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Loan Default Prediction in Ukrainian Retail Banking

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Abstract:

Using a large proprietary dataset provided by the tenth largest Ukrainian banking institution, we posit reasons for loan defaults within two major groups of retail borrowers; car loans and mortgages. Two model types were used, namely logistic regression and neural networks. The results of our estimations suggest that a) data currently collected by banks are sufficient to predict defaults, but bankers should collect more information, and that b) the neural networks model slightly outperforms the logit model in predictive power.

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Keywords: loan default, credit risk, bank

Contents

Non-technical summary

The stability of the banking sector has assumed importance as a topic in financial literature since the beginning of the current economic crisis. When individual-borrower loan defaults become a system-wide problem, they affect interest rates, budget deficits and economic growth. The issue, however, has not been studied sufficiently in Ukraine.

This paper focuses on the micro level causes of retail loan defaults. Using a large proprietary dataset kindly provided by the eighth largest Ukrainian bank, we discuss reasons for loan defaults within two major groups of retail borrowers, namely car loans and mortgages. We also added some Ukraine-specific variables, such as foreign currency usage, and the housing bubble. Unfortunately, our results failed to confirm directly whether the variables studied affect credit risk.

Two model types were used: logit models and neural networks (NN). In using these models, we were able to compare the performance of old-school and contemporary approaches to our analysis. Logit is a common and simple instrument used to handle datasets with categorical dependent variables, while NN is the most common example of statistical learning machines. As it turns out, neural networks outperform logistic regression, but not significantly.

We found factors that affect the probability of a retail loan default. Our results could be used by loan officers of the bank whose data we used for the estimations. Logit results could be easily transformed into spreadsheet formulae, while neural networks could be compiled into usable plugins or stand-alone software. We recommend, however, using NN because of their better ability to identify potential defaulters. At the same time, so far we cannot recommend these tools to other banks, because of representational issues.

1. Introduction

I got myself a Cadillac
But I can't afford the gasoline

(AC/DC, "Down payment blues", from "Powerage", 1978)

The stability of the banking sector has assumed importance as a topic in financial literature since the beginning of the current economic crisis. When individual-borrower loan defaults become a system-wide problem, they impact interest rates, budget deficits and economic growth. The issue, however, has not been studied sufficiently in Ukraine.

With more data on individual defaults, it is now feasible to investigate the issue at a micro level. The amount of non-performing loans (NPL) reached its peak just before we launched our research. In addition, banks have started to relax requirements for potential borrowers significantly, which could mean that lessons from the crisis were not learnt and we needed to develop a tool to convince banks (and their regulators) to exercise caution.

This paper focuses on the micro level causes of retail loan defaults. Using a large proprietary dataset kindly provided by the eighth largest Ukrainian bank, we discuss reasons for loan defaults within two major groups of retail borrowers, namely car loans and mortgages. We also added some Ukraine-specific variables, such as foreign currency usage, and the housing bubble. Unfortunately, our results failed to confirm directly whether the variables studied affect credit risk.

Two model types were used: logit models and neural networks (NN). In using these models, we were able to compare the performance of old-school and contemporary approaches to our analysis. Logit is a common and simple instrument used to handle datasets with categorical dependent variables, while NN is the most common example of statistical learning machines. As it turns out, neural networks outperform logistic regression, but not significantly.

Our contribution to credit risk analysis literature consists of three main foci. 1) Retail banking (most other papers focus on companies). 2) Ukraine. There is a dearth of papers on emerging markets, with the ones currently available being on Colombia and Turkey. 3) Comparison of old and new approaches (most other researchers used only one type of model for empirical estimations). There are some discussions of methods in other papers, but they are largely theoretical.

This paper has the following structure. *Section 2* gives some stylized facts on bad loans in Ukraine. *Section 3* reviews literature on the topic, including the description of all generations of default prediction models as well as the discussion of their properties. *Section 4* describes empirical models employed to measure credit risk, and also contains data description. *Section 5* is devoted to the results of our research.

2. Bad loans in Ukraine

Bad loans are a widespread problem for all Ukrainian banks, and possibly the most important one. According to the data provided by the National Bank of Ukraine, the amount of non-performing loans in the banking system (which, technically, means loans overdue more than 90 days) rose almost tenfold, from 10.655 billion UAH as of October 1, 2008 to 90.363 billion UAH as of December 1, 2010 (*see Figure 1*). In relative terms, those numbers indicate a rise from 1.7% to 11.92% of the total amount of loans. The current figure is lower (8.9% as of 01.01.2013), showing on average downward trend (*see Figure 2*).

However, the ratio depends on the definition of a bad loan. Credit rating agency Fitch Ratings estimated the percent of bad loans at 56.6% as of the beginning of 2011 (*see Figure 3*). Some banks also reported ratios that are significantly higher than the official figures. For instance, the largest Ukrainian bank PrivatBank reported 23.8% of non-performing loans as of April 1, 2010, the second largest bank Raiffeisen Bank Aval reported 29.1% of bad loans as of September 1, 2010.

One reason for this discrepancy is the issue of debt restructuring and prolongation. Such debts are not counted as problem loans by the National Bank of Ukraine. According to the statistics published by the central bank, banks have restructured or prolonged 184 thousand loans valued at 217.5 billion UAH as of July 1, 2010. This constituted 30.3% of the total credit portfolio of the Ukrainian banking system. The ratio was even higher for some individual banks. For example, Fitch reported 47.6% for the State Export Import Bank (Ukreximbank) as of July 1, 2010. This issue needs to be taken into account since it still represents the inability of a borrower to meet the initial payment schedule. Also, it affects the balance sheets of banks.

Regardless of the methodology, all figures mentioned above are far from normal. According to the past regulations of the National Bank (abandoned on December 1, 2009), a bank exceeding the 10% NPL threshold can be fined by the regulatory agency, while one exceeding more than 30% can be placed under temporary administration. This is exactly the measure that was applied to 27 banks since the beginning of the financial crisis. Moreover, 15 banks (total assets exceeding 18 billion UAH), including the 18th largest bank Ukrprombank (more than 10 billion UAH in assets), were closed down by the NBU.

Some large banks were saved by the government. In 2009 three large banks, Ukrgasbank, Kiev and Rodovid, were bailed out. In total, 23.32 billion UAH of state budget monies were spent. But it was not the end of the story. In September, 2010 it turned out that 12.5 billion UAH more were needed. In late March and early April of 2011, the government decided to inject 4.2 billion UAH in Rodovid Bank and 4.3 billion UAH in Ukrgasbank. As yet it is inconclusive if the bailout worked. Moreover, the IMF suggests that both Kiev and Rodovid should be closed down.

Surviving banks did not emerge unscathed. Creating reserves for bad loans resulted in huge losses for the banking system. According to the NBU, in 2009 total losses of all Ukrainian banks constituted 38.4 billion UAH and in 2010, they dropped to 13 billion UAH. Only in the last months of 2010 and first months of 2011 did banks start to return to profitable operation. The profitability however, is not a trend. On average, banks reported losses for July and September of the year 2012.

To comply with the regulatory requirements, banks need to raise their capital. According to the NBU estimates, in 2009 fifty-six Ukrainian banks should have raised capital by 30 billion UAH; similar calculations for 2010 implied 40 billion UAH for 61 banks. This caused the banking business to lose some of its attractiveness, which led to some negotiations regarding the sell-off of some Ukrainian banks by foreign owners. For example, this year Commerzbank sold Bank Forum.

Currency risk as a source of credit risk is a special case. As of October 1, 2008 (the closest reporting date before the depreciation of UAH has begun), 51.4% of total loans were nominated in hard currency (44.8% for corporate borrowers and 62.7% for private ones), which places our country among the most currency exposed banking markets (*see Figure 6*).

Over the next several months, Ukrainian currency depreciated by 60% against the US dollar, which made UAH one of the fastest depreciating currencies in the world during this crisis. However, it is worth considering this issue more carefully. First, there were many UAH defaults as well. Second, volumes of bad loans have continued to rise for a significant period of time even after the depreciation had stopped.

The currency risk, however, is not the only risk taken on by the banks. Their credit policy was too lax, and could now be weakened further. Every month more banks provide retail loans. According to Prostobank Consulting, over the last 33 months the number of banks providing car loans rose from 11 to 43, mortgages are provided by 27 banks (compared to 5 before). Interest rates have dropped and even products with zero down payments have started to re-appear. This worrying sign therefore creates a need for a tool that can warn the banking industry as well as the National Bank.

3. Literature review

While credit risk measurement has been recorded for the past eighty years, statistical methods have only started to be used in the last four decades (*see Table 2.1*). Since then, there have been about 165 economic papers focused on the bankruptcy analysis as of winter 2007 (see Bellovary at al., 2007 for a complete list).

The first generation approach is the discriminant analysis. The idea is to use one or more financial ratios to discriminate between non-failed and failed firms. See Beaver (1966), Altman (1968), Deakin (1972), Altman at al. (1977), and Altman (2000) for the detailed description. The approach is very simple, but it suffers some econometric issues (see Eisenbeis (1977), Wiginton (1980) and Hardle at al. (2005)).

Problems in the above-cited research are resolved using logit and probit models, which were created in the 1970s and flourished in the 1980s. Logit assumes that a cumulative default probability has a logistic form (varying from 0 to 1 by definition). This line of investigation was started by Martin (1977) and Ohlson (1980) and continued by Wiginton (1980), Zavgren (1983) and Zmijewski (1984). The most accurate logit model is by Dambolena at al. (1988), which reached 98% accuracy.

The approach is still in use for some applications; for example, Westgaard at al. (2001) used it for the estimation of default probabilities in a corporate bank portfolio. Probit models require a non-linear estimation, which makes them less popular. The first attempt to exploit this approach was made by Hanweck (l977). The best probit model is by Skogsvik (1990); it has 84% accuracy.

All the above-mentioned models lack theoretical justification. There is no clear reason as to why some financial ratios are better than others. This cannot be said about risk-of-ruin/option pricing models. The idea is that once the market value of the company's assets drops below its short-term liabilities, the company is essentially bankrupt. Market value and market value volatility are typically used in estimations. The most prominent studies are by Black at al. (1973) and Merton (1974).

According to Altman (1998), there are two main problems with this model type. First, one cannot tell with certainty whether stock price volatility represents the volatility of the asset value. Second, not all companies are listed, and it is unclear how to measure the value of an unlisted company. This is exactly why we cannot use these models for Ukraine. There are only about three hundred listed companies and only a few of them went bankrupt.

Another approach is to predict not only the fact of the default, but also its scope. Double hurdle models introduced by Moffatt (2003) could be used for this. These models were earlier proven successful for modeling employment decisions or cigarette consumption. The underlying assumption is that there is a certain group of individuals (companies) that will never do something (smoke, default etc.) under any circumstances. It is argued that their behavior essentially differs from the behavior of others.

