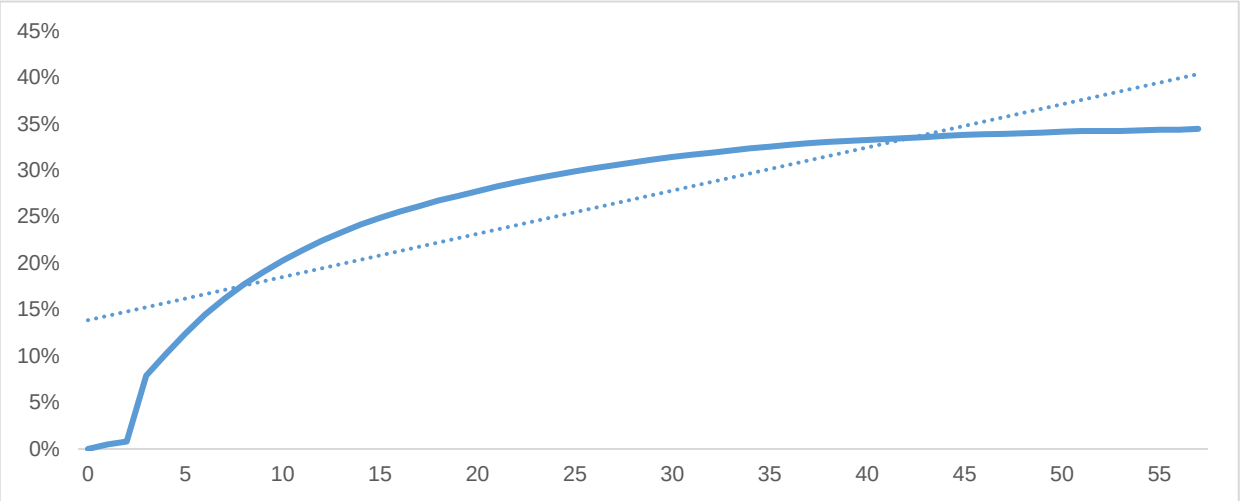

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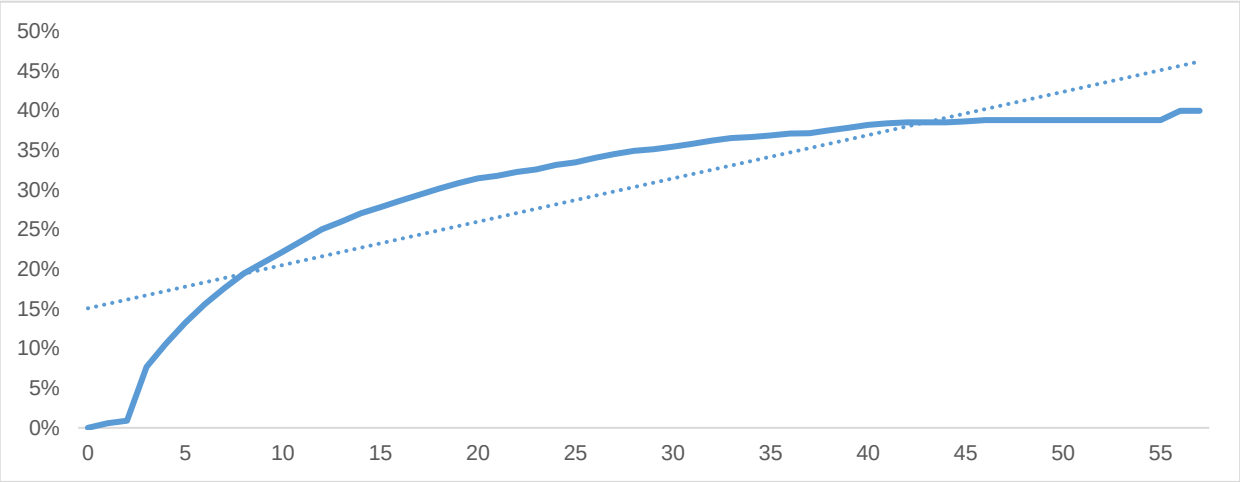
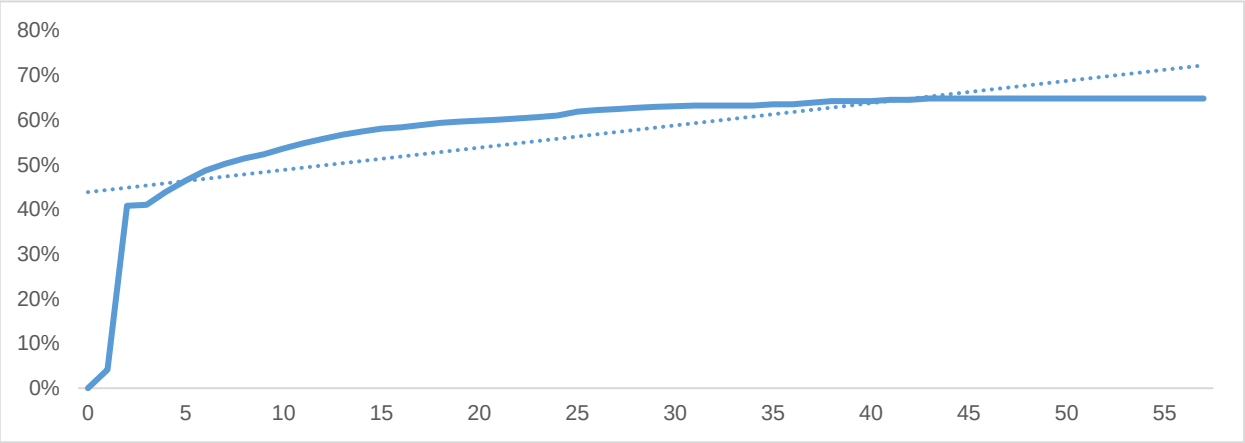
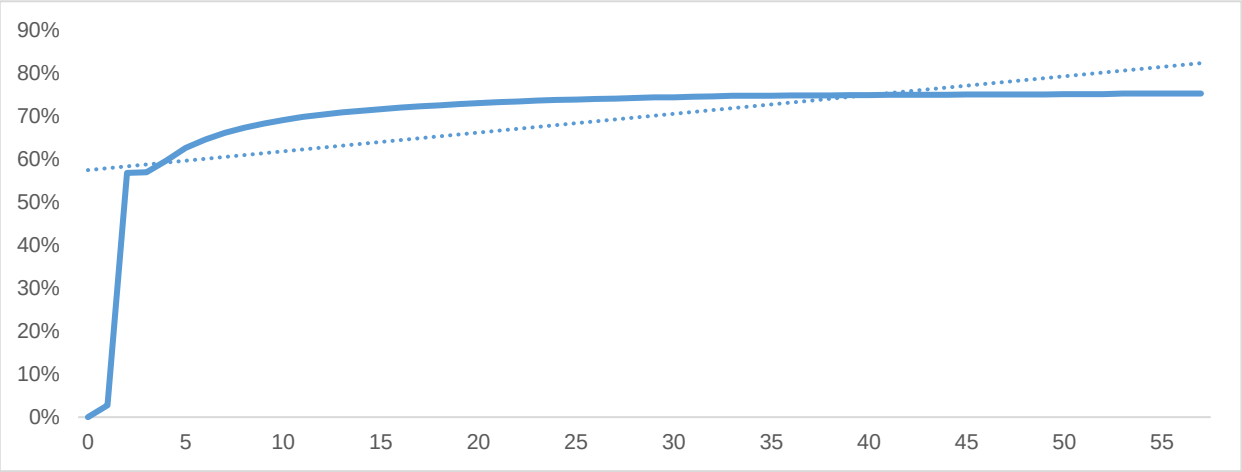


