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DÁNIEL HOLLÓ–MÓNIKA PAPP

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**Assessing household credit risk: evidence from a household survey***

(A háztartási hitelkockázat becslése: egy kérdőíves felmérés tanulságai)

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# Contents

# Abstract

This paper investigates the main individual driving forces of Hungarian household credit risk and measures the shock-absorbing capacity of the banking system in relation to adverse macroeconomic events. The analysis relies on survey evidence gathered by the Magyar Nemzeti Bank (MNB) in January 2007. Our study presents three alternative ways of modelling household credit risk, namely the financial margin, the logit and the neural network approaches, and uses these methods for stress testing. Our results suggest that the main individual factors affecting household credit risk are disposable income, the income share of monthly debt servicing costs, the number of dependants and the employment status of the head of the household. The findings also indicate that the current state of indebtedness is unfavourable from a financial stability point of view, as a relatively high proportion of debt is concentrated in the group of risky households. However, risks are somewhat mitigated by the fact that a substantial part of risky debt is comprised of mortgage loans, which are able to provide considerable security for banks in the case of default. Finally, our findings reveal that the shock-absorbing capacity of the banking sector, as well as individual banks, is sufficient under the given loss rate (LGD) assumptions (i.e. the capital adequacy ratio would not fall below the current regulatory minimum of 8 per cent) even if the most extreme stress scenarios were to occur.

**JEL:** C45, D14, E47, G21.
**Keywords:** financing stability, financial margin, logit model, neural network, stress test.

# Összefoglaló

A tanulmány a háztartási hitelkockázatra ható főbb egyedi tényezők hatásait vizsgálja, illetve a különféle kedvezőtlen makrogazdasági eseményeknek a bankrendszeri sokktűrő képességre gyakorolt azon hatását elemzi mely a háztartási hitelkockázat változásán keresztül jelentkezik. A tanulmány a Magyar Nemzeti Bank által 2007 januárjában az eladósodott háztartások körében végzett kérdőíves felmérés eredményeire épül. A hitelkockázat mérését három módszerrel végezzük el (jövedelemtartalék-számítás, logit és neurális háló modellek), melyeket stressztesztelésre is felhasználunk. Eredményeink szerint a fő egyéni kockázati tényezők a háztartás rendelkezésre álló jövedelme, a jövedelemarányos törlesztési teher az eltartottak száma és a családfő munkaerő-piaci helyzete. Elmondható továbbá, hogy az eladósodottság jelenlegi szerkezete kedvezőtlen pénzügyi stabilitási szempontból, mivel a hitelállomány relatíve jelentős hányada van kifeszített pénzügyi és jövedelmi helyzetű háztartások birtokában. A kockázatokat azonban némileg csökkenti, hogy a kockázatos hitelállomány számottevő része jelzálogalapú hitel, mely azonban megfelelő fedezetet nyújthat a bankok számára az ügyfél nem teljesítése esetén is. Végül stresszteszt-eredményeink szerint, mind az egyes bankok, mind a bankrendszer sokktűrő képessége megfelelő, vagyis a veszteségrátákra tett feltevések mellett a legszélsőségesebb forgatókönyvek bekövetkezése esetén sem csökkenne a tőkemegfelelési mutató a jelenlegi szabályozói minimumnak tekintett 8 százalékos szint alá.

# 1. Introduction

The indebtedness of Hungarian households has grown substantially in recent years. The total debt outstanding rose from HUF 516 billion at the end of 1999 to HUF 6,074 billion by the end of 2006. In line with this, the debt to yearly disposable income ratio rose from 8 per cent to 39 per cent over the same period. Both the demand and the supply side, as well as regulatory factors contributed to this phenomenon. On the demand side favourable macroeconomic circumstances (decreasing inflationary environment, strong economic growth) and improving income prospects (EU convergence) were the main driving forces. On the other hand, regulatory and supply-side factors also supported growth. In 2000 the government introduced an interest subsidy scheme in connection with forint mortgage loans for housing construction, which was a substantial driving force of growing indebtedness. This effect was further accelerated by the banks' aggressive expansion strategies, which aimed at extracting the untapped possibilities in the retail lending market and which forced them to focus on product innovation (FX lending) and ease the credit standards.

However, the prevailing trends in the retail lending market raised concerns about the sustainability of credit expansion and the ability of individuals to meet their debt obligations comfortably. The recent slowdown in economic activity has intensified these concerns.[1]

Although in the household sector the level of indebtedness is far below that of developed economies,[2] the debt service burden (principal and interest payment) as a share of yearly disposable income is 10 per cent, which is approaching the level of western EU countries, due to the unfavourable (i.e. short) maturity structure of loans. This is exaggerated by the degree of leverage (debt to financial assets), which rose from 6 per cent to 26 per cent between 1999 and 2006, and the growing share of foreign currency debt. The latter induces additional risk components: the change of debt servicing costs as a result of exchange rate movements.

Calculating these indicators for the indebted households which are most relevant to the financial sector, a far more unfavourable picture emerges. Within the group of indebted households the debt to yearly disposable income ratio is 94 per cent, indebted households spend on average 18 per cent of their income on debt servicing and the stock of debt within this category is 7.5 times higher than the stock of financial savings.[3] This phenomenon is unfavourable from a financial stability point of view, as it indicates that a substantial part of debt is granted to households with limited resources.

In these circumstances, adverse developments in the macro economy may lead to a large number of households defaulting. This may result in a decrease in consumption and investment expenditures, and also worsens the profitability of the financial sector by generating higher loan losses. As a consequence, it is of great importance to continuously monitor and measure household credit risk.

In the empirical literature two research directions can be distinguished in the measurement of households' credit risk, the 'macro' and 'micro' approaches. They differ along two principal dimensions, namely whether individual information about households is utilised or not, and the econometric techniques used for measuring the effects of macroeconomic developments on bank losses. While the 'macro' approach employs only aggregate information and interrelates bank losses and macroeconomic developments directly by usually applying time series econometric techniques, the 'micro' approach uses individual data as well, and measures the effects of the macro environment on bank losses indirectly by commonly using discrete choice models.

In the 'macro' approach the short-term evolution of losses (usually proxied by loan loss provisions, nonperforming loan ratios, write off to loan ratios, etc.) and their interactions with aggregate sector specific and macro variables are analysed. Froyland

[1] As it is noted by the Report on Financial Stability 2007, the fiscal package announced in the summer of 2006 imposes substantial burdens on economic agents. Due to higher taxes and inflation, households' real income is projected to drop by more than 3 per cent in 2007, and may only rise modestly in 2008. In the corporate sector, higher taxes will push up the cost of capital and the wage costs, which may resulted in a decline of the profitability level.

[2] The level of indebtedness (debt to yearly disposable income) in some selected western EU countries is as follows: France 83 per cent, Italy 60 per cent, Spain 105 per cent, United Kingdom 160 per cent (Source: OECD).

[3] The results are based on survey evidence gathered by the MNB in January 2007.

and Larsen (2002) applied linear regression techniques for analysing the effects of the macro environment on banking sector losses. The main drawback of their approach is that the possible feedback effects from the banking sector to the economy cannot be detected and the problem of endogeneity arises. In their model estimation those macro and household sector related variables which significantly influence banks' household loan portfolio quality were the debt to income ratio, real housing wealth, banks' nominal lending rate and the unemployment rate.