With the development of artificial intelligence systems, econometricians started to use these for various applications. One type of such systems is a neural network (NN) that mimics the behavior of neurons in the human brain. Such networks try to extract relationships from the data and then develop a decision-making model. They became very popular for default prediction in the 1990s, when enough evidence of their potential emerged from other fields such as medicine, as well as text and speech recognition.

Examples of the application of NN to credit risk estimation can be found in Messier at al. (1988), Tam at al. (1992), Guan (1993), Fanning at al. (1994), Desai at al. (1996), and Zhang at al. (1999). Also see Atiya (2001) for a review and comparison of such studies. Altman (1996) criticized the neural networks approach for the absence of a theoretical foundation, referring to them as a "fishing expedition", and having accuracy not significantly exceeding that of the discriminant models.

A similar approach is represented by the support vector machines (SVM), which are essentially statistical learning systems. The idea of this approach is to transform a dataset with a function (called kernel function, usually radial basis function is used) in such a way that the categories of observations (vectors) could then be separated by a hyperplane. The search for a maximum-margin hyperplane in a transformed feature space allows the best classification/regression to be made.

Using SVM, Hardle at al. (2005) revealed that safe companies combine into a cluster while bankrupt firms could be located elsewhere. Shin at al. (2005) found that for small samples, SVM performs better than the backward-propagation neural network.

Hardle at al. (2005) divided all methods into three main groups. Discriminant analysis, logit and probit models are parametric (or structural) models. They all assume that a relationship between predictors and the default probability could be described a priori. Each such model includes a finite number of known parameters; empirical strategy is the estimation of the model on a training set. Other classes of models are non-parametric and semi-parametric.

Non-parametric models, like neural networks are more flexible, and are capable of extracting more information from the data but are harder to interpret. Between these two extremes lie semi-parametric models. They are basically parametric models, in which predictors are transformed in a non-parametric way. An example of such a model is RiskCals developed and used by credit rating agency Moody's (see Falkenstein at al. (2000) for details).

Bellovary at al. (2007) argue that complexity does not automatically imply accuracy (*see Table 2.2*). Some relatively new models like logit and probit analysis have very poor (20%) low-end accuracy. Neural networks are the most accurate, but there are several MDAs that have 100% maximum accuracy as well (and one of them keeps reaching 100% accuracy even for the five year horizon). Moreover, among absolutely accurate models there is one that uses only two predictors, and the maximum for 100% accurate models is 21 predictors. For comparison, a model with 57 predictors (the largest model) has 86% accuracy.

A recent wave of papers is mostly devoted to the US subprime crisis, and especially to securitization issues. Unfortunately, these studies have no new methodology. We still could benefit from them by comparing reasons for mortgage default. Notable examples of such papers include Foote at al. (2008), Sherlund (2008) and Mayer at al. (2009).

The Ukrainian context is largely not analyzed. There are only several papers devoted to bank failures — see Popruga (2001), Nikolsko-Rzhevsky (2003), Dryha (2009), and Bobykin (2010). As to loan defaults, we are aware of only two papers by the same author, Kruchok (2009) and Kruchok (2010). The author developed simple MDA models to estimate the default probability for corporate and mortgage loans, respectively; however, she did not disclose the derivation of the models. In addition, there is a proprietary model for cash flow analysis (see Galasyuk at al. (2006)) with an unknown structure. Advanced models have never been used for Ukraine, which leaves room for our contribution.

4. Empirical strategies

4.1 Models

4.1.1 Logistic probability function

This model deals with the probability of default. The logarithm of the likelihood of an outcome could be derived as:

$$l(\beta) = \sum_{i \in failed} \log P(X_i, \beta) + \sum_{i \in safe} \log\big(1 - P(X_i, \beta)\big) \quad (1)$$

Here X_i is a vector of predictors for an observation i, β is a vector of coefficients to be found, and P is a probability function. The values of vector β components could be found by solving a maximization problem for (1). The appropriate functional form of P is usually chosen such that it will be easier to estimate the model and interpret the results. In our case it is the logistic function:

$$P = (1 + \exp\{-y_i\}^{-1}), \quad (2)$$

where

$$y_i = \sum_j \beta_j X_{ij} = \beta' X_i \,. \quad (3)$$

The model also does not impose a specific list of predictors, which should be chosen by an investigator. However, there are some limitations. First, logistic regression tends to overestimate the coefficients in small and medium samples (<500 observations). Second, it is recommended to have at least ten events per an independent variable.

Our primary specifications are multinomial and ordered logit. However, after we have studied terms and conditions for a loan to be restructured, we decided to test binary specifications as well, since restructuring does not necessarily represent the inability of a borrower to repay his/her debt. Moreover, there are three types of restructuring (credit holiday, currency conversion, and term extension) that are not captured by the available data. That is why we run binomial regressions treating restructured loans either as performing or as non-performing loans.

4.1.2 Neural networks

Since neural network construction is a very complex process, we used software that automates this. In this case, the only major input parameter that must be selected by a researcher is the type. Our primary tool is the Statistica 7 package, which limits the range of available NN types to a multilayer perception, radial basis, probabilistic, and linear neural networks. According to the literature, these four types are sufficient for most applications.

Multilayer perception neural network (MLP) is the most common type. Such a network usually contains an input layer, an output layer, and a number of hidden layers (usually only one, rarely two, and even zero in the case of linear networks, which could still be rather efficient). The input layer normalizes predictors and feeds them to all neurons of a hidden layer simultaneously. At each hidden neuron, the values are weighted (coefficients are individual), and the sum is fed into the transfer function. Output neurons collect all signals and weight them (coefficients are individual again). Technically, we need to find all mentioned weights such that a network will model our data. The solution is found during the so called training process.

The number of layers and the number of hidden neurons is determined by automated procedures according to the following criteria. First, we should avoid local minima. Second, we should avoid overfitting. The idea of overfitting is that if a network is complex enough, it starts to model not only general relationships but also noise. Such a network will not generalize well and therefore is not useful for prediction purposes. Third, we need to minimize the computational cost. These principles apply to other types of networks as well. Linear networks are similar to MLP, but they do not have a hidden layer.

Radial basis function neural networks (RBF) use three layers. The input layer standardizes predictors and feeds them to the hidden layer, which consists of radial basis functions located in hyperspace. Influence (weight) of each hidden neuron depends on the distance from a predictor point (spread is individual for each dimension). Neurons of summation layers weight the signals and add bias. During the training process we determine the number of hidden neurons, the coordinates of the center and the radii of each hidden-layer RBF function, as well as the summation weights.

Probabilistic neural networks (PNN) are very similar to RBF, but have a separate function for each training point. This allows the training process to be skipped, but slows down the practical implementation. In the case of large datasets it could become very slow. Moreover, it tends to overfit.

We conducted tests for all four types of neural networks offered by Statistica 7 — multilayer perception, linear, radial basis, and probabilistic. Since the software generates a lot of models with a given set of parameters, we decided to try 50 models of each type, which allowed us to retain the top 10 models (according to their performance).

4.2 Data

Both model types are data-driven, i.e. they do not imply explicit choice of predictors. Ideally, we must get as much data on borrowers as possible. But since this is private information, collecting of this data is limited. As a result, the only available source of information is the banking system, which imposes two limits on data. First, banks are not usually willing to share this information, even cleared of private data. Second, one can get only variables that banks collect during the loan application process.

This may deteriorate the accuracy of the model, but it reflects real world practices. The only implication of (possible) poor efficiency could be advice to banks to collect some new data that may appear to be relevant.

We managed to get access to the borrower database of the tenth largest Ukrainian bank. There are two major groups of retail borrowers, namely car loans and mortgages. In total, there are about 4000 car loans and about 6000 mortgages (total amount for both types is 9.5 billion UAH). This total volume of retail loans represents 5% of retail loans of the whole banking sector of Ukraine (and even more in terms of car loans and mortgages, because the bank did not issue point-of-sale loans).

Because of data quality, the sample was reduced to 1348 observations (totaling about 200 million UAH) that have the full set of predictors, which is still a large sample. The dataset for mortgage loans is larger (1821 observations, 3.2 billion UAH), but it contains almost no defaults (only 26 cases).

The dataset has several advantages. First, it is large. The second advantage is data quality. Our dataset lacks the drawbacks of data collection procedures, described in Zmijewski (1984). The first mentioned issue is extremely low frequency of bankruptcies. In our case, we have a fair number of defaults, at least for car loans. The second issue is the lack of data for distressed borrowers. Again, since we deal with clients of the bank, we have enough data, at least for the period prior to default.

Both samples have the same data structure (6 continuous and 20 categorical variables), but they are estimated separately, since we have added one more sample-specific continuous variable to each sample. The complete list of variables and their description is presented in *Appendix 3*. Dependent variable has three categories: "good borrower" (0), "restructured debt" (1), and "default" (2).

In order to take the Ukrainian context into account, we have added several variables which are not typical in the default prediction literature. For example, for mortgages we used the phase of the housing bubble (price as a percentage of the bubble peak price) as a predictor. Also, currency was used for both samples.

Representativeness of the samples with regards to output variable depends on the loan type. The OTP Bank has market-average numbers for car loan defaults and restructuring. At the same time, the bank has a lower default rate on mortgages (and higher restructuring rate) due to three factors. 1) The bank had stricter risk assessment policies before a loan was granted. 2) The bank was the first in the market to start offering restructuring to its borrowers. 3) The restructuring rules of the bank were lax — it granted restructuring to everyone who applied.

As for input variables, unfortunately, there is no "average Ukrainian borrower" statistical portrait we can rely upon. However we can draw comparisons to some population averages. Both samples are heavily biased towards a) males (33-68% more likely), b) young (84-108% more likely to be under 40), c) well-educated (5 times more likely to have university degree), d) single (0-28% more likely), e) having less children (105-129% more likely not to have children at all) and f) well-earning people (8 times more likely to earn more than 1920 UAH per month). See *Table 3.3* for the detailed breakdown.

However, these differences are natural, because usually young well-educated males earn more, while absence of a spouse and children implies more disposable cash. Both factors are crucial for being a car/home borrower.

5. Results

5.1 Logistic regression

Depending on the specification, between six to ten predictors turned out to be significant for car loans — loan/value (+), loan amount (+), term (+), contract type (+ for constant principal payment), gender (+ for males), company type, work experience, family status, and credit history (*see Table 4.1.1*).

The difference between specifications is larger for mortgages (*see Table 4.1.2*). No single predictor enters all equations simultaneously. Three variables are used four times; five more are used three times. More diverse structure is caused by a less symmetrical dataset, which means more significant transformations for binomial specifications. Basically, all variables are the same as in the case of car loans. Besides, price-to-income, loan term, real estate, and assets were added, comparing to car loans.