Delay from 1 to 2 months

Mortgage



Consumer



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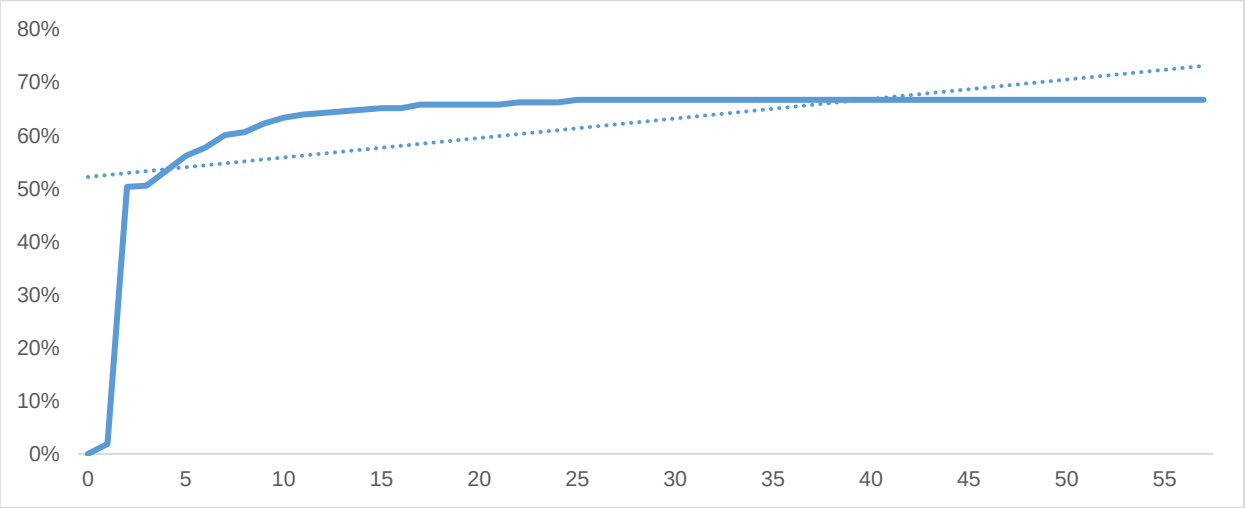
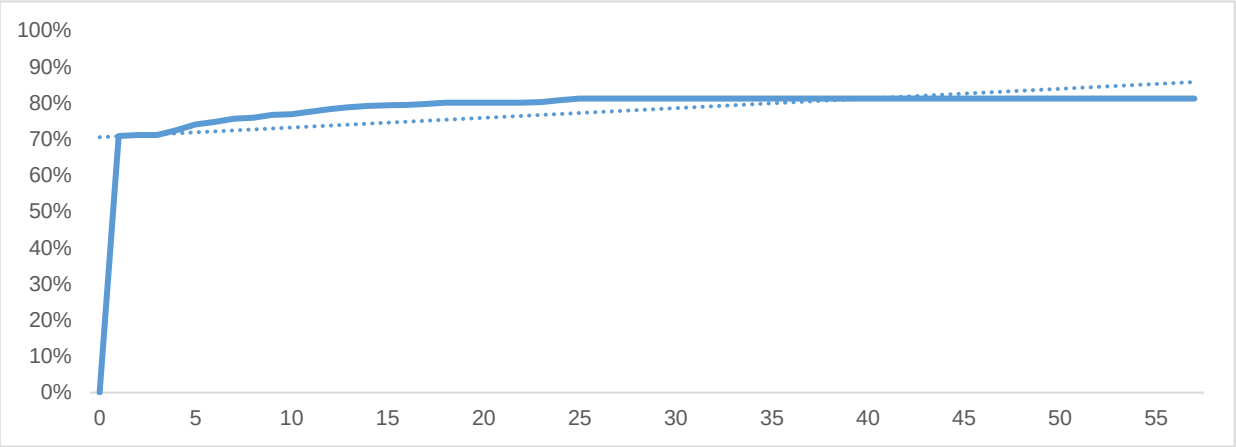
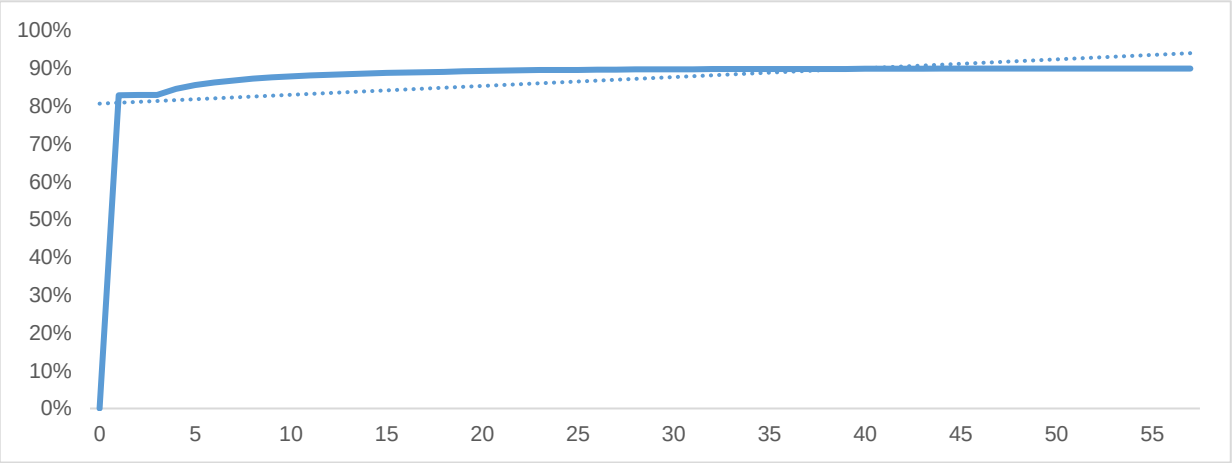