On the other hand, Hoggart and Zicchino (2004), and Marcucci and Quagliariello (2005) used vector autoregressions (VAR). The main advantage of VARs is that they allow capturing the interactions among variables and the feedback effects from the banking sector to the real economy. In this sense VARs provide an ideal framework for financial stability purposes, although it has to be mentioned that simple VARs are not capable of handling the problem of asymmetries, whose role is strengthened under stress conditions – Drehmann et al. (2006). Therefore, the effects of adverse macroeconomic developments on bank losses might be underestimated. Marcucci and Quagliariello (2005) found that the main macro drivers of banks' household portfolio quality are the output gap, the level of indebtedness and the inflation rate. In the study of Hoggart and Zicchino (2004) the authors found little evidence that changes in macroeconomic activity have a substantial impact on aggregate and unsecured write-offs. In contrast, they found a clear statistical impact of income gearing, interest rates and the output gap on secured write-offs.

The 'micro' approach provides an alternative way of modelling risks. It handles the problem of 'aggregation' by utilising individual information and is able to link both idiosyncratic and systemic factors of credit risk to bank losses. Therefore, it provides a more accurate way of loss measurement by using default probability (PD), exposure and loss given default (LGD) data. The 'micro' approach was employed by May and Tudela (2005), who estimated a random effect probit model for studying the effects of household micro attributes and some selected macro variables on the probability of secured debt payment problems. Their results suggest that the main macro driving force of payment problems is the mortgage interest rate. At the household level, interest gearing of 20 per cent and above and high LTVs significantly influence the probability of payment problems.

Herrala and Kauko (2007) within a simple logit framework analyse how the probability of being financially distressed depends on household disposable income and debt servicing costs. They found that the two macro factors which substantially influence households' payment ability were unemployment and interest rates.

The adaptation of the macro approach for Hungary would not provide accurate information about the potential risks and vulnerabilities for the household sector for at least three reasons. The lack of an adequate loss indicator is one of the main drawbacks. Neither the stock (non performing loan), nor the flow (loan loss provision) measures of losses can proxy accurately the risks on the aggregate, as they suffer from the substantial role of portfolio cleaning. In addition, the former cannot reflect promptly the evolution of the business cycle. The second 'drawback' is that the period in which retail lending became dominant (the past 7-8 years) was not characterised by substantial macro turbulences, therefore the portfolio quality was rather stable (i.e. aggregate loss indicators do not show much variability through time). As a result, we are unable to correctly judge the effects of adverse macro movements on banks' portfolio quality by using these measures in a macro econometric framework. Finally, these indicators for different household loan products before 2004 are not available.

As a result we decided to analyse household sector credit risk by applying the 'micro' approach, building on survey evidence gathered by the MNB in January 2007.

The aim of the present paper is twofold. First, by using micro level household data we determine the main idiosyncratic driving forces of credit risk and analyse whether the current state of indebtedness threatens financial stability. Second, we examine the shock-absorbing capacity of the banking system in relation to adverse shocks.

Our study extends the existing literature on household credit risk modelling in two ways. This is the first study which uses micro level data for analysing household credit risk, the potential sources of vulnerabilities and the shock-absorbing capacity of the banking system in Hungary. Second, we compare three different methods (logit, artificial neural network and financial margin approaches) of household credit risk measurement and use these for stress testing.

Our findings suggest that the main individual factors affecting household credit risk are disposable income, the income share of monthly debt servicing costs, the number of dependants and the employment status of the head of the household. The results also show that the current state of indebtedness is unfavourable from a financial stability point of view, as a relatively high share of debt is concentrated in the group of risky households. Risks are somewhat mitigated by the fact that a substantial part of risky debt is comprised of mortgage loans, which are able to provide considerable security for banks in the case of default. In the stress testing exercise, by analysing the effects of declining employment and rising debt servicing costs, the results indicate that the household loan portfolio quality is more sensitive to exchange rate depreciation and a CHF interest rate rise than to an HUF interest rate increase, which is due to the denomination and repricing structure of the portfolio. In the case of declining employment, the banking sector would face the highest losses if the total number of new unemployed is concentrated within services, followed by industry, commerce and agriculture. Finally, our findings suggest that the shock-absorbing capacity of the banking sector, as well as individual banks, is sufficient under the given loss rate (LGD) assumptions, that is the capital adequacy ratio would not fall below the current regulatory minimum of 8 per cent even if the most extreme stress scenarios were to occur.

The remainder of the paper is organised as follows. In Section 2 we describe the data set used and provide the theoretical set-up of the models. Section 3 presents the empirical analysis and finally section 4 offers a concluding summary.

# 2. Methodological background

In this section, first we briefly describe the data set employed and then give a short technical overview about the methods used for calculating the probability of default and risky debt (we refer to this as debt at risk). Finally, the model validation approach is presented.

## 2.1. DATA DESCRIPTION[4]

The employed data set derives from a survey conducted by the MNB among indebted households in January 2007.[5]

For the survey a questionnaire was compiled containing four different sections: financial standing of households, credit block, financial savings and personal characteristics. The two main parts of the questionnaire were the financial standing and credit blocks. The former included information about the household's disposable income, real wealth, consumption and overhead expenditures. The credit block was divided further into three sub parts: secured, unsecured blocks and the third part included general questions about debt (i.e. relation to debt, future plans about credit market participation, etc.) and payment problems. In the credit block the respondents were asked about the parameters of their loan(s) (amount, maturity, monthly debt servicing costs, denomination, year of borrowing, number of loan contracts, etc.). The final sample included 1,046 households having some type of credit.

The information received concerning wealth and income was treated with caution for two reasons. On the one hand, it is difficult to involve high-income groups in a questionnaire-based survey, which might bias the sample's income distribution. On the other hand, obtaining reliable information on households' financial situation is difficult in general, given the high degree of distrust in Hungary. There is not a generally accepted technique handling the uncertainty apparent in income information, but as the results might be sensitive to this we tried to look at this issue as deeply as possible.[6]

Since we received information about each household member (age, qualification, employment status), it allowed us to determine the minimal income a certain household with specific parameters should have.[7] In cases when the income calculated in this way was higher than disclosed, we made an adjustment (allowing only one category shift, that is a HUF 20,000 increase). As the high degree of uncertainty in connection with black income remained still relevant after the first correction, we decided to increase income data by an additional 10 per cent.[8]

## 2.2. NON-PARAMETRIC CREDIT RISK MEASUREMENT

A simple way of measuring household credit risk involves the calculation of the households' financial margin (or income reserve). The idea behind this approach is that the margin can be an appropriate proxy of default risk, as its size promptly reflects the evolution of households' payment ability. The financial margin is the difference between monthly disposable income and the sum of consumption expenditures and debt servicing costs, and can be expressed as follows:

$$fm^i \equiv y^i - \left(c^i + ds^i\right) \tag{2.1}$$

where *fm* is the financial margin, is the disposable income, *y* is the consumption expenditures and *ds* is the debt servicing costs of household *i*.

[4] Descriptive statistics of some selected variables can be found in Table A in Appendix 2.