Alternative specifications do not offer too much value added in comparison to the multivariate logit. Ordered logit provided the same lists of significant predictors and the number of hits, but had lower R^2. Effects of the binomial logit depend on the sample. For car loans, lists are the same, but the goodness of fit is higher. For mortgages, treating restructured loans as performing provides some change in the list of significant predictors and better R^2. But this should be treated with caution because of huge data transformation.

A. Significant variables

Loan-to-value has a positive effect on the probability of default. The lower is the down payment, the higher are the odds that a borrower either has the current income only for a short period of time or cannot manage his/her finances in an effective way. However, the effect is not very large. In either case, banks or their regulators should either set an explicit minimum amount of down payment or trace the potential borrower's income for a longer period of time.

Another fundamental property, initial payment-to-income ratio, appears only in mortgage results. Here the reasons are obvious. For larger ratios, it is more likely that in case of a decreasing income or increasing other expenses a borrower will not be able to pay all his/her bills. In this case, maybe some explicit threshold level should be introduced by banks or their regulators.

Size does matter too. The larger is the loan amount, the more likely it is to default. This contradicts the findings of some other researchers. For example, Moffatt (2003) found that loan amount has positive effect on the probability of passing the first circle of the double-hurdle model. However, the effect for mortgage restructuring has that pattern. Anyway, the effect is very small, and this should not be reflected in regulations. Still some banks have introduced a maximum loan amount because of some other regulations of the National bank.

Term has the expected effect. The greater is the period of loan repayment, the higher is the probability that income or other expenses of a borrower will deteriorate.

Type is a unique variable that appeared to be significant. Developed economies like US do not have decreasing payment scheme that we have. See *Case study #1* below for detailed discussion.

Gender also appeared to be significant. Males default more often (Moffatt (2003) has the opposite result). However the matter of interest is primarily the very fact of this variable's significance. At least 2/3 of purchases were made by households (according to the family status), and in this case decisions to default were probably made by two people.

Coefficients for a small group of other qualitative predictors have expected signs. The larger is the employer of a borrower, the lower is the probability of default. The same is true for the duration of employment, family status and previous credit history. From the behavioral point of view, all those variables represent the level of life experience, consciousness, and responsibility. History here is of most importance, since there is no legal requirement to submit data on borrowers to credit history bureaus. We think that such a requirement should be introduced.

Coefficients for variables that represent financial status exhibit the expected trend as well. One can easily explain the fact that ownership of real estate or financial assets positively affects loan repayment discipline. Credit cards represent another burden so they increase the probability of default. Banks should check other burdens of a potential borrower more carefully.

Case study #1. Loan type

The result for the loan type, which is one of the fundamental properties of a loan, is controversial. We found that constant principal repayment increases the probability of default. On the one hand, constant principal repayment means that total payments are decreasing over time, which should ease the burden. The total amount of money paid is also less.

On the other hand, at a given moment, monthly payments for this type could significantly exceed the payments for increasing principle repayment (and constant total payment), which could lead to default.

In order to check the second hypothesis, we ran a simple simulation using average loan parameters from the car loan sample. It turned out that repayment schedules intersect at 35 months. Unfortunately, our sample does not contain dates of defaults, thus we should use proxies.

First, average loan life before the depreciation of Ukrainian hryvna was about 10 month. Second, most private defaults happened during the year 2009 (*see Figures 1 and 2*). As a result, type 2 payment exceeded type 1 payment by 16.5% as of the date of strong depreciation, by 11% as of the middle of the year 2009, and by 7% as of the end of the year.

These numbers support the hypothesis (*see Figure 8*). As a result, the regulator may consider some measures to motivate banks and their borrowers to use increasing principle repayment scheme.

B. Dropped variables

While not having very high goodness of fit, which means presence of some important unobservable factors, our model dropped about half of all variables as irrerevant for default prediction.

Interest rate could not affect our dependent variable for two reasons. First, variance of this predictor is very low. Second, it is a part of total loan repayment cost for borrowers, which is already captured by PTI (payment to income) variable.

Age was not a source of credit risk. We could offer an explanation at least for the logit model. As Moffatt (2003) found, there is U-shape, i.e. non-linear relationship between age and the probability of default. Indeed, young people may not have stable income, while senior borrowers have more chances to lose their jobs.

Being a resident for some period of time did not matter, because most borrowers had the highest score (more than 5 years). If the variable had greater variance, it could help because of bank's access to soft information (see Agarwal at al. (2010) for discussion).

Statistical insignificance of occupation means that income stability does not depend on the position. Even worse, the very variable may not be constructed in a right way, because pension is a stable income, while profit of a company's owner is not.

Military duty was dropped because most borrowers were past the age of enlisting. Most males of military age do not have sufficient income to take on a car loan or mortgage.

Education was not significant due to low variability as well. Most borrowers have higher education.

Recommendations were not very helpful. Most borrowers either did not have recommendations at all, or provided oral recommendations from an associate, which is essentially the same. Anyway, this is rather soft evidence, because even in the case of written recommendations, an employee can count on his/her colleagues or even managers and provide strong recommendation letters to the bank.

The presence of a home, a mobile phone, or a bank account proves nothing. Everyone can afford all of these options. And in fact most borrowers do have cell phones and bank accounts.

A car is a more expensive item, but its significance was lower compared to real estate or financial assets.

Cycle term for car loans does not matter. This is hard to explain, because loan repayment stage could significantly affect current PTI. Maybe the reason for dropping is that it matters only for decreasing payment loan type, while they represent only 40% of the total sample.

The bubble term was irrelevant. We found no evidence that an overheated housing market created incentives to default. Usually, negative equity (when liability before a bank exceeds the market value of a home) leads to more foreclosures (see Mayer, Pence, and Sherlund (2009) for evidence and references to other papers on this topic). But it was not the case with our findings.

There are two possible explanations for this. Foote at al. (2008) point out why negative equity is a necessary, but not a sufficient reason to default. First, a defaulted borrower needs to rent or purchase a new home, so the decision to default will depend on mortgage balance, rent fees, and new mortgage terms. There are also transaction costs associated with the default, such as a moving cost.

Currency, which is a Ukraine-specific variable introduced by us, also failed. Despite 60% UAH depreciation, we found no evidence that foreign currency loans were more prone to defaults. Here the reason for failure is very straightforward. Only 3% of car loans and 5% of mortgages were in national currency, so models could not differentiate defaulters and non-defaulters on the basis of an almost constant variable.

5.2 Neural networks

Best results are for two multi-layer perception networks. However, other network types provide similar accuracy (up to 64% for test sub-samples).

Explicit relationships between predictors and a dependent variable are very complex and cannot be easily described. However, there is a tool to point out which variables are more important than others. This is the sensitivity analysis provided by Statistica. After counting how many times each variable is used in various models, we conclude that the most important predictors are the loan amount, contract type, recommendations, loan/value, work experience, gender, and company type (see *Table 4.2.2*).

This actually supports the list of variables that turned out to be significant for the logit model. Results for mortgages are different. Here neural networks use mostly qualitative predictors (see *Table 4.2.4*). As a result, lists for NN and for logit are very different. The probable reason is data quality, especially extremely low frequency of defaults.

In any case, all these results should be interpreted with caution, because usually one needs at least five times (ultimately, ten times) more observations than links between neurons (calculated as square of the number of hidden neurons). In our case, only networks with up to 16 hidden neurons satisfy the minimal condition. Besides, sensitivity ratios for most variables are close to 1, which means that such a variable could be dropped without a significant effect.

We compared the results of different approaches with regards to Type I (false positive) and Type II (false negative) errors. Type II error is far more important for credit risk analysis, because it leads to the loss of a significant part of the loan amount (or even the whole amount), while Type I only leads to the loss of potential profit.

The logit model provided rather poor results, because error rates were 0% and 23%, respectively. Moreover, the model correctly identified only one third of all defaults. At the same time, it turned out that neural networks have much better Type II error rate (on average, 13% versus 18% for Type I, and about 9% for the best models; see *Table 4.2.5* for more details).

Better accuracy of non-linear models (such as NN) could be explained by the factors pointed out by Atiya (2001). According to the author, there are saturation effects in the relationships between the financial ratios and the prediction of default, and there are multiplicative factors as well.

In order to check this, we generated predictor-output response graphs for logit (see *Figures 9-44* for salient examples). For categorical predictors they are not very useful, but this is not the case for continuous variables. First, these graphs show us that there are some saturation effects (LTV and amount). Second, there are non-linear effects, and relationships are both convex and concave. For example, graphs for LTV are mostly convex, which supports the need for some policy action.

These findings correlate with the results of other scholars. Desai at al. (1996) used three credit union loan samples to find that even the simplest NN version (MLP) outperforms logit. Later, Desai at al. (1997) explained the small difference in performance by small nonlinearities in data, which limit the ability of neural networks to unfold to full strength. West (2000) also found that logistic regression, while being the most accurate method among traditional techniques, is inferior in comparison to RBF and mixture-of-experts neural networks.

Case study #2. ROC curve

Following Kristof (2008), we decided to use ROC (receiver operator characteristic) to estimate the efficiency of each method. Initially developed for the radar signals analysis during World War II, it later became an important tool to assess quality of signal detection in various fields, including machine learning. The drawback is that it can be used only in the case of a binary dependent variable.

The idea is to plot the ratio of true positives to all positives against the ratio of false positives to all negatives for various threshold levels. The closer the resulting curve is located to the upper left corner of the graph, the better. The diagonal represents random guessing. See *Figure 45* for the best curves for car loans.

There is an even simpler way to compare the classification models. One can use the area under the ROC curve to choose the best forecasting technique (1 for ultimate discriminatory power, 0.5 for random guessing). In our case, the area for logit is 0.74, which is good. Best neural networks perform even better (about 0.80), while values for other NN models are within range (0.67; 0.71). See *Table 4.2.6* for details.

5.3. Policy implications

Lending policies. One of the statistically significant predictors is the loan-to-value ratio. In this case the National bank of Ukraine could impose an explicit minimal down payment level. Loan type matters too, and this will need a regulatory response. Unfortunately, we do not have recommendations concerning currency.

Infrastructure. First, the use of credit rating bureaus should be legally reinforced. The first such bureau in Ukraine was established in 2005, and now there are four bureaus. Banks submit and retrieve the data on borrowers to/from bureaus increasingly, but this is not currently mandatory. We think that this should be the case. Also, data on other payment discipline (utilities etc.) should be included.