Delay from 2 to 3 months

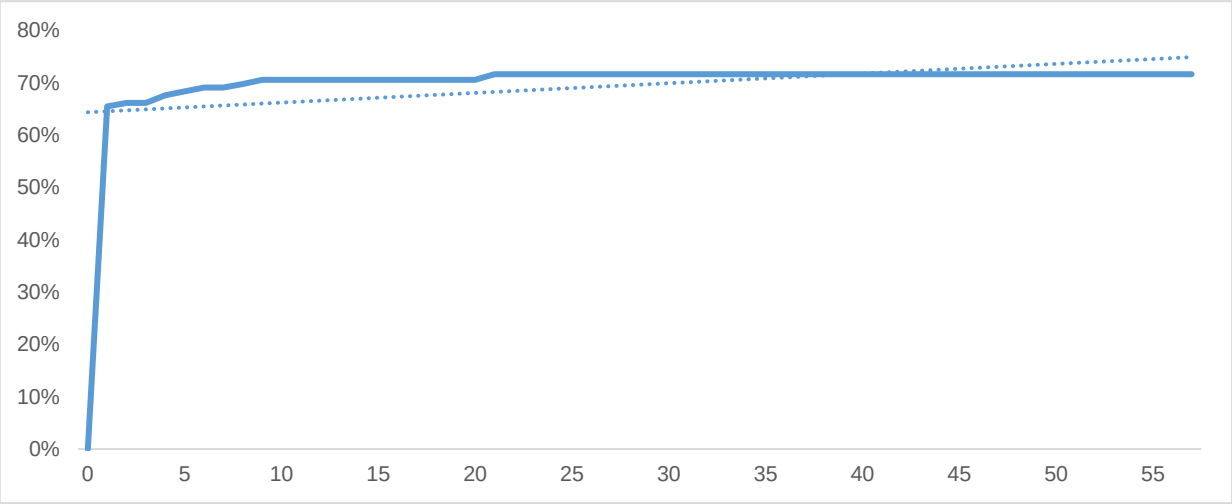
Mortgage



Consumer



Car



Appendix 14. LGD for Retail borrowers

Recovery rate (Without delays)

Mortgage RR		Horizon					
		6m	12m	24m	36m	48m	60m
Averaging period	All statistics	12,10%	23,90%	41,20%	54,20%	58,30%	69,40%
	48m	12,20%	23,90%	41,20%	54,30%	58,40%	69,40%
	36m	10,90%	22,50%	39,40%	52,40%	56,60%	67,60%
	24m	8,60%	19,90%	35,90%	48,40%	52,50%	63,60%
	12m	7,80%	23,30%	42,70%	55,50%	60,00%	71,10%
	6m	6,50%	21,20%	39,50%	50,70%	56,00%	67,10%

Consumer RR		Horizon					
		6m	12m	24m	36m	48m	60m
Averaging period	All statistics	7,60%	13,30%	21,90%	25,40%	27,00%	27,70%
	48m	7,80%	13,50%	22,10%	25,60%	27,20%	27,90%
	36m	8,90%	14,90%	23,70%	27,20%	28,80%	29,50%
	24m	10,70%	18,10%	27,70%	31,30%	32,80%	33,60%
	12m	12,30%	20,10%	33,30%	37,40%	39,00%	39,70%
	6m	13,20%	22,30%	32,90%	37,70%	39,40%	40,10%