[5] Data were collected by the market research institute Gfk Hungária Kft. In the data collection processes, the aim was to ensure both the regional as well as the income representativity of the sample. Concerning the regional distribution of loans, previous surveys of Gfk Hungária Kft. provided a priori information, while income representativity was assured by posterior weighting. Data collection was performed with the 'random walk method' as this ensures that households have equal probability of getting into the sample. Selected households were sought personally.

[6] The high degree of uncertainty regarding the income information is especially problematic in the case of the non-parametric calculations and simulations.

[7] We determined the minimum income for a household based on the prevailing minimum wage, unemployment aid and old-age pension.

[8] The calculations are prepared in the case of the non-parametric approach by using the original and the adjusted (i.e. additional 10 per cent higher) income as well. Regarding the parametric approaches, it is irrespective from the results viewpoint which income data is used, since not the income levels but the position of the household in the income distribution is employed in the calculations.

Using this simple static framework for measuring credit risk, we make two simplifying assumptions. First, it is assumed that only those households default whose financial margin is negative (strict default interpretation), which means that after paying out the basic living costs the remaining income is less than the debt servicing costs. Second, we presume that assets and liabilities are fixed in the short run, so borrowing further when problems occur is not possible. Interpreting default in this framework denotes that households with negative financial margin have a default probability of one, and those with positive have a zero probability of default. The average unconditional default probability is the share of households with negative financial margin within the sample, and debt at risk is the share of the exposure of the financial sector to these households within total loans outstanding.

The main shortcomings of this approach are the implicit assumption of homogeneous individual default probabilities within risk categories and the identical zero default barrier, which might substantially differ among households. What we do know is that households with negative margin might be riskier than those with positive margin, but to what extent is not known. From a financial stability point of view, the 'underestimation' of default probabilities in the 'non default' category (i.e. zero PDs) is more problematic than the 'overestimation' of PDs in the 'default category' (i.e. PD is equal to one), as we do not know the net effect (i.e. whether the 'underestimation effect' is more than offset by the 'overestimation effect' or not).

## 2.3. PARAMETRIC CREDIT RISK MEASUREMENT

This section presents a simple logit and an artificial neural network model for calculating default probabilities and debt at risk. The methods employed are also static (i.e. the assumption of fixed assets and liabilities in the short run is still held), but for each household in the sample an individual conditional PD can be assigned in relation to their financial and personal characteristics. The main advantage of these models is that the results depend less on the ambiguous income and consumption levels than in the case of the financial margin for at least two reasons. First, the dependent variable differs[9] (i.e. falling into a more than one month payment arrear or not) in a way which is not directly sensitive for consumption and income data; second, the methods used for calculating default probabilities are not linear, that is the calculated average conditional PD is less sensitive to income uncertainty than the average unconditional PD of the non-parametric approach.[10]

### 2.3.1. The logit approach

#### Model description

The default problem can be analysed within a simple binary choice framework. The respondent either did not *(Y=0)* or did have *(Y=1)* payment problems during the period in which the survey was conducted. It is assumed that a set of factors in vector $x$ explains the decision, that is

$$\Pr ob\left(Y=1\,|\,x\right)=F\left(x,\beta\right) \tag{2.2}$$

$$\Pr ob\left(Y=0\,|\,x\right)=1-F\left(x,\beta\right) \tag{2.3}$$

The parameters $\beta$ reflect the impact of changes in $x$ on the probability. Assuming that the error term is logistically distributed, the conditional default probability is calculated as follows:

[9] Default variable for the parametric approaches could have been constructed by using the financial margin of households (i.e. households with negative financial margin are considered to be in default, those having positive have no payment problems). As this definition by construction is very sensitive to income and consumption data quality and has other shortcomings as well (namely the identically zero default barrier assumption described above), in the parametric approaches this default definition was not employed.

[10] The relationship between the two default definitions (i.e. those are in default whose financial margin is negative, and, according to the second, those are in default whose arrears exceed one month) applied in this paper might be biased by several factors. First, the uncertainty regarding the disposable income can be mentioned; second, the time inconsistency originated from the difference of the financial situation of the households when default happened and when the survey was conducted. In the 'optimal case', when a household falls into arrears or defaulting, then its margin is the lowest or might be negative; therefore, the two definitions coincide with each other. Despite the previously mentioned problems, it can be observed that the financial margin of those whose arrears exceed one month is by 30,000 HUF lower on average than the margin of those having no payment problems, so in this sense both definitions can be used as a good proxy of default risk and also show some coincidence.

$$\Pr ob(Y=1|x)=\frac{\exp(\beta x')}{1+\exp(\beta x')}=\Lambda(\beta x') \tag{2.4}$$

where $\Lambda(\beta x')$ indicates the logistic cumulative distribution function. By using the individual PDs and debt outstanding, debt at risk can be expressed as follows:

$$D@R=\frac{\sum_{i=1}^{N}\mathrm{Prob_i}*z_i}{\sum_{i=1}^{N}z_i} \tag{2.5}$$

where $z$ is the loan amount of household $i$ and $N$ is the number of observations.

## Estimation of the logit model

The estimations are performed in two ways. In the first case the total sample is applied, while in the second case the calculations are performed on a sub sample, which consists of an equal number of defaulters and non-defaulters. In both cases 75 per cent of the samples are used for estimation, while 25 per cent is employed for model validation purposes. The observations are randomly selected into the particular groups.

We divide the explanatory variables into two categories, groups of financial and personal characteristics. The financial characteristics category contains the households' disposable income,[11] the income share of monthly debt servicing costs, the debt to income ratio (debt to yearly disposable income), financial savings, real wealth, number of debt contracts and type of debt contracts (FX, HUF, both). The personal characteristics group includes the job status, age, qualification, gender of the head of the household, the number of dependants and the region of residence. In defining the dependent variable we considered a household to be in default if it had experienced payment problems in the previous 12 months and the arrears exceeded one month.[12]

The covariates, except the debt servicing cost, debt to income, number of loan contracts, real and financial wealth, and number of dependants get into the model as dummies, since dummies capture the position of the particular household in the distribution of the variable in question.[13]

For the estimations the stepwise maximum likelihood method is employed, as it enables us to find the optimal regression function. The stepwise method is a widely used approach of variable selection and is especially useful when theory gives no clear direction regarding which inputs to include when the set of available potential covariates is large. The inclusion of irrelevant variables not only does not help prediction, it reduces forecasting accuracy through added noise or systemic bias.[14] The stepwise procedure involves identifying an initial model, iteratively adding or removing a predictor variable from the model previously visited according to a stepping criterion and, finally, terminating the search when adding or removing variables is no longer possible given the specified criteria. The regression was run by using the p-value of 0.1 as a criterion for adding or deleting variables from the subsets considered at each iteration.

We also test the heteroscedasticity of the residuals by carrying out the LM test using the artificial regression method described by Davidson and MacKinnon (1993). The results suggest that we have little evidence against the null hypothesis of homoscedasticity. Table 1 presents the estimated model parameters.

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[11] As in the models, due to income uncertainty, the relative position of households in the income distribution is used, the results are not sensitive to correction in income levels (i.e. 10 per cent higher income).

[12] A table about the explanatory variable set used can be found in Table B in Appendix 2.