Second, we found that the bank's scoring systems have very weak predictive properties. The correlation between the score assigned and the output is only 7% for car loans and 4% for mortgages. We do not have data on other banks, but we could infer from their bad loan portfolios that their systems are no better. As a result, authorities should consider licensing of such systems, whether they are commercial or proprietary. At least, those systems should be tuned to take the peculiarities of the Ukrainian banking system into account. Also some additional variables might need to be included, because R^2 is low for all specifications of our models.

The very risk score also could be used for new risk management approaches. On November 17, 2011 the National bank stated that it is going to implement Basel II requirements, and the standard requires banks to charge borrowers with individual interest rates depending on credit risk and also to hold client-specific reserves (see *Table 4.3*). That is why having a quick and reliable risk estimate is very important.

5.4. Conclusions and future research

We found factors that affect the probability of a retail loan default. Our results could be used by loan officers of the bank whose data we used for the estimations. Logit results could be easily transformed into spreadsheet formulae, while neural networks could be compiled into usable plugins or stand-alone software. We recommend, however, using NN because of their better ability to identify potential defaulters.

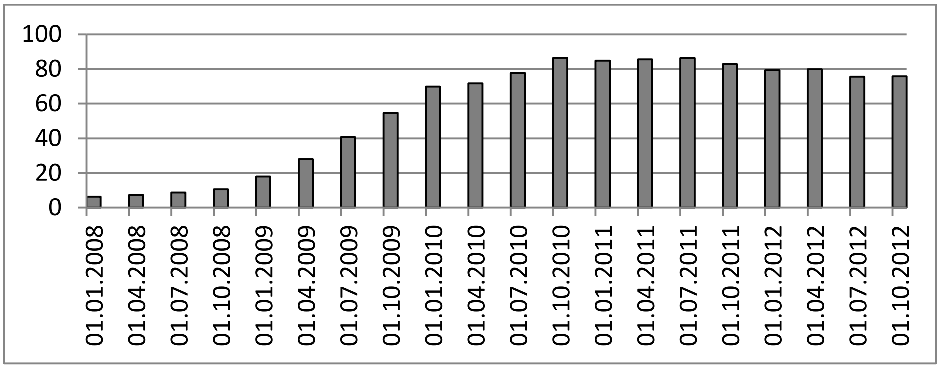
At the same time, so far we cannot recommend these tools to other banks, because of representational issues. With regards to policy implications, the results should be also treated with some caution because our samples are not quite representative. This is especially the case with mortgage samples that have NPL share which is too low and restructured loans share which is too high. Indeed, explicit comparison of a customized and the generic NN model made by Desai at al. (1996) reveal latter is inferior (but still is superior or comparable to logit).

To overcome this problem one needs access to richer and/or more representative datasets, for example from a larger bank. Even some small sample could help; we may use it in order to check whether our models generalize well or they suffer from the selection bias. As for the full-scale system research, the ultimate source is credit history bureaus; they have the most comprehensive databases on borrowers. However, the access to their data is limited as well, thus one possibility is for the bureaus to conduct such a study themselves.

There are also other directions for further research in this field that we would like to outline. Methodologically, the research could be enhanced by adding new types of neural networks that are not covered by Statistica 7. For example, West (2007) found that the mixture-of-experts network is as good as the radial basis function network. Also, the analysis could benefit from adding another type of the statistical learning machine, namely support vector machines. There is software product, DTREG, which implements various types of this technique.

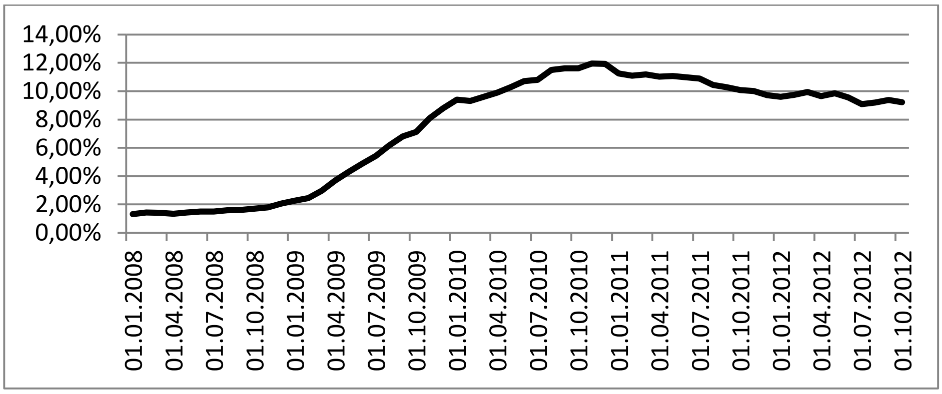
Appendix 1. Stylized facts on loan defaults in Ukraine

Figure 1. Volume of NPL in Ukrainian banks, billion UAH



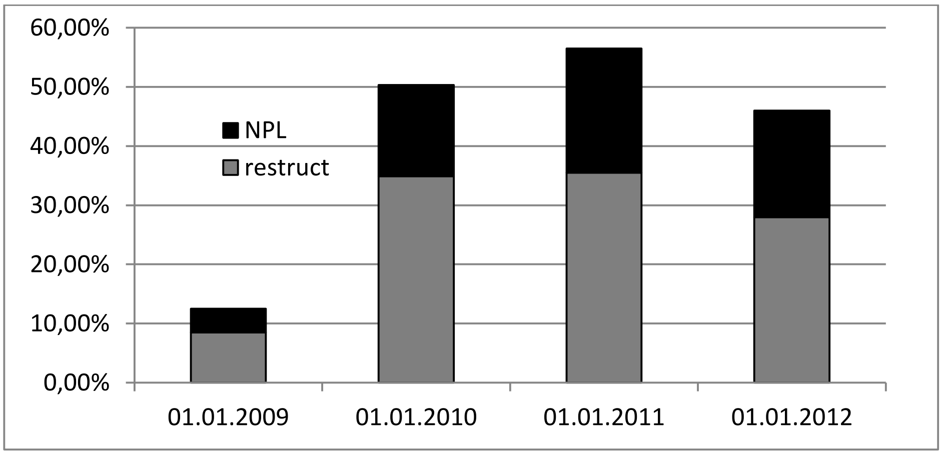
Source: National Bank of Ukraine

Figure 2. Volume of NPL in Ukrainian banks, % of portfolio



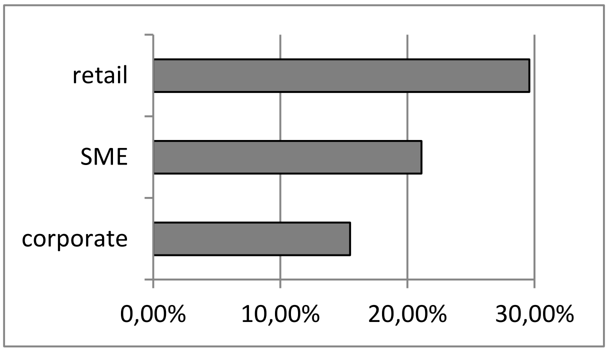
Source: National Bank of Ukraine

Figure 3. NPL and restructured loans, % of portfolio



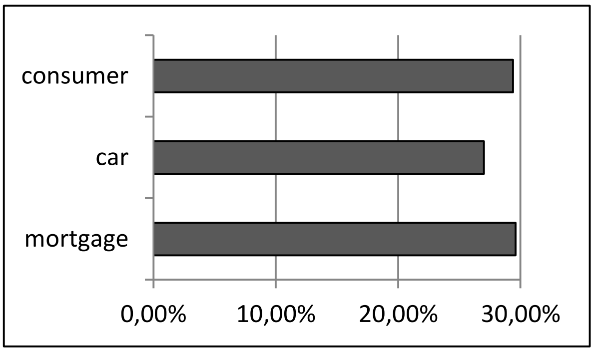
Source: Fitch Ratings

Figure 4. NPL for groups of borrowers, % of portfolio, 01.01.2011



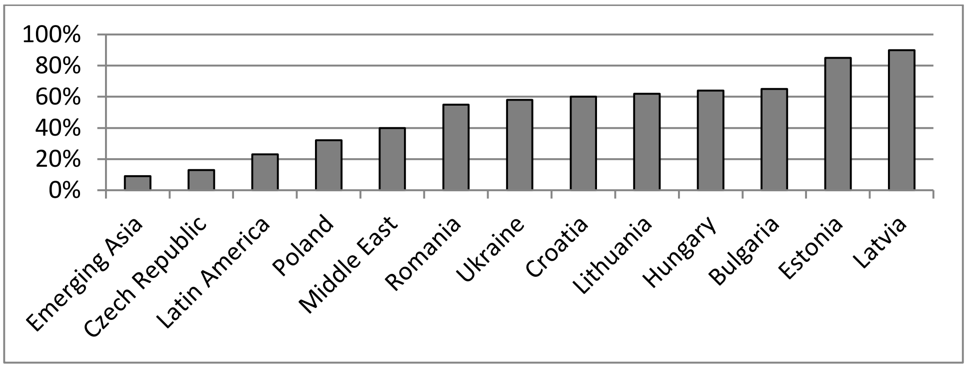
Source: Fitch Ratings

Figure 5. NPL for groups of retail borrowers, % of portfolio, 01.01.2011



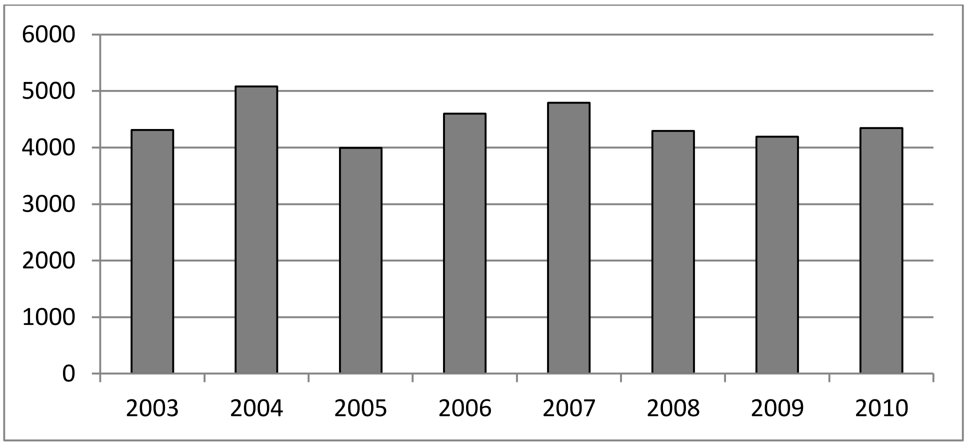
Source: Fitch Ratings

Figure 6. Foreign currency exposure of credit portfolios



Source: Ranciere, Tornell and Vamvakidis (2010)

Figure 7. Number of bankruptcy cases



Source: Liga Business Inform

Appendix 2. The development of default prediction models

Table 2.1. Model chronology (number of papers)