Credit cards RR		Horizon					
		6m	12m	24m	36m	48m	60m
Averaging period	All statistics	14,00%	23,20%	31,80%	35,50%	37,30%	37,90%
	48m	14,00%	23,20%	31,80%	35,50%	37,30%	37,80%
	36m	14,30%	23,60%	32,30%	36,00%	37,80%	38,30%
	24m	15,20%	24,90%	34,00%	37,80%	39,60%	40,10%
	12m	16,50%	26,30%	36,50%	40,70%	42,50%	43,00%
	6m	16,40%	27,50%	37,90%	42,50%	44,40%	44,90%

Car	Value
Recovery	39,60%

Loss given default (Without delays)

Mortgage LGD		Horizon					
		6m	12m	24m	36m	48m	60m
Averaging period	All statistics	87,90%	76,10%	58,80%	45,80%	41,70%	30,60%
	48m	87,80%	76,10%	58,80%	45,70%	41,60%	30,60%
	36m	89,10%	77,50%	60,60%	47,60%	43,40%	32,40%
	24m	91,40%	80,10%	64,10%	51,60%	47,50%	36,40%
	12m	92,20%	76,70%	57,30%	44,50%	40,00%	28,90%
	6m	93,50%	78,80%	60,50%	49,30%	44,00%	32,90%

Consumer LGD		Horizon					
		6m	12m	24m	36m	48m	60m
Averaging period	All statistics	92,40%	86,70%	78,10%	74,60%	73,00%	72,30%
	48m	92,20%	86,50%	77,90%	74,40%	72,80%	72,10%
	36m	91,10%	85,10%	76,30%	72,80%	71,20%	70,50%
	24m	89,30%	81,90%	72,30%	68,70%	67,20%	66,40%
	12m	87,70%	79,90%	66,70%	62,60%	61,00%	60,30%
	6m	86,80%	77,70%	67,10%	62,30%	60,60%	59,90%

Credit cards LGD		Horizon					
		6m	12m	24m	36m	48m	60m
Averaging period	All statistics	86,00%	76,80%	68,20%	64,50%	62,70%	62,10%
	48m	86,00%	76,80%	68,20%	64,50%	62,70%	62,20%
	36m	85,70%	76,40%	67,70%	64,00%	62,20%	61,70%
	24m	84,80%	75,10%	66,00%	62,20%	60,40%	59,90%
	12m	83,50%	73,70%	63,50%	59,30%	57,50%	57,00%
	6m	83,60%	72,50%	62,10%	57,50%	55,60%	55,10%

Car	Value
LGD	60,40%

Recovery rate and Loss given default (with delays)

Mortgage

Delay bucket	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Recovery	60,0%	60,0%	60,0%	60,0%	58,5%	57,3%	56,1%	54,6%	53,4%	52,3%	50,5%	48,6%	46,6%	44,5%	39,7%	36,8%	33,9%	32,9%	29,5%	27,6%	25,9%	24,9%	23,5%	21,6%
LGD	40,0%	40,0%	40,0%	40,0%	41,5%	42,7%	43,9%	45,4%	46,6%	47,7%	49,5%	51,4%	53,4%	55,5%	60,3%	63,2%	66,1%	67,1%	70,5%	72,4%	74,1%	75,1%	76,5%	78,4%

Consumer

Delay bucket	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Recovery	33,3%	33,3%	33,3%	33,3%	30,6%	28,6%	26,8%	24,9%	22,9%	21,0%	19,5%	17,9%	16,7%	15,7%	14,2%	13,2%	12,2%	11,2%	9,9%	8,8%	8,1%	7,1%	6,3%	5,2%
LGD	66,7%	66,7%	66,7%	66,7%	69,4%	71,4%	73,2%	75,1%	77,1%	79,0%	80,5%	82,1%	83,3%	84,3%	85,8%	86,8%	87,8%	88,8%	90,1%	91,2%	91,9%	92,9%	93,7%	94,8%