[13] In order to avoid perfect collinearity a control group has to be selected. The reference household possesses the following attributes: the household income is in the third quintile, it has FX debt, lives in central Hungary, the head of the household has a medium qualification, works as an employee, is between 31 and 39 years old and is male. The reference group is selected to describe the attributes of an average household in the sample.

[14] The main limitation of the stepwise procedure is that it presumes the existence of a single subset of variables and seeks to identify it.

## Table 1
### Estimated model parameters

| Model | Logit 1 | | Logit 2 | |
|---|---|---|---|---|
| | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Dependent variable | | | | |
| *Default* | | | | |
| Expalantory variables | | | | |
| *Constant* | -5.197*** | (0.517) | -2.898*** | (0.806) |
| Job status | | | | |
| *Unemployed* | 1.806*** | (0.467) | 2.023*** | (0.835) |
| *Other inactive* | | | 1.462* | (0.850) |
| Share of monthly debt serv. cost | 3.921*** | (1.016) | 6.264*** | (2.073) |
| Income | | | | |
| *Quintile 1* | 0.716* | (0.372) | | |
| *Quintile 5* | -1.631* | (0.935) | -2.012* | (1.213) |
| Number of dependants | 0.314** | (0.143) | 0.495** | (0.239) |
| Goodness of fit measures | | | | |
| *R2* | 0.151 | | 0.288 | |
| LM_test for heteroskedasticity | | | | |
| *LM test-stat* | 2.034 | | 3.560 | |
| *p-value* | 0.154 | | 0.060 | |
| Number of observations | | | | |
| Total | 785 | | 54 | |
| *Defaulted* | 27 | | 27 | |
| *Non-defaulted* | 758 | | 27 | |

*Note: *, **, *** denote that the estimated parameter is significantly different from zero at the 10%, 5% or 1% level.*

The results indicate that, irrespective of the data set used (i.e. whether the number of defaulted households are balanced or not), the job status of the head of the household (i.e. whether he/she is unemployed or not), the number of dependants, the income share of debt servicing costs and income have significant effects with the expected signs[15] regarding probability of default. The job status of the head proxies whether the household is in the 'low income' state. Unemployment increases the likelihood of having payment problems as this is the main source of unexpected changes in income. The relationship between payment problems and the number of dependants is also positive, as the larger the family the more it is exposed to expense shocks. The effect of income on the default probability is also evident, as being in higher income quintiles decreases the probability of payment problems. In addition to its traditional channels, the 'income effect' also exerts its effect through the debt servicing cost ratio, i.e. a fall in disposable income increases the debt servicing cost ratio. If this ratio is high, it increases the likelihood of payment problems as it prevents the accumulation of reserves and makes these households more exposed to the negative consequences of rising debt servicing, basic living costs or income loss.

## 2.3.2. The neural network approach

As an alternative of the logit, we use artificial neural networks (ANN) to model default probability. The main advantage of artificial network models is the ability to deal with problems in which relationships among variables and the underlying nonlinearities are not well known. For a detailed description of neural networks, their main attributes, architectures and workings see Sargent (1993) and Beltratti et al. (1996). Here we give a brief overview of the simple network model used.

[15] In order to get information about the size of these effects on the probability of default, the marginal effects of the variables of interest have to be determined. As two logit models are estimated, the marginal effects are calculated from the one that performs better according to the model validation test. We return to this question in the results chapter.

## Model description

The network has three basic components: neurons, an interconnection 'rule' and a learning scheme. Depending on its complexity, a network consists of one input layer, one or more intermediate or hidden layers, and one output layer.

The key element of the network is the neuron, which is composed of two parts – a combination and an activation function. The combination function computes the net input of the neuron, which is usually the weighted sum of the inputs, while the activation function is a function which generates output given the net input.

We begin with the specification of the combination function for the output layer as

$$y = \theta_0 + \sum_{j=1}^{q} \theta_j a_j \tag{2.6}$$

where $y$ is the output (default, non-default), $a_j$ is the hidden node value for node $j$, $\theta_j$'s are the node weights and $q$ is the number of hidden nodes. Constraining the output of a neuron to be within the 0 and 1 interval is a standard procedure. For this purpose we use the sigmoid function.[16]

The $a_j$'s are the values at hidden node $j$, and are expressed as follows:

$$a_j = S\left(\sum_{i=1}^{q_j} w_{ji} x_i\right) \tag{2.7}$$

if $S$ has a sigmoid form, then

$$a_j = 1 / \left(1 + \exp\left(-\left(\sum_{i=1}^{q_j} w_{ji} x_i\right)\right)\right) \tag{2.8}$$

where the $x_i$'s are the inputs at node $i$ and $S$ is the activation function. There are $q_j$ inputs at hidden node $j$. The $w_{ji}$'s are the parameters at the $j^{th}$ hidden node for the $i^{th}$ input. Thus, by inputting the variables (i.e. the household's personal and financial characteristics and the variable that proxies the default), our goal is to find the parameters $\theta$ and $w$ which make our functions most closely fit the data.

The predicted individual default probabilities come directly from the model and are denoted by $\hat{y}_t$. Using the individual PDs from the network, debt at risk is calculated as follows:

$$D@\mathrm{R} = \frac{\sum_{i=1}^{N} \hat{y}_i * z_i}{\sum_{i=1}^{N} z_i} \tag{2.9}$$

where $z$ is the loan amount of household $i$ and $N$ is the number of observations.

## Training the network

The selection of input variables in neural network models is also a crucial question, as the final models' performance heavily depends on the inputs used. Regarding the networks, we apply the variables selected by a feature selection algorithm called minimal-redundancy-maximal-relevance criterion (mRMR). A detailed description of mRMR can be found in Peng et al. (2005).[17]

[16] Other functions such as the logistic are also suitable.

[17] The MATLAB code of the mRMR can be downloaded from the following website: http://research.janelia.org/peng/proj/mRMR/index.htm.

**Table 2**

**Selected input variables by the mRMR and stepwise methods**

| | mRMR method | | stepwise method | |
|---|---|---|---|---|
| Selected input\Training sample size | 785 | 54 | 785 | 54 |
| Job status | | | | |
| *Unemployed* | X | X | X | X |
| *Other inactive* | | | | X |
| Number of dependants | X | X | X | X |
| Income | | | | |
| *Quintile 1* | | X | X | |
| *Quintile 5* | X | | X | X |
| Financial saving | X | X | | |
| Share of monthly debt serv. cost | X | X | X | X |
| Number of selected variables | 5 | 5 | 5 | 5 |

Here we briefly summarise the main aspects of feature selection based on this method. As a first step of the variable selection procedure the mRMR incremental selection is used to select a predefined number of sequential features $n$ from the input variable set $X$. This leads to $n$ sequential feature sets $(S_1 \subset S_2 \subset \dots S_n)$. Following comparison of the feature sets, the next step is to find a range of $k$, $(1 \le k \le n)$ within which the cross validation classification error has both small mean and variance. Within the set of the classification errors the smallest has to be found, and the optimal size of the candidate feature set is chosen as the smallest $k$ corresponds to the smallest classification error. The main advantages of mRMR are that it both maximises dependency and minimises redundancy between the output and input variables, it handles the problem of bivariate variable selection (i.e. individually good features do not necessarily lead to good classification performance), and it is computationally efficient. Table 2 presents the selected variables by the stepwise and mRMR methods.