	Discriminant analysis	Logit analysis	Probit analysis	Neural networks	Other
1960's	2	0	0	0	1
1970's	22	1	1	0	4
1980's	28	16	3	1	7
1990's	9	16	3	35	11
2000's	2	3	0	4	3
Overall	63	36	7	40	26

Source: Bellovary, Giacomino and Akers (2007). Other models include linear probability, judgmental, Cusp catastrophe, and Cox proportional hazards models

Table 2.2. Accuracy of default prediction models

	Lowest accuracy	Highest accuracy
Discriminant analysis	32%	100%
Logit analysis	20%	98%
Probit analysis	20%	84%
Neural networks	71%	100%

Source: Bellovary, Giacomino and Akers (2007)

Appendix 3. Data description

Table 3.1. Variable description

Variable	Description	Units	Value meaning
LTV	Loan / value	(0,1)	
PTI	Payment / income	(0,1)	
cycle	Loan repayment stage (for car loans)	(0,1)	
bubble	Estimated negative equity (for mortgages)	(0,1)	
UAH	Currency of a loan, UAH or FX	Binary	
amount	Loan amount	UAH	
term	Loan term	Years	
int_rate	Interest rate	Percent	
type	Loan type, constant repayment or decreasing repayment	Binary	
age	Borrower's age	Years	
male	Gender	Binary	
resident	Duration of local residency	Ordered	1: < 1 year 2: 1-2 years 3: 2-5 years 4: > 5 years
company	Employer's name and size	Ordered	1: other 2: known average 3: known large
occupation	Borrower's position in the company	Ordered	1: pensioner 2: technical worker 3: associate 4: middle management 5: top-management 6: owner
experience	Duration of working experience	Ordered	1: < 1 year 2: 1-2 years 3: 2-5 years 4: > 5 years
military	Military duty	Binary	
education	Level of education	Ordered	1: primary 2: secondary 3: special secondary 4: technical secondary 5: unfinished higher 6: higher 7: degree or 2 higher
family	Marital status and the number of children	Ordered	1: single, no children 2: single, 1-2 children 3: single, 3+ children 4: married, no children 5: married, 1-2 children 6: married, 3+ children

recommendations	Presence of recommendations from employer	Ordered	1: none 2: oral from associate 3: written from associate or oral from manager 4: written from manager
home_phone	Presence of home phone	Binary	
mobile	Presence of cell phone	Ordered	1: None 2: < 1 year 3: 1-5 years 4: > 5 years
bank_cards	Presence of payment cards	Ordered	1: none 2: debit 3: credit
card_type	Type of payment cards	Ordered	1: none 2: pension 3: salary 4: electron 5: business 6: classic 7: gold
accounts	Presence of bank accounts	Ordered	1: none 2: has 3: has, OPT Bank
history	Previous credit history	Ordered	1: none 2: performing 3: no information 4: overdue 1-5 days 5: overdue >5 days
real_estate	Presence of owned real estate	Ordered	1: none 2: mutual property 3: private property
car	Presence of owned car	Ordered	1: none 2: mutual property 3: private property
assets	Presence of financial assets	Ordered	1: < 2 000 UAH 2: 2 000 - 10 000 UAH 3: > 10 000 UAH

Table 3.2.1. Descriptive statistics, car loans

Variable	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
	all				**performing**			
LTV	79,47	12,14	14,85	100	74,90	15,33	16,83	92,43
PTI	33,11	14,80	2,47	61,2	33,16	15,11	2,47	59,87
Cycle	10,31	3,77	5	23	10,53	3,73	6	23
UAH	0,03	0,17	0	1	0,03	0,17	0	1
amount	148 604,20	112 392,30	20 000	1076 559,00	120 807,90	89 854,35	20 000,00	675 417,30
term	78,09	11,68	18	84	75,63	14,38	18	84
Int_rate	11,39	1,29	7,49	18,49	11,32	1,14	7,49	18,49
type	0,39	0,49	0	1	0,28	0,45	0	1
AGE	36,33	8,40	20,31	61,63	36,73	8,83	20,31	61,63
male	0,69	0,46	0	1	0,65	0,48	0	1
resident	3,95	0,29	1	4	3,94	0,31	1	4
company	1,26	0,59	1	3	1,35	0,67	1	3
occupation	4,60	1,19	1	6	4,34	1,21	1	6
experience	2,89	1,03	1	4	2,98	1,06	1	4
military	0,99	0,09	0	1	0,99	0,11	0	1
education	5,79	1,02	1	7	5,81	1,03	1	7
family	3,54	1,70	1	6	3,71	1,62	1	6
recommenda~s	1,17	0,57	1	4	1,13	0,52	1	4
home_phone	0,27	0,44	0	1	0,24	0,43	0	1
mobile	3,91	0,47	1	4	3,92	0,43	1	4
bank_cards	1,82	0,82	1	3	1,71	0,75	1	3
card_type	3,32	2,30	1	7	3,05	2,19	1	7
accounts	1,88	0,70	1	3	1,79	0,68	1	3
history	1,42	0,70	1	5	1,29	0,55	1	4
real_estate	1,99	0,75	1	3	1,99	0,71	1	3
car	1,59	0,77	1	3	1,52	0,73	1	3
assets	1,04	0,28	1	3	1,03	0,25	1	3
	restructured				**non-performing**			
LTV	81,64	9,28	30,18	92,43	82,44	8,58	14,85	100
PTI	33,32	14,41	3,21	61,20	32,86	14,86	2,90	59,98
Cycle	9,79	3,41	5	23	10,56	4,07	5	22
UAH	0,02	0,15	0	1	0,03	0,18	0	1
amount	146 643,60	102 752,80	28 532,50	1076 559,00	180 780,20	133 078,00	34 340,00	863 121,00
term	80,35	8,65	24	84	78,67	10,28	31	84
int_rate	11,38	1,37	8,49	18,49	11,48	1,36	8,49	18,49
type	0,42	0,49	0	1	0,47	0,50	0	1
AGE	36,55	8,08	21,53	56,39	35,70	8,18	21,71585	61,61
male	0,69	0,46	0	1	0,74	0,44	0	1
resident	3,95	0,29	1	4	3,95	0,28	1	4
company	1,26	0,59	1	3	1,16	0,46	1	3
occupation	4,61	1,19	1	6	4,87	1,11	1	6
experience	2,90	1,02	1	4	2,77	1,00	1	4
military	0,99	0,10	0	1	1,00	0,05	0	1
education	5,83	0,97	1	7	5,74	1,06	1	7
family	3,72	1,66	1	6	3,19	1,78	1	6
recommenda~s	1,19	0,58	1	4	1,19	0,62	1	4
home_phone	0,26	0,44	0	1	0,31	0,46	0	1
mobile	3,92	0,46	1	4	3,89	0,53	1	4
bank_cards	1,87	0,84	1	3	1,90	0,85	1	3
card_type	3,44	2,33	1	7	3,51	2,35	1	7
accounts	1,94	0,71	1	3	1,91	0,70	1	3
history	1,47	0,72	1	5	1,53	0,79	1	5
real_estate	2,01	0,76	1	3	1,97	0,79	1	3
car	1,57	0,74	1	3	1,70	0,82	1	3
assets	1,05	0,31	1	3	1,04	0,27	1	3

Table 3.2.2. Descriptive statistics, mortgages

Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
	all				performing			
bubble	0,95	0,04	0,30	1	0,95	0,04	0,49	1
LTV	70,98	16,36	7,59	102,03	69,41	17,42	11,86	100
PTI	39,33	14,04	0,02	60,62	38,60	14,15	3,43	60,62
UAH	0,05	0,22	0	1	0,06	0,23	0	1
amount	1759 620,00	2081 512,00	25 000,00	4,34E+07	1653 468,00	1981 312,00	25 000,00	4,34E+07
term	255,41	83,90	56	360	250,67	85,50	56	360
int_rate	12,13	1,91	2,49	18,99	12,19	1,92	2,49	18,99
type	0,50	0,50	0	1	0,46	0,50	0	1
AGE	34,19	7,78	19,67	63,67	34,13	7,76	19,67	63,67
male	0,61	0,49	0	1	0,63	0,48	0	1
resident	3,94	0,32	1	4	3,94	0,33	1	4
company	1,23	0,54	1	3	1,27	0,58	1	3
occupation	4,24	1,40	1	6	4,28	1,31	1	6
experience	2,82	1,06	1	4	2,88	1,05	1	4
military	0,99	0,09	0	1	0,99	0,09	0	1
education	5,69	1,02	1	7	5,71	0,99	1	7
family	3,39	1,72	1	6	3,43	1,71	1	6
recommenda~s	1,15	0,52	1	4	1,14	0,51	1	4
home_phone	0,00	0,00	0	0	0,00	0,00	0	0
mobile	3,87	0,48	1	4	3,87	0,48	1	4
bank_cards	1,68	0,75	1	3	1,70	0,74	1	3
card_type	2,98	2,17	1	7	3,02	2,14	1	7
accounts	1,77	0,68	1	3	1,77	0,66	1	3
history	1,32	0,65	1	5	1,27	0,55	1	4
real_estate	2,15	0,80	1	3	1,93	0,78	1	3
car	1,54	0,76	1	3	1,52	0,73	1	3
assets	1,08	0,37	1	3	1,10	0,42	1	3
	restructured				non-performing			
bubble	0,95	0,05	0,30	1	0,95	0,04	0,84	0,98
LTV	73,14	14,59	7,59	86,27	73,87	11,13	56,7	102,03
PTI	40,32	13,84	0,02	59,92	40,85	13,89	14,61	60,38
UAH	0,04	0,20	0	1	0,00	0,00	0	0
amount	1803 546,00	2045 923,00	50 500,00	3,42E+07	4839 826,00	3978 059,00	823 457,20	1,59E+07
term	262,10	81,25	60	360	258,85	81,62	60	360
int_rate	12,04	1,91	3,49	18,99	12,10	1,65	6,99	13,99
type	0,57	0,50	0	1	0,54	0,51	0	1
AGE	34,26	7,82	20,08	56,92	34,37	7,81	24,08	52,58
male	0,59	0,49	0	1	0,62	0,50	0	1
resident	3,94	0,31	1	4	4,00	0,00	4	4
company	1,18	0,47	1	3	1,27	0,60	1	3
occupation	4,16	1,51	1	6	4,73	1,40	1	6
experience	2,74	1,07	1	4	2,77	1,21	1	4
military	0,99	0,09	0	1	1,00	0,00	1	1
education	5,66	1,06	1	7	5,81	1,10	3	7
family	3,31	1,73	1	6	3,73	1,76	1	6
recommenda~s	1,15	0,53	1	4	1,27	0,78	1	4
home_phone	0,00	0,00	0	0	0,00	0,00	0	0
mobile	3,88	0,45	1	4	3,65	0,98	1	4
bank_cards	1,65	0,76	1	3	1,69	0,88	1	3
card_type	2,93	2,22	1	7	2,77	2,34	1	7
accounts	1,76	0,70	1	3	1,88	0,86	1	3
history	1,36	0,72	1	5	2,08	1,32	1	5
real_estate	2,44	0,73	1	3	2,58	0,64	1	3
car	1,57	0,79	1	3	1,81	0,94	1	3
assets	1,05	0,29	1	3	1,00	0,00	1	1