Credit cards

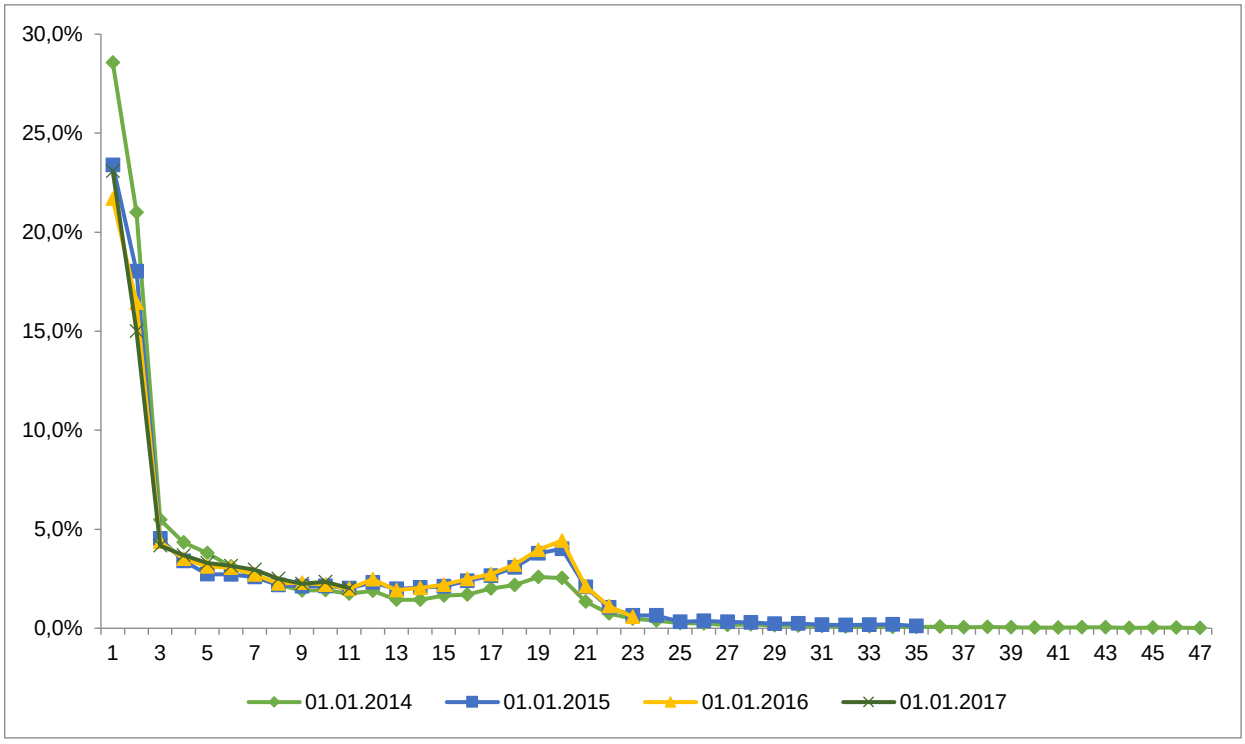
Delay bucket	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Recovery	36,5%	36,5%	36,5%	36,5%	33,4%	29,7%	26,9%	24,5%	22,3%	20,0%	17,9%	16,0%	14,5%	12,5%	11,4%	10,1%	8,8%	7,4%	6,4%	5,5%	4,7%	4,0%	3,1%	2,4%
LGD	63,5%	63,5%	63,5%	63,5%	66,6%	70,3%	73,1%	75,5%	77,7%	80,0%	82,1%	84,0%	85,5%	87,5%	88,6%	89,9%	91,2%	92,6%	93,6%	94,5%	95,3%	96,0%	96,9%	97,6%

Car

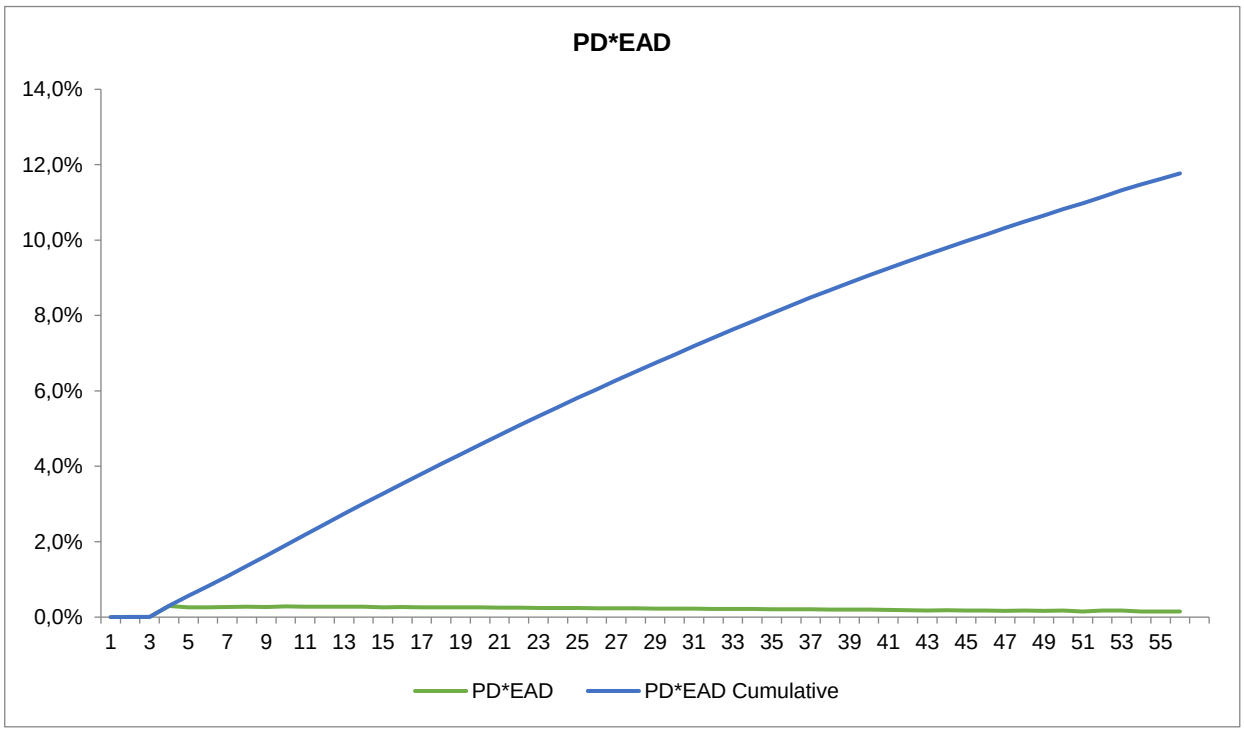
Delay bucket	1-4	5-12	12+
Recovery	39,6%	31,5%	16,0%
LGD	60,4%	68,5%	84,0%