The network training process begins by choosing the starting values of the weights. Then by feeding the network with the selected inputs (i.e. $x_i$), the output is calculated and compared to a known target (i.e. the binary outcomes – default, non default), and the corresponding error is computed. The optimisation is done by changing the weights $\theta$ and $w$, so that the square of the separation between the predicted and actual values of $y$ is minimised:[18]

$$Norm = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{2.10}$$

where $N$ refers to the number of observations.

As estimation problems are sometimes characterised by non convexities and may have local optimal solutions which might differ from the global optimal ones, we employ a number of different starting values in order to check for global convergence.

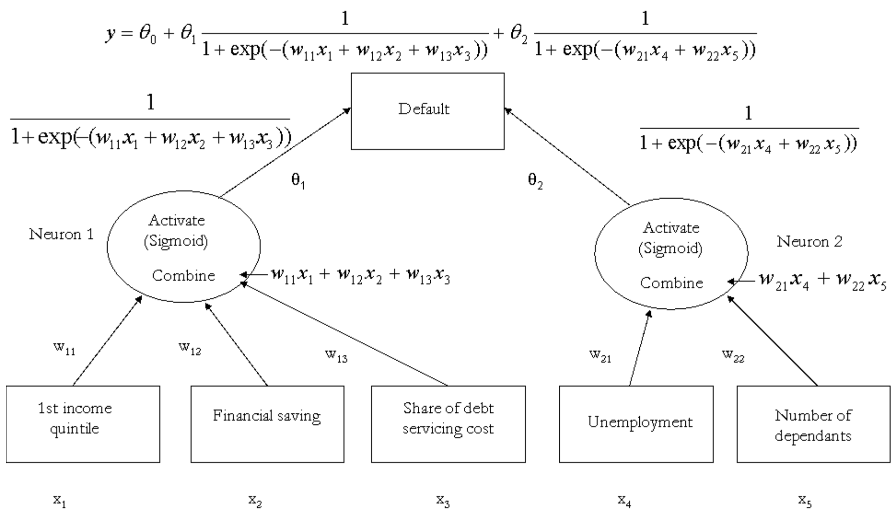
It also has to be mentioned that when using neural networks for default modelling purposes the sample size and its ‘composition’ regarding the output variable is a crucial issue. On the one hand, the literature suggests that the predictive power of the networks strongly depends on the share of defaulters and non-defaulters, i.e. when the share of defaulters and non-defaulters is balanced, the network gives the most reliable prediction. On the other hand, small samples allow only limited degrees of freedom, as a relatively simple neural network contains numerous weights that may lead to ‘overtraining’ – Gonzalez (2000).

[18] For this nonlinear optimisation procedure the Newton method is used.

Overtraining means that, instead of the general problem, the 'nature' of the data set is 'learned'. In order to avoid this, the same 75 per cent of the data sets as in the logit models is employed for training the network, and the remaining 25 per cent for validation purposes.[19] The modelling experiments suggest that the network architecture with three layers (one input, one hidden and one output layer) and with two neurons in the hidden (or intermediate) layer produces the most reliable results in terms of classification accuracy on the validation sample. In the first neuron of the hidden layer the effects from the financial characteristics are aggregated, while in the second neuron the effects from the personal characteristics of the household are grouped. On Chart 1 the network architecture of the second network (Network 2) model is portrayed. Table 3 shows the input weights and the estimated logit coefficients. Network weights with positive signs indicate an amplifier effect of the weight in question, while the negative signs denote the 'attenuative' effect of the particular weight. As the variables in the data set have very different magnitudes, data were scaled to be roughly of the same magnitude and thereby increase the probability of finding an optimal set of parameter estimates.

## Chart 1

### Network architecture of the second network model (Network 2)




[19] There is no theoretical or empirical rule about the optimal share of 'training' and 'testing' sub samples, the 75-25 per cent partition is often used in the literature.

**Table 3**

**Estimated logit parameters and neural network weights**

| | Logit 1 | Network 1 | Logit 2 | Network 2 |
|---|---|---|---|---|
| | Coefficients | Input weights | Coefficients | Input weights |
| Dependent variable | | | | |
| *Default* | | | | |
| Expalantory variables | | | | |
| *Constant* | -5.197*** | | -2.898*** | |
| Job status | | | | |
| *Unemployed* | 1.806*** | 1.724 | 2.023*** | 0.332 |
| *Other inactive* | | | 1.462* | |
| Share of monthly debt serv. cost | 3.921*** | 3.651 | 6.264*** | 13.006 |
| Financial saving | | -0.921 | | -5.868 |
| Income | | | | |
| *Quintile 1* | 0.716* | | | 48.469 |
| *Quintile 5* | -1.631* | 3.314 | -2.012* | |
| Number of dependands | 0.314** | 0.973 | 0.495** | 24.099 |
| Goodness of fit measures | | | | |
| *R2* | 0.151 | | 0.288 | |
| Number of observations | | | | |
| Total | 785 | 785 | 54 | 54 |
| *Defaulted* | 27 | 27 | 27 | 27 |
| *Non-defaulted* | 758 | 758 | 27 | 27 |

*Note: *, **, *** denote that the estimated parameter is significantly different from zero at the 10%, 5% or 1% level.*

## 2.4. MODEL VALIDATION AND SELECTION

As we have four different models (two logits and two networks), validating them is necessary in order to select the best ones for further analysis. The main purpose of the application of sound model validation techniques is to reduce model risk. When comparing two or more credit risk models, irrespective of the particular performance measures used, there are at least four rules which should be considered. First, when performance measures are sample dependent, the different models have to be compared on the same dataset.[20] Second, samples should be representative of the general population of obligors. Third, the data sets used for model estimations and validations should differ. Fourth, robustness of the employed performance measures has to be determined by calculating confidence intervals.

The literature of model selection and validation techniques is quite broad – for a detailed description see Burnham and Anderson (1998). Here we limit our attention to the most commonly used validation technique, the receiver operating characteristic (ROC) method.[21] Its use is a standard part of establishing model performance in accordance with the New Capital Accords of the Basel Committee on Banking Supervision. Below we briefly explain the ROC curve concept by using Sobehart and Keenan's (2001) notation; then we present our model validation results based on the ROC concept.

[20] To see this, consider two default prediction models, X and Y, and assume that both models are capable of sorting riskiness with perfect accuracy. Model X is applied to sample X1, where 4 per cent of the observations are defaults, and Y is applied to sample Y1, where 8 per cent of the observations are defaults. Then we sort the samples and select a cut-off value of the worst 4 per cent of scored observations. Since the models have, by assumption, perfect accuracy, the fact that the performance of model X on sample X1 is 100 per cent, while the performance of model Y on sample Y1 is only 50 per cent at the same cut-off, indicates that model X is better than model Y because of the higher capture rate – though this is wrong. The problem is that the selected cut-off has a different meaning in terms of sample rejection for any two samples with a different number of defaults.