Table 3.3. Samples vs population of Ukraine

Variable / range	Ukraine	Samples	
		Car loans	Mortgages
SEX			
Male	46,1%	69,4%	61,2%
Female	53,9%	30,6%	38,8%
AGE (for 20+ years)			
20..24	9,6%	6,1%	8,3%
25..29	9,4%	21,1%	25,9%
30..34	8,6%	22,4%	28,0%
35..39	9,4%	18,0%	15,2%
40..44	10,5%	14,6%	11,6%
45..49	9,5%	10,5%	6,9%
50..54	8,7%	5,3%	3,4%
55..59	5,7%	1,6%	0,7%
60+	28,4%	0,3%	0,2%
EDUCATION (for 20+ years)			
Primary	22,6%	0,2%	0,2%
Secondary	38,8%	1,3%	1,0%
College	22,5%	15,1%	17,6%
University	16,1%	83,4%	81,3%
MARITAL STATUS (for 20+ years)			
Not married	35,1%	34,4%	43,9%
Married	64,9%	65,6%	56,1%
CHILDREN (for 15+ years)			
No children	21,6%	44,2%	49,4%
1-2 children	64,1%	54,3%	48,7%
3+ children	14,3%	1,5%	1,9%
INCOME			
< 1920 UAH per month	88,1%	0,5%	0,3%
> 1920 UAH per month	11,9%	99,5%	99,7%

Appendix 4. Results

4.1 Logistic regression

Table 4.1.1. Significant coefficients for car loans

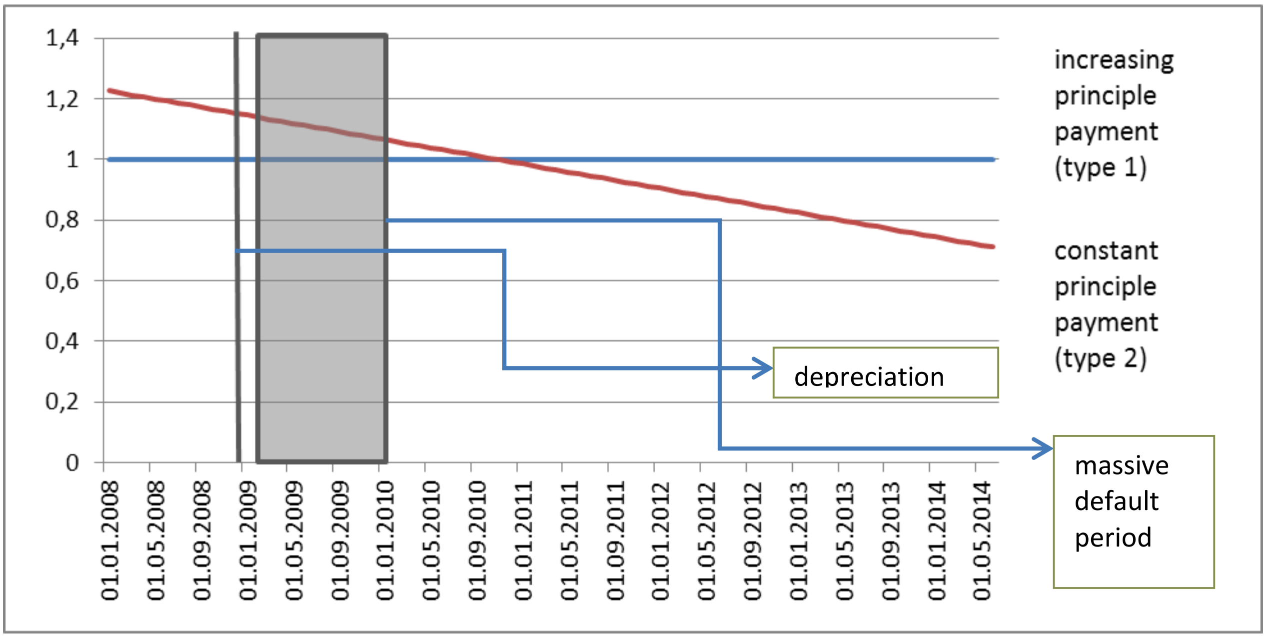
var \ spec	Multinomial		Ordered	Binomial Restr => PL	Binomial Restr => NPL
	Restr vs. PL	NPL vs. PL			
LTV	0.039	.049	0.040	0.036	0.042
Amount		3.26e-06	2.52e-06	3.05e-06	2.15e-06
Term	0.031				0.020
Type	0.579	0.721	0.506	0.392	0.643
Male		0.427	0.294	0.366	
Company	-0.205	-0.453	-0.317		-0.308
Experience		-0.258	-0.182	-0.227	-0.176
Family		-0.158	-0.128	-0.171	
Cards	0.407	0.598	0.427	0.409	0.500
History	0.402	0.473	0.314	0.251	0.431
Pseudo R^2		0.120	0.099	0.131	0.149
Hits all rest	69%	—	69%	—	—
Hits rest	6%	—	0%	—	—
Hits all NPL	—	72%	70%	71%	73%
Hits NPL	—	35%	33%	40%	89%

Table 4.2.2. Significant coefficients for mortgages

var \ spec	Multinomial		Ordered	Binomial Restr => PL	Binomial Restr => NPL
	PL vs. Restr	PL vs. NPL			
LTV	0.016		0.016		0.016
PTI	0.010		0.010		0.010
Amount		2.58e-07		2.26e-07	
Term	0.002		0.002		0.002
Type	0.340		0.330		0.325
Male					
Company	-0.317		-0.293		-0.314
Experience					-0.120
Cards				2.201	
Card type				-0.829	
History		0.854	0.260	0.821	0.198
Real estate	0.807	0.983	0.789		0.801
Assets	-0.372		-0.373		-0.377
Pseudo R^2		0.123	0.104	0.197	0.112
Hits all rest	68%	—	68%		
Hits rest	52%	—	52%	–	–
Hits all NPL	—	99%	99%	98%	68%
Hits NPL	—	0%	0%	0%	55%

Case study #1. Loan type

Figure 8. Payments for an average car loan over time



Parameters of simulation:

Duration = 78 months
Interest rate = 11.4%

4.2 Neural Networks

Car loans

Table 4.2.1. Neural networks summary

#	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Inputs	Hidden
MLP	0.8965876	0.3798219	0.393175	0.4962317	3.56125	3.4587	26.0	17.1
LIN	0.461721	0.4679524	0.419584	0.4549102	0.4571478	3.25E+12	8.1	
RBF	0.4820475	0.4747775	0.419881	0.453066	0.4577834	0.470625	20.6	22.2
PNN	0.7385759	0.4308605	0.376855	0.3769264	0.4628236	0.467809	20.7	674.0

Table 4.2.2. Neural networks variables

	MLP	LIN	RBF	PNN	total
Amount	7	7	10	10	34
Type	10	4	10	10	34
Recommendations	10	3	10	10	33
LTV	10	4	7	10	31
Experience	10	4	7	10	31
Male	10	1	10	9	30
Company	10	0	10	10	30
Mobile	10	0	10	10	30
Occupation	10	10	7	2	29
Term	4	4	9	10	27
Position	10	9	8	0	27
Education	10	0	10	7	27
History	10	0	7	10	27
Assets	10	4	7	6	27
Bank cards	10	8	7	1	26
Card type	10	9	7	0	26
PTI	6	0	8	10	24
Resident	10	0	3	10	23
Military	9	0	3	10	22
Family	10	1	10	0	21
Age	7	0	3	10	20
Home phone	8	0	8	4	20
Accounts	10	0	7	3	20
Real estate	10	1	7	2	20
Car	10	2	7	0	19
UAH	10	0	0	5	15
Interest	1	0	2	10	13

Mortgages

Table 4.2.3. Neural networks summary

#	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Inputs	Hidden
MLP	0.889462	0.594945	0.580659	0.497977	2.423189	2.621989	21.4	14.4
LIN	0.628540	0.631209	0.615604	0.391268	2.518E+11	0.400016	8.4	—
RBF	0.668057	0.666374	0.649670	0.383416	0.382442	0.390999	18.9	28.4
PNN	0.731175	0.667692	0.649231	0.353799	0.385277	0.388697	15	911

Table 4.2.4. Neural networks variables

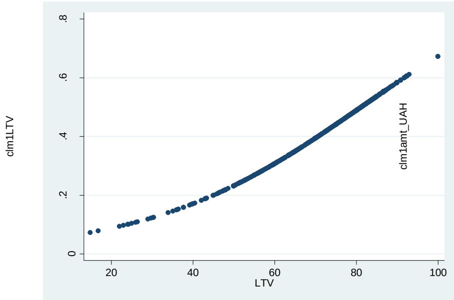
	MLP	LIN	RBF	PNN	total
Real estate	10	4	10	10	34
Recommendations	10	2	10	10	32
Resident	10	1	10	10	31
Card type	10	8	10	2	30
Occupation	10	10	8	0	28
Bank cards	10	7	10	1	28
Mobile	10	1	6	10	27
History	10	1	10	6	27
Term	5	5	6	10	26
Company	10	1	5	10	26
Experience	10	1	10	5	26
Position	10	9	5	1	25
UAH	10	1	3	10	24
Type	10	4	10	0	24
LTV	5	6	5	7	23
PTI	9	1	7	6	23
Accounts	10	3	10	0	23
Car	10	3	10	0	23
Education	10	4	5	3	22
Family	10	1	9	0	20
Assets	10	2	4	4	20
Male	7	3	5	4	19
Interest	0	1	6	9	16
Amount	1	1	6	6	14
Age	4	1	1	8	14
Bubble	0	1	6	6	13
Military	3	1	1	6	11
Home phone	0	1	1	6	8