Appendix 15. Simplified approach for Credit cards

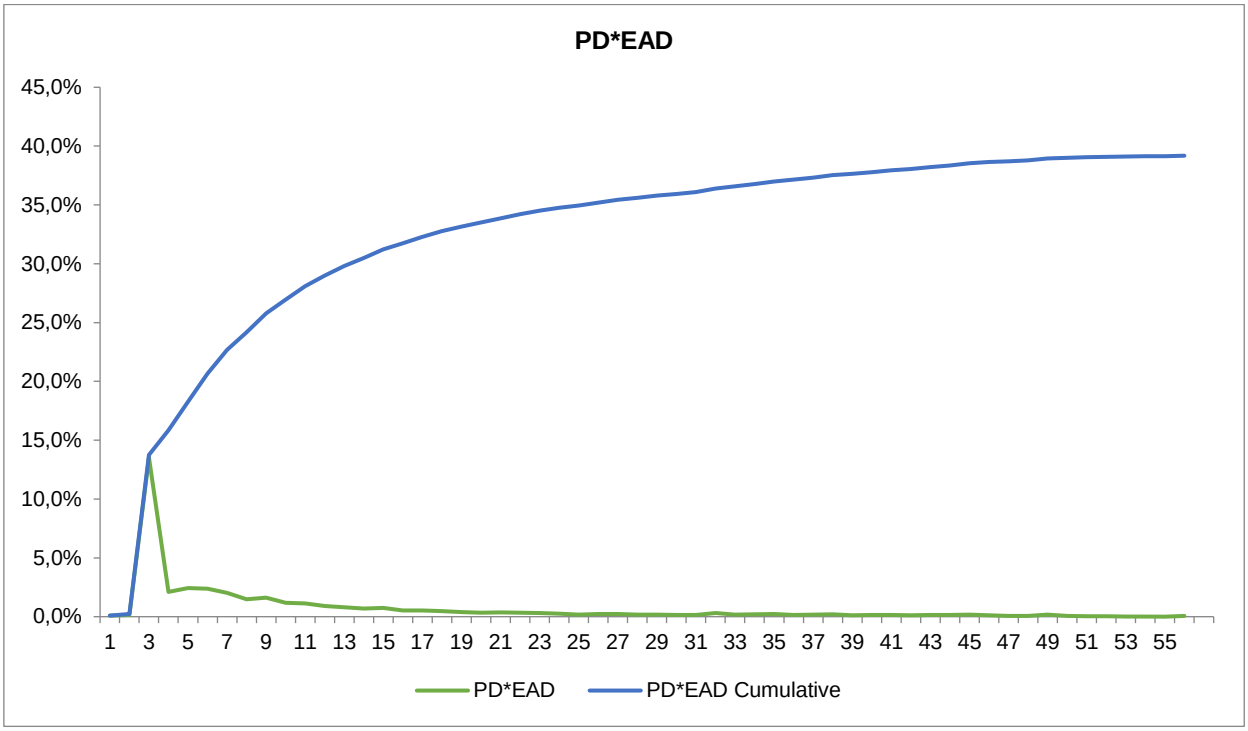
Lifetime



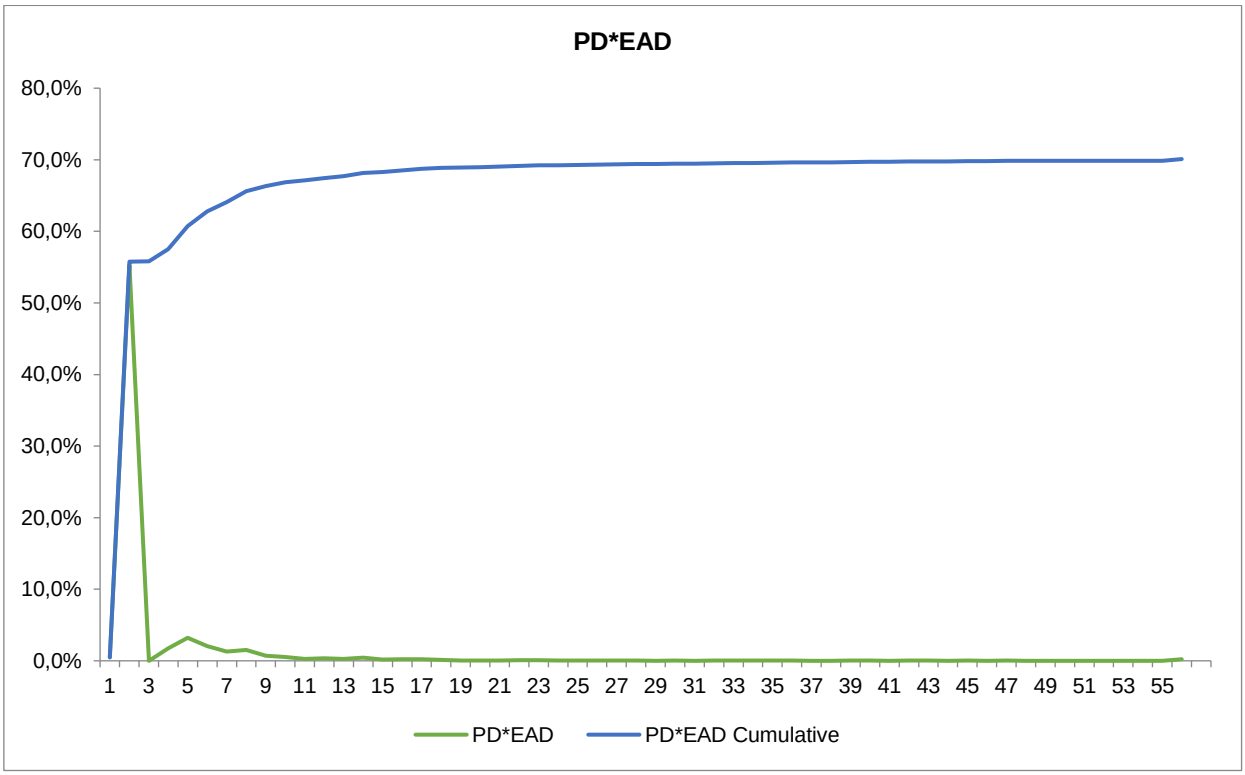
Loss curve (without delays)