[21] There other widely used measures are the cumulative accuracy profile (CAP) and its summary statistics, the accuracy ratio (AR), and the conditional information entropy ratio (CIER). The CAP is similar to the described ROC curve concept. The basic idea of CIER is to compare the uncertainty of the unconditional default probability of the sample (frequency of defaults), with the uncertainty of the conditional default probability.

## 2.4.1. The ROC curve concept

When the classification accuracy of a model is analysed, a cut-off value *(C)* is selected in order to classify the debtors. Debtors with rating scores or PDs below the cut-off value are considered as defaulters and debtors with scores above the cut-off value are considered as non-defaulters. If the score is below the cut-off value and the debtor defaults, the classification decision was correct. If the score is above the cut-off value and the debtor does not default, the classification was also correct. In all other cases, the obligors were wrongly classified.

Employing Sobehart and Keenan's (2001) notation, the hit rate *HR(C)* is defined as follows:

$$HR(C) = \frac{H(C)}{ND} \tag{2.11}$$

where *H(C)* is the number of defaulters correctly predicted with cut-off value *C,* and *ND* is the total number of defaulters in the sample. The false alarm rate *FAR(C)* can be expressed as follows:

$$FAR(C) = \frac{F(C)}{NND} \tag{2.12}$$

where *F(C)* is the number of non-defaulters incorrectly classified as defaulters, by using the cut-off value *C,* and *NND* refers to the total number of non-defaulters in the sample.

For all the cut-off values that are contained in the range of the scores the quantities of *HR(C)* and *FAR(C)* are calculated.

The ROC curve is the plot of *HR(C)* versus *FAR(C)*. The better the model's performance, the closer the ROC curve is to the point (0,1). Denoting the area below the ROC curve by *A* it can be calculated as follows:

$$A = \int_0^1 HR(FAR)\, d(FAR) \tag{2.13}$$

This measure is usually between 0.5 and 1.0 for rating models in practice. A perfect model would have an area below the ROC curve of 1 or 100 per cent, because this means all of the defaulting observations have a default probability greater than the PDs of the remaining observations. When the value is 0.5 or 50 per cent it indicates a worthless model because the defaulters are indistinguishable from the median non-defaulter. For calculating the confidence interval for *A* the concept of Bamber (1975) is followed. Derivations and proofs can be found in Bamber's article.[22]

## 2.4.2. Model validation results

Calculating the area below the ROC curves, *A* and confidence intervals, for both the logit and the neural network models, the remaining 25 per cent of the sample, the validation sample is used. In Table 4 the estimated size of the area below the ROC curve and its confidence band can be seen for the four models.[23] Although the number of defaults in both samples is the same, the share of defaulters within the samples is different. Therefore, only those models are comparable whose database is the same in size. It has to be noted that, when judging models' classification accuracy, not only the size of the area below the ROC curve matters but also its standard error and the range of its confidence band. Regarding the larger samples, the logit seems to perform better. Although the area below the ROC curve is slightly smaller than in the network model (Network 1), both the standard deviation and the confidence band range are smaller. When the number of defaulters and non-defaulters is

[22] It should be noted that for a good approximation of the confidence band for A by using Bamber's method there should be at least around 50 defaults in the sample. When there are a few numbers of defaults, the normal approximation might be problematic. However, Engelmann and Tasche (2003) empirically showed that for the cases with very few defaults in the validation sample, the approximation does not lead to completely misleading results. We also check the robustness of our validation results by randomly drawing three sub portfolios. The first sub-group contains 36 defaulters and 225 non-defaulters, the second 25 defaulters and 236 non-defaulters; the third consists of 10 defaulters and 251 non-defaulters. Our results suggest that the boundaries of the confidence bands differ by about 3-6 percentage points.

[23] The ROC curves of the four models can be found in Appendix 1.

## Table 4

### Estimated areas below the ROC curve and their confidence bands

| | ROC area | Std. Err. | [95% Conf. Interval] | Validation sample size (N) | Non defaulted (N) |
|---|---|---|---|---|---|
| Logit 1 | 0.820 | 0.032 | [0.757 , 0.883] | 261 | 252 |
| Network 1 | 0.827 | 0.070 | [0.690 , 0.964] | 261 | 252 |
| Logit 2 | 0.796 | 0.050 | [0.697 , 0.894] | 18 | 9 |
| Network 2 | 0.889 | 0.079 | [0.735 , 0.978] | 18 | 9 |

balanced, the network outperforms the logit. This result coincides with the literature showing that the performance of neural networks in default modelling depends on the sample share of defaulters and non-defaulters. The consequence of the validation process is that the first logit model (Logit 1) and the second network model (Network 2) are employed for further analysis.

# 3. Results

In this chapter we first determine the effects of the model variables on the probability of default by using the first logit (Logit1) and the second network (Network 2) models, then we analyse how the PDs and debt at risk are distributed along various dimensions and determine the concentration risk. Finally we present our stress testing exercise and analyse the shock-absorbing capacity of the banking system.

## 3.1. MARGINAL EFFECTS

The estimation results suggested that six variables have sizeable effects on the default probability (1st and 5th income quintiles, share of debt servicing cost, number of dependants, the job status of the head of the household, and the financial saving). As the estimated coefficients give the direction but not necessarily the size of the effect the particular variable has on the probability of default, the marginal effects have to be calculated. In the logit framework the marginal effect of a continuous variable can be expressed as follows:

$$\frac{\partial E[y|x]}{\partial x} = \Lambda(x'\beta)[1-\Lambda(x'\beta)]\beta = \frac{\exp(x'\beta)}{(1+\exp(x'\beta))^2}\beta \qquad (2.14)$$

where $x'$ is the vector of covariates and $\beta$ is the vector of estimated parameters, while the marginal effects[23] from the above described network model can be calculated according to the following formula:

$$\frac{\partial y}{\partial x_i} = \theta_j \frac{\exp\left(\sum_{i=1}^{q} w_{ji}x_i\right)(w_{ji})}{\left(\exp\left(\sum_{i=1}^{q} w_{ji}x_i\right)+1\right)^2} \qquad (2.15)$$

The marginal effects of the model variables are presented in Table 5.

**Table 5**

**Marginal effects from the logit and network models**

*(percentage points)*

| | Logit 1 | Network 2 |
|---|---|---|
| Job status | | |
| Unemployed | 5.66 | 0.81 |
| Share of monthly debt serv. cost | 7.38 | 8.94 |
| Income | | |
| Quintile 1 | 1.93 | 3.20 |
| Quintile 5 | -2.33 | |
| Financial saving | | -3.87 |
| Number of dependants | 0.58 | 0.09 |

*Note: the marginal effects were first evaluated at every observation and then the individual effects were averaged.*

[24] It should be mentioned that when using this formula for computing the marginal effect a dummy variable is not appropriate; however, the derivative approximation is often accurate.

Table 5 suggest that among the factors analysed, the employment status of the head (i.e. whether he/she is unemployed or not) and the share of debt servicing cost have the most sizeable impact (in absolute value) on default probability. This means that when comparing two households which differ only in the employment status of the household's head but are otherwise the same, the two models used for calculating the marginal effects, Logit 1 and the Network 2, produce a 5.66 and a 0.81 percentage point default probability difference respectively. The difference in the default probability between the two households differs only in the debt servicing cost ratio, which is 7.38 and 8.94 percentage points respectively.