Table 4.2.5. Type I and Type II error rates for neural networks, car loans

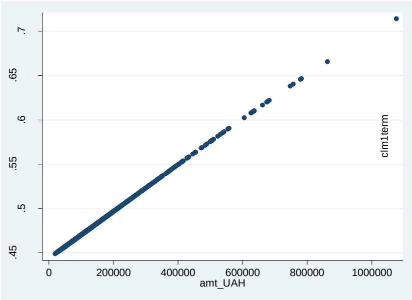
Model	Type I	Type II
MLP 1	16,77%	8,90%
MLP 2	17,43%	9,20%
Linear 2	23,44%	12,54%
RBF 1	24,63%	12,69%
Linear 3	24,18%	12,69%
Linear 1	21,29%	12,83%
RBF 3	24,26%	12,91%
RBF 2	25,22%	13,20%
PNN 1	1,93%	17,66%
PNN 2	1,85%	18,47%
min	1,85%	8,90%
avg	18,10%	13,11%
max	25,22%	18,47%

Figures 9-11. Car loans / multinomial / restructured

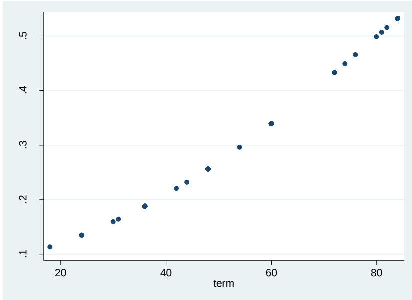
LTV (0-0.8)



amount (0.45-0.7)

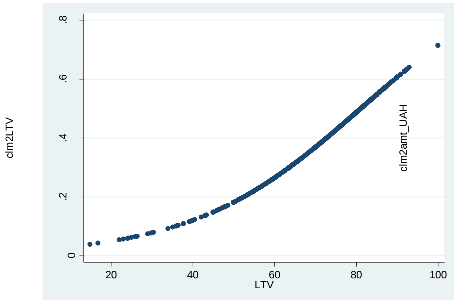


term (0.1-0.5)

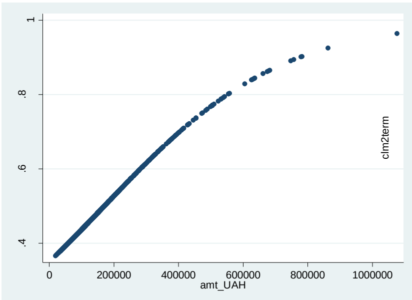


Figures 12-14. Car loans / multinomial / default

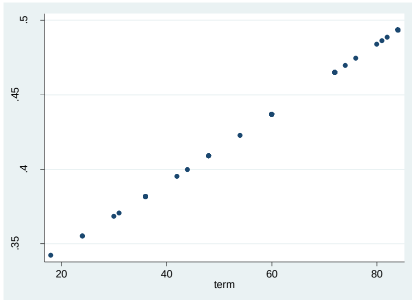
LTV (0-0.8)



amount (0.4-1)

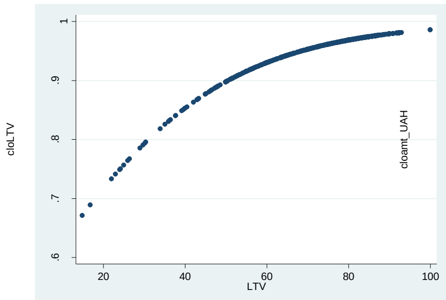


term (0.35-0.5)

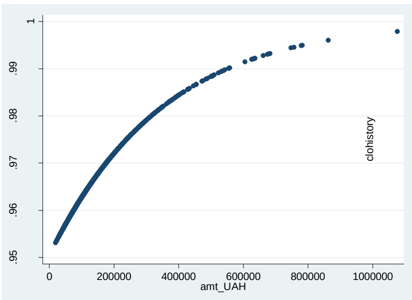


Figures 15-17. Car loans / ordered

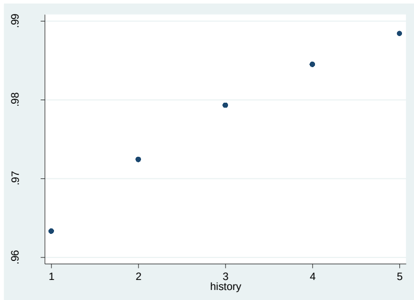
LTV (0.6-1)



amount (0.95-1)

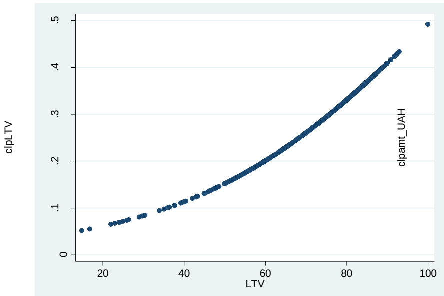


history (0.96-0.99)

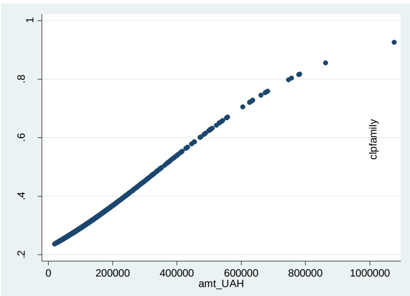


Figures 18-20. Car loans / binomial / restructured => performing

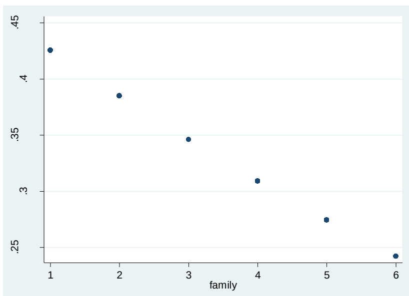
LTV (0-0.5)



amount (0.2-1)

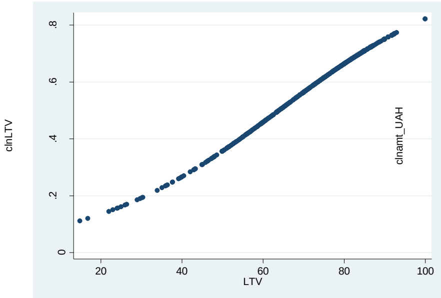


family (0.25-0.45)

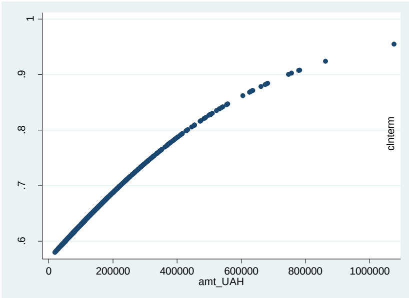


Figures 21-23. Car loans / binomial / restructured => non-performing

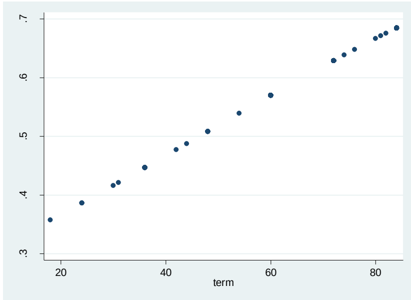
LTV (0-0.8)



amount (0.6-1)

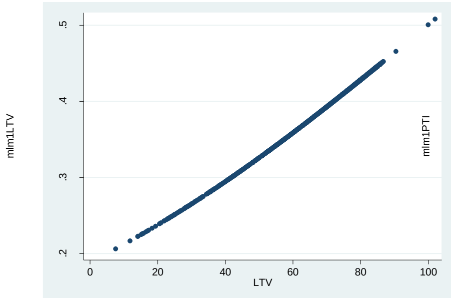


term (0.3-0.7)

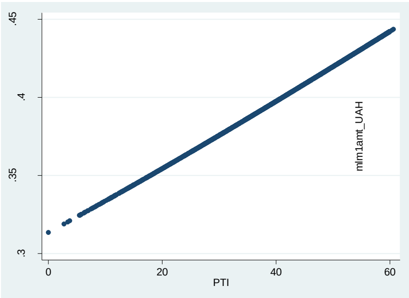


Figures 24-29. Mortgage / multinomial / restructured

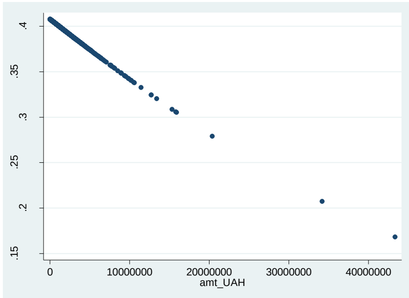
LTV (0.2-0.5)



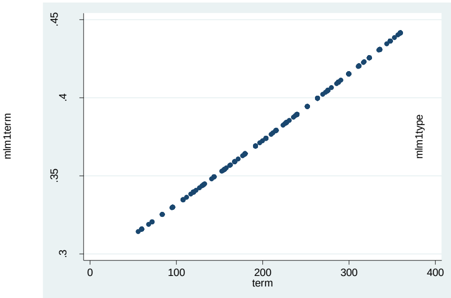
PTI (0.3-0.45)



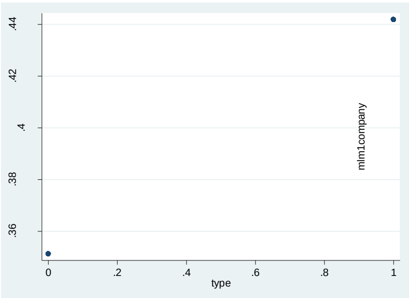
amount (0.15-0.4)



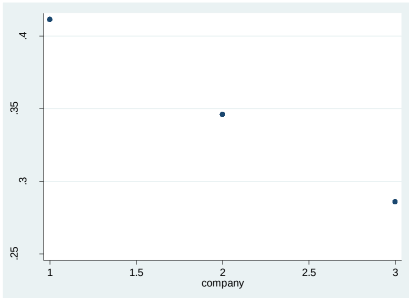
term (0.4-0.45)



type (0.36-0.44)

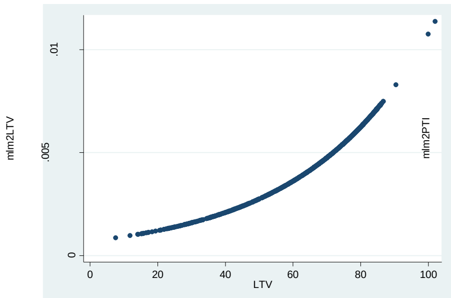


company (0.25-0.4)

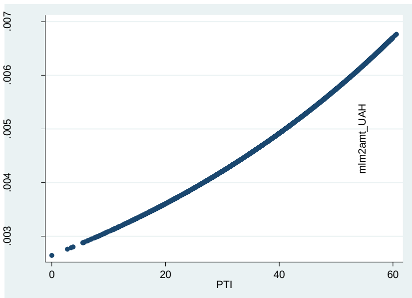


Figures 30-35. Mortgage / multinomial / default

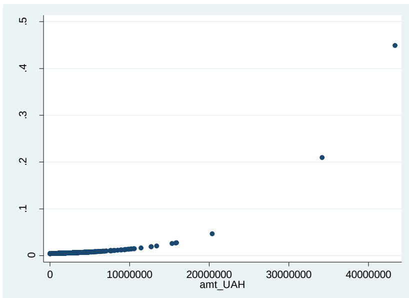
LTV (0-0.01)