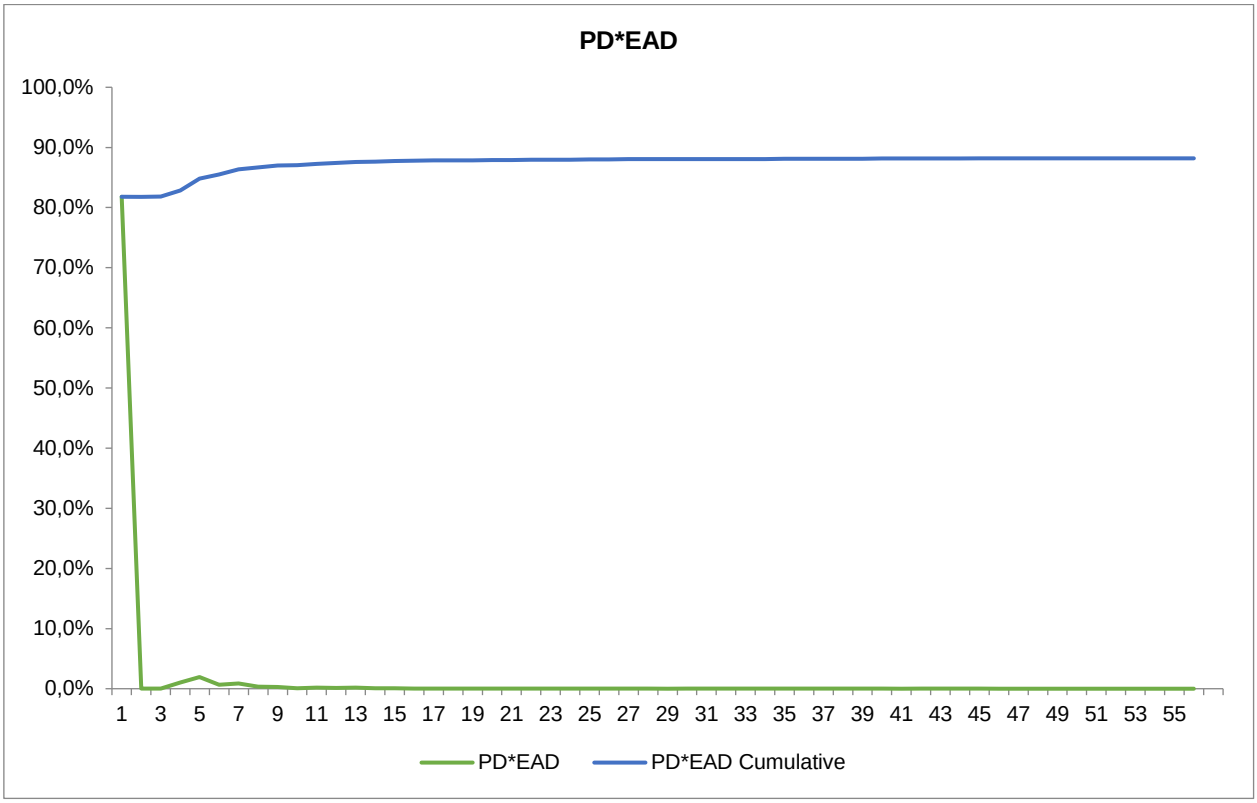
Loss curve (with delay up to 1 month)



Loss curve (with delay from 1 to 2 months)



Loss curve (with delay from 2 to 3 months)



Appendix 16. Transition effect for corporate borrowers

Segment	1 stage							
	Exposure	IAS 39	PD wa	LGD wa	IFRS 9	PD wa	LGD wa	Effect
LCB	13 730 907	125 648	1,4%	64,1%	111 917	1,3%	64,1%	-13 731
LC	2 947 804	12 365	0,6%	72,9%	11 339	0,5%	72,9%	-1 025
SSB	5 000 000	15 000	0,3%	100,0%	22 590	0,5%	100,0%	7 590
SB	1 021 134	3 911	0,5%	72,6%	16 000	2,2%	72,4%	12 089
MB	442 777	8 542	3,7%	52,5%	13 304	5,7%	52,5%	4 762
Total	**23 142 623**	**165 467**	**1,08%**	**73,12%**	**175 151**	**1,12%**	**73,11%**	**9 684**
Off-balance	9 292 951	0	0,00%	0,00%	18 206	0,71%	68,75%	18 206
Grand total for 1 stage	**32 435 574**	**165 467**	**0,77%**	**52,17%**	**193 357**	**1,01%**	**71,86%**	**27 890**

Segment	2 stage							
	Exposure	IAS 39	PD wa	LGD wa	IFRS 9	PD wa	LGD wa	Effect
LCB	1 928 024	51 621	4,9%	55,2%	172 083	16,2%	55,2%	120 462
LC	0	0	0,0%	0,0%	0	0,0%	0,0%	0
SSB	0	0	0,0%	0,0%	0	0,0%	0,0%	0
SB	103 826	5 080	6,7%	72,9%	31 881	42,4%	72,4%	26 801
MB	57 223	1 458	4,3%	59,4%	7 364	21,7%	59,4%	5 906
Total	**2 089 073**	**58 159**	**4,93%**	**56,15%**	**211 328**	**17,64%**	**56,13%**	**153 169**
Off-balance	156 294	0	0,00%	0,00%	7 518	7,72%	68,48%	7 518
Grand total for 2 stage	**2 245 367**	**58 159**	**4,59%**	**52,25%**	**218 846**	**16,95%**	**56,99%**	**160 687**