The effect of dummies can be evaluated not only at the sample mean but on the whole probability distribution by plotting the probability response curves (PRC) – Greene (2003).[25] With these curves it is possible to examine how the predicted probabilities vary with an independent variable. We analyse the effects of unemployment and 5$^{th}$ quintile dummies in this way as a function of the number of dependants and the share of monthly debt servicing cost. The marginal effect in this case is the difference between the two functions.

Chart 2 shows the probability response curves of unemployment as a function of the number of dependants, while Chart 3 depicts the 'unemployment effect' as a function of the share of debt servicing cost. The marginal effect of unemployment ranges from 2 when the number of dependants is 1, to about 13 percentage points when it approaches 6, which shows that the probability a household will default after the job loss of the main wage earner is far greater for those where the number of dependants is high. Similarly, if we analyse the unemployment effect as a function of the share of debt servicing cost, the marginal effect ranges from 2.7 to 29 percentage points, which indicates that the probability of default after the job loss of the main wage earner is far greater among overindebted households.

**Chart 2**

**Probability response curves of unemployment as a function of the number of dependants (Network 2)**

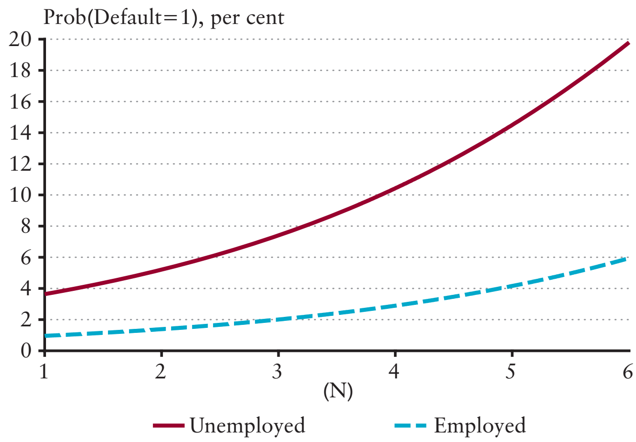
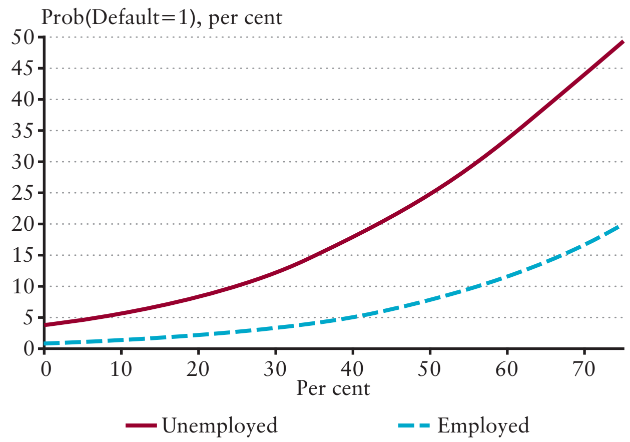



**Chart 3**

**Probability response curves of unemployment as a function of the income share of monthly debt servicing cost**




Charts 4 and 5 portray the probability response curves of the 5th income quintile dummy. The marginal effect of income is also increasing monotonically with the number of dependants and the share of debt servicing cost. The marginal effects as a function of the number of dependants and the share of debt servicing cost range from 1 to 6.3 and from 1 to 19 percentage points respectively.

[25] The first logit model (Logit 1) is used for calculating the probability response curves.

**Chart 4**

**Probability response curves of income as a function of the number of dependants**

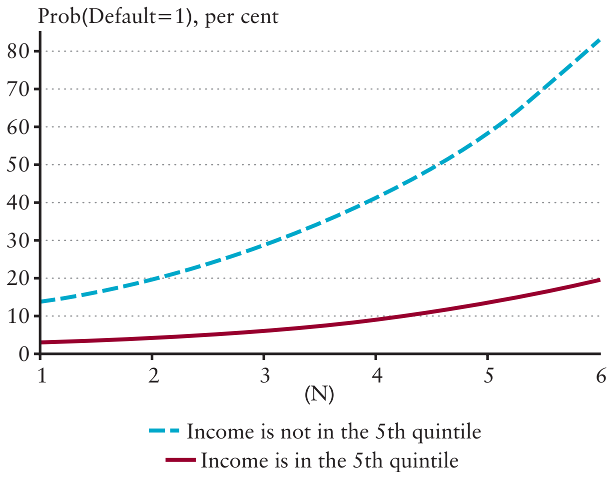
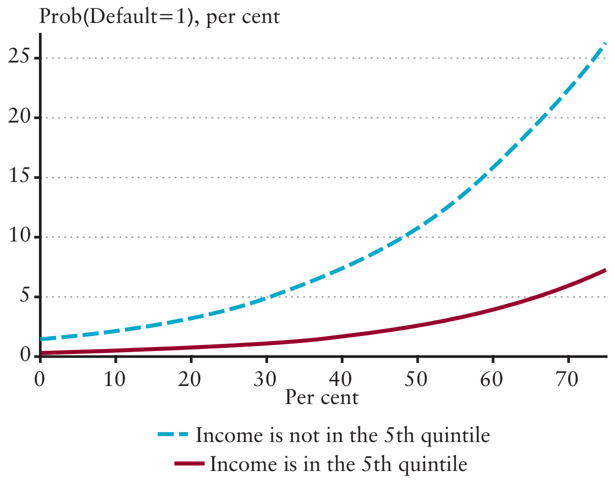



**Chart 5**

**Probability response curves of income as a function of the income share of monthly debt servicing cost**




## 3.2. DISTRIBUTION OF ESTIMATED PROBABILITIES AND DEBT AT RISK

The above described analysis showed the influence of different factors on the default probability. In this section we look at default probabilities and debt at risk by grouping households along various single dimensions, taking account of their different attributes and not allowing for unobserved individual effects.[26] Table C in Appendix 2 shows the mean default probabilities and debt at risk calculated from the above described models, by the households' region of residence, disposable income, the qualification of the household's head, taking account of the actual circumstances of those in each group.

Regarding the region of residence,[27] the mean PDs and the standard deviation of the probability of default are higher among households in less developed parts of the country (North-Eastern Hungary, Northern and Southern Plain). Debt at risk is also the highest in these regions. Depending on the methods used for calculating these risk measures the average PD ranges between 2 and 7.4 per cent, while debt at risk ranges between 3.5 and 22 per cent. The results are not surprising, as these areas are characterised by the lowest net average wage income, which is approximately 85 per cent of the county average, and the highest unemployment and lowest employment rates – 11 and 44 per cent respectively.[28] As a consequence, the share of debt servicing costs is on average higher, which prevents the accumulation of any reserves and makes these households more sensitive to shocks.

Analysing risks by the qualification of the household's head, the results suggest that the average PDs are the highest among those whose head has a low qualification (mean PDs range between 1.8 and 6.7 per cent, debt at risk ranges between 6.2 and 10.3 per cent). It is true in general that qualification determines both the permanent income and the labour market possibilities. Low skilled persons are more exposed to adverse movements in the economy, as their work can be easily substituted. In times of economic downturn firms usually lay off their low skilled workers and keep their high skilled ones. Therefore, low skilled workers' income might be more exposed to the cyclical fluctuations of the economy. As a result, high income variance might contribute to higher variance in the probability of default within this category. This assumption might be supported by the fact that the standard deviation of the probability of default is the highest among them.