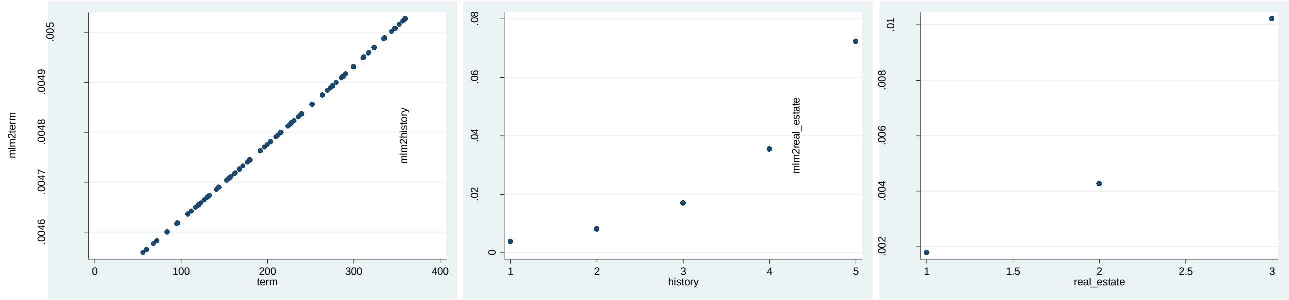
PTI (0.003-0.007)



amount (0-0.5)

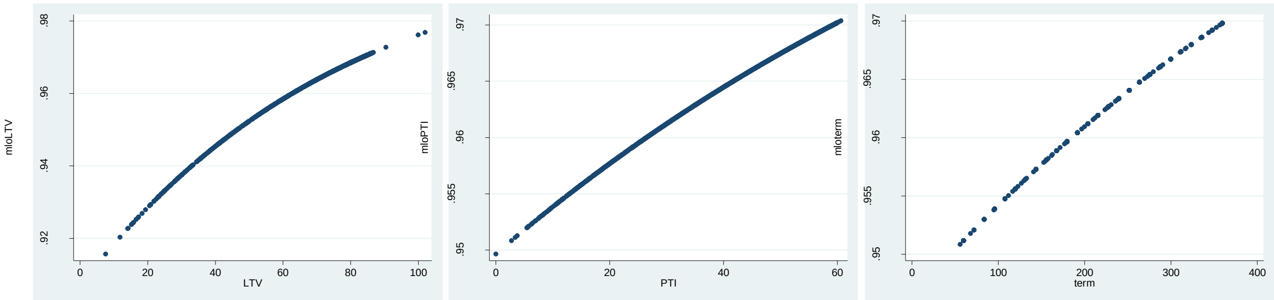


term (0.0046-0.005) | history (0-0.08) | real_estate (0.002-0.01)



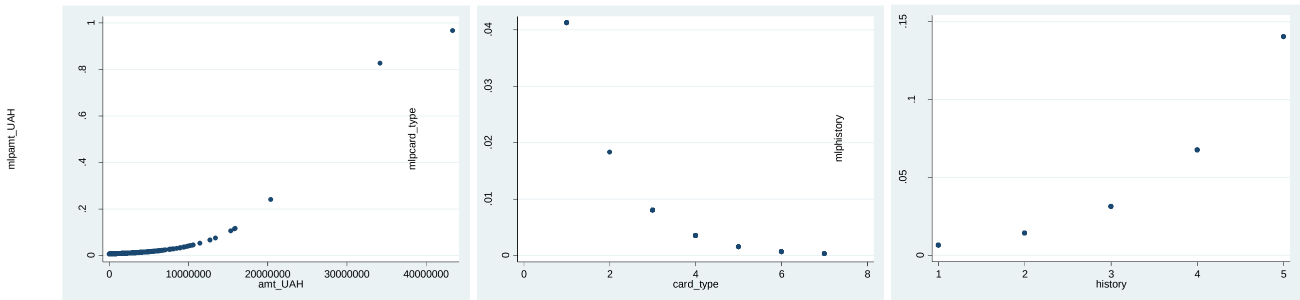
Figures 36-38. Mortgage / ordered

LTV (0.92-0.98) | PTI (0.95-0.97) | term (0.95-0.97)



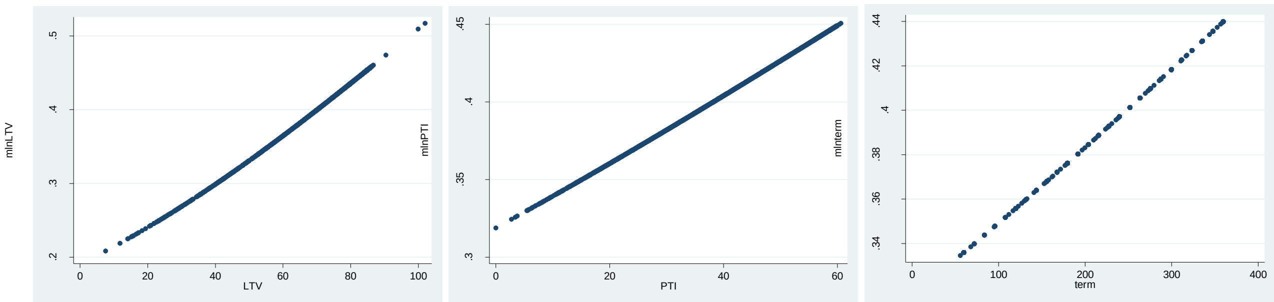
Figures 39-41. Mortgage / binomial / restructured => performing

amount (0-1) | card_type (0-0.04) | history (0-0.15)



Figures 42-44. Mortgage / binomial / restructured => non-performing

LTV (0.2-0.5) | PTI (0.3-0.45) | term (0.34-0.44)



Case study #2. Receiver operating characteristic

Figure 45. ROC curve, car loans

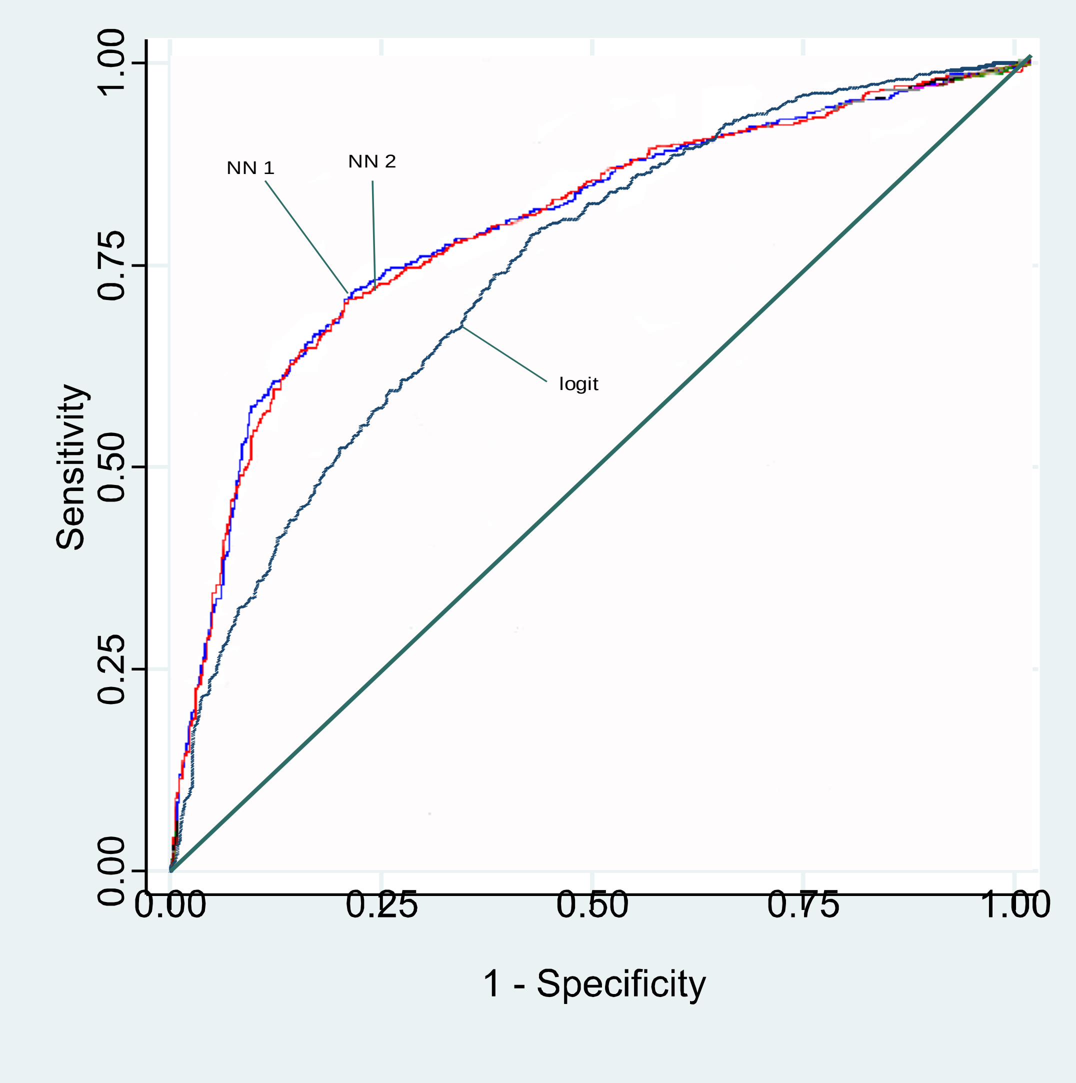


Table 4.2.6. Area under ROC curve, car loans

Model	Area
NN MLP 1	0,797564
NN MLP 2	0,797564
Logit	0,7410
NN Linear 1	0,708275
NN Linear 2	0,699888
NN RBF 1	0,667372
NN RBF 2	0,679868
NN RBF 3	0,678243
NN Linear 3	0,674849

4.3. Policy implication

Table 4.3. Financial effects of probability of default

Rating (S&P)	One year probability of default, %	Risk premium, %	Capital requirements (Basel II), %
AAA	0.01	0.75	0.63
AA	0.02-0.04	1.00	0.93-1.40
A+	0.05	1.50	1.60
A	0.08	1.80	2.12
A-	0.11	2.00	2.55
BBB	0.15-0.40	2.25	3.05-5.17
BB	0.65-1.95	3.50	6.50-9.97
B+	3.20	4.75	11.90
B	7.00	6.50	16.70
B-	13.00	8.00	22.89
CCC	>13	10.00	>22.89
CC		11.50	
C		12.70	
D		14.00	

Source: Hardle, Moro and Schafer (2005)

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