Segment	3 stage							
	Exposure	IAS 39	PD wa	LGD wa	IFRS 9	PD wa	LGD wa	Effect
LCB	1 341 068	1 012 731	100,0%	75,5%	1 175 193	100,0%	87,6%	162 463
LC	52 196	47 635	100,0%	91,3%	52 196	100,0%	100,0%	4 561
SSB	0	0	0,0%	0,0%	0	0,0%	0,0%	0
SB	375 039	366 009	100,0%	97,6%	295 307	100,0%	78,7%	-70 702
MB	0	0	0,0%	0,0%	0	0,0%	0,0%	0
Total	**1 768 304**	**1 426 374**	**100,00%**	**80,66%**	**1 522 697**	**100,00%**	**86,11%**	**96 322**
Off-balance	755	0	0,00%	0,00%	755	100,00%	100,00%	755
Grand total for 3 stage	**1 769 059**	**1 426 374**	**99,96%**	**80,63%**	**1 523 452**	**100,00%**	**86,12%**	**97 077**
Grand total for all stages	**36 450 000**	**1 650 000**	**5,82%**	**53,56%**	**1 935 654**	**6,79%**	**71,64%**	**285 654**

Appendix 17. Transition effect for retail borrowers

				IAS 39				IFRS 9				
Segment	**Stage**	**Exposure**	**Share of stage**	**Provision**	**Rate, %**	**PD aw**	**LGD aw**	**Provision**	**Rate, %**	**PD aw**	**LGD aw**	**Effect**
Mortgage	1	32 505 661	92,87%	15 988	0,05%	0,11%	43,39%	74 107	0,23%	1,25%	18,19%	58 118
	2	1 312 110	3,75%	22 694	1,73%	3,99%	43,39%	189 102	14,41%	79,23%	18,19%	166 407
	3	1 182 229	3,38%	761 317	64,40%	85,43%	75,38%	919 913	77,81%	95,64%	81,36%	158 595
	Total	**35 000 000**	**100,00%**	**800 000**	**2,29%**	**3,14%**	**44,47%**	**1 183 121**	**3,38%**	**7,36%**	**20,32%**	**383 121**
Consumer	1	12 833 795	85,56%	18 675	0,15%	0,16%	88,68%	72 209	0,56%	0,80%	70,03%	53 534
	2	440 967	2,94%	34 702	7,87%	8,87%	88,68%	104 156	23,62%	33,73%	70,03%	69 454
	3	1 725 238	11,50%	1 446 624	83,85%	86,28%	97,18%	1 427 990	82,77%	87,35%	94,76%	- 18 633
	Total	**15 000 000**	**100,00%**	**1 500 000**	**10,00%**	**10,32%**	**89,66%**	**1 604 355**	**10,70%**	**11,73%**	**72,87%**	**104 355**
Credit cards	1	2 696 074	89,87%	10 163	0,38%	0,44%	85,09%	58 762	2,18%	3,14%	69,33%	48 600
	2	28 510	0,95%	11 137	39,06%	45,91%	85,09%	13 825	48,49%	69,95%	69,33%	2 688
	3	275 416	9,18%	228 700	83,04%	90,21%	92,05%	252 970	91,85%	98,62%	93,13%	24 269
	Total	**3 000 000**	**100,00%**	**250 000**	**8,33%**	**9,12%**	**85,73%**	**325 557**	**10,85%**	**12,54%**	**71,52%**	**75 557**
Car	1	295 318	59,06%	530	0,18%	0,23%	77,71%	2 053	0,70%	1,30%	53,27%	1 523
	2	36 024	7,20%	812	2,25%	2,90%	77,71%	8 079	22,43%	42,10%	53,27%	7 267
	3	168 658	33,73%	148 658	88,14%	100,00%	88,14%	154 775	91,77%	98,85%	92,83%	6 117
	Total	**500 000**	**100,00%**	**150 000**	**30,00%**	**34,08%**	**81,23%**	**164 907**	**32,98%**	**37,15%**	**66,62%**	**14 907**
	Grand total	**53 500 000**		**2 700 000**	**5,05%**	**5,78%**	**59,79%**	**3 277 940**	**6,13%**	**9,16%**	**38,36%**	**577 940**

1 and 2 stage

Segment	Exposure	Provision IAS 39	Provision IFRS 9	Provision with PD PIT	Effect total	LT effect	Effect from models	Effect from models: PD TTC effect	Effect from models: Macroeconomy effect	Effect from models: LGD effect
Mortgage	33 817 771	38 683	263 208	46 093	224 525	217 115	7 411	345 211	- 5 689	- 332 111
Consumer	13 274 762	53 376	176 365	85 862	122 988	90 503	32 486	196 855	- 4 262	- 160 107
Credit cards	2 724 584	21 300	72 588	50 413	51 288	22 175	29 113	57 692		- 28 579
Car	331 342	1 342	10 132	1 037	8 790	9 095	- 305	5 561	- 58	- 5 808
Total	**50 148 459**	**114 701**	**522 292**	**183 405**	**407 592**	**338 887**	**68 704**	**605 318**	**- 10 009**	**- 526 605**

3 stage

Segment	Exposure	Provision IAS 39	Provision IFRS 9	Provision with PD PIT	Effect total	LT effect	Effect from models	Effect from models: PD TTC effect	Effect from models: Macroeconomy effect	Effect from models: LGD effect
Mortgage	1 182 229	761 317	919 913		158 595		158 595	163 393		- 4 798
Consumer	1 725 238	1 446 624	1 427 990		- 18 633		- 18 633	154 565		- 173 199
Credit cards	275 416	228 700	252 970		24 269		24 269	17 462		6 807
Car	168 658	148 658	154 775		6 117		6 117	5 787		329
Total	**3 351 541**	**2 585 299**	**2 755 647**	**-**	**170 348**		**170 348**	**341 208**		**- 170 860**