[26] Analysing the distribution by multiple dimensions is of no relevance, due to small sample bias.

[27] Central Transdanubium includes the following counties: Fejér, Komárom-Esztergom, Veszprém; Western Transdanubium includes the following counties: Győr-Moson-Sopron, Vas, Zala; Southern Transdanubium includes the following counties: Baranya, Somogy, Tolna; Northeastern Hungary includes the following counties: Borsod-Abaúj-Zemplén, Heves, Nógrád; Northern Plain includes the following counties: Hajdú-Bihar, Szabolcs-Szatmár-Bereg, Jász-Nagykun-Szolnok; Southern Plain includes the following counties: Bács-Kiskun, Békés, Csongrád; Central Hungary includes the following: Pest county and Budapest.

[28] Hungary 2006, http://portal.ksh.hu/pls/ksh/docs/hun/xftp/idoszaki/mo/mo2006.pdf, available only in Hungarian.

Analysing risks by income, both the average PDs and debt at risk are the highest among those households whose income is in the 1st quintile. The average PDs range between 6.2 and 8.6 per cent, while debt at risk is between 10 and 24.2 per cent. The differences in these measures among other income quintiles are not substantial. It has to be mentioned that the effect of income is not necessarily separable from the above analysed factors, as mainly these determine which part of the income distribution the household is located in. Therefore, income is more or less a condensate of information about household's riskiness stemming from their given sociodemographic features.

In summary, debt payment problems are most likely to occur among households which possess the following attributes: the region of residence is in North-Eastern Hungary, Northern or Southern Plain, the main wage earner has a low qualification and the household disposable income is in the 1st income quintile.

In order to get an overall picture about risk concentration within the group of indebted households we employ the index of concentration of debt at risk – May and Tudela (2005). The index is the ratio of debt at risk and the average probability of default. As the index varies, either because of the probability of default, the value of the debt outstanding, or the combination of these, it may promptly reflect the evolution of risks related to retail lending. If the index value exceeds one it indicates that debt is concentrated among risky households, while values less than or equal to one imply that the risk concentration is not substantial.[29]

The values of the concentration index are 1.37 and 1.36 in the case of the logit and the network models, while 3.07 by using the non-parametric based framework with original income data, and 2.59 by taking into account the income distortion. The results suggest that, regardless of the methods used for calculating the concentration index, a substantial part of the loan portfolio is owed by potentially risky households, which is unfavourable from a financial stability point of view. Risks are somewhat mitigated by the fact that a substantial part of risky debt is comprised of mortgage loans, which are able to provide considerable security for banks in the case of default.

## 3.3. THE STRESS TESTING EXERCISE

Stress tests are tools for analysing the shock-absorbing capacity of the banking system in relation to adverse macroeconomic events. With stress tests we can judge whether the banking system acts as a 'stabiliser' in the economy, i.e. it is able to absorb shocks and mitigate the negative consequences of business cycle fluctuations or more serious adverse economic events. The key aspects of stress testing are to identify the sources of risks and the channels through which they are transmitted, and to measure their effects on the financial system.

From households' credit risk point of view two main sources of risks can be considered which have a relatively large significance: declining employment, and fluctuating exchange and interest rates.[30] The main consequence of the first is declining disposable income, while the impact of the second on household credit risk develops through the rising cost of debt servicing (the foreign currency finance of Hungarian households, for instance, makes their balance sheet position sensitive to exchange rate and foreign interest rate fluctuations, as they do not have natural hedge).

Regarding the risk transmission channels, three can be detected through which the banking activity is principally affected: the credit risk, the income generation risk and funding risk channels. Funding risk might arise through the credit risk channel as a result of the worsening profitability related to household lending, which might lower market confidence and raise the cost of external finance. Banks are faced with income generation risk when the operational environment becomes unfavourable, which reduces banks' capacity to generate income (especially net interest and fee income, a substantial proportion of which is related to household lending). Finally, increasing write-offs reflects the deterioration in households' payment ability.

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[29] For a better understanding of this concept we present a similar example as May and Tudela (2005). Suppose that there are two households A and B. Household A has a debt of 1,000,000 HUF and B has a debt of 500,000 HUF. Suppose that each household has an equal default probability (10 per cent). Then the total debt at risk is 0.1*1,000,000+0.1*500,000=150,000 HUF, that is 10 per cent of the total debt outstanding and the mean PD is 10 per cent. Suppose instead that household A has a 15 per cent probability of having payment problems, while household B has a PD of 5 per cent. In this case the debt at risk is 0.15*1,000,000+0.05*500,000 = 175,000 HUF and the share of risky debt is 11.6 per cent, which is higher than in the previous case. The mean probability of default is still 10 per cent. The index of concentration of debt at risk in the former case (i.e. PDs were equal) is 1 while in the latter case (i.e. PDs differ) it is equal to 1.16 since the household with the larger amount of debt is now more risky.

[30] Probabilities were not assigned to the occurrence of the various scenarios. This is the task of future research.

In this paper we separately analyse the effects of the most severe employment and financial shock scenarios on banks' capital adequacy, and among the risk transmission channels we take into account the credit risk channel. However, the combined effect of real and financial shocks might have a greater impact on banks capital position than each of the individual shocks alone.

As our simulations are static, we have to adopt some simplifying assumptions. First, we presume that, as a result of the shocks, neither the volume nor the composition of household consumption changes, the household's labour supply remains unchanged, and there is no banking adjustment, that is banks do not react to increasing losses by curtailing credit supply, or portfolio restructuring. In the calculations we further assume that the shocks are permanently maintained, as this ensures that debt at risk calculated along various shock scenarios becomes defaulted. Data suggest that at least one year is necessary for the default of all the risky households (i.e. they eat up all their financial savings).[31] Finally, we presume that banks' household loan portfolio from a quality point of view is similar to the representative portfolio used. Based on this latter assumption, as no information on household default probabilities from individual banks is available, when calculating the losses, we use the same default probability for each bank. The difference between banks is constituted by the product composition of their portfolio and the product specific loss rates (LGD), which, however, adequately reflects the differences in quality across individual banking portfolios.

### 3.3.1. The effect of rising debt servicing costs on portfolio quality

In the calculation of the effect of rising debt servicing costs we considered the occurrence of the following financial shocks: a 100, 250 and 500 basis points increase in HUF yields, a 100 and 200 basis points increase in CHF yields, and a 10, 20, 30 per cent depreciation of the forint exchange rate.[32] Depreciation affects monthly debt servicing costs straight-line, while the effect of interest rates rise is not linear.[33] Since there is uncertainty regarding households' disposable income, the calculations regarding the non-parametric approach are performed with the original, and with 10 per cent higher incomes as well.[34] In this case, both the average PDs, which are the share of households' with negative financial margin within the total of indebted households, and debt at risk, which is the debt outstanding of households with negative financial margin, are calculated directly.

The 'shocked' PDs and debt at risk are also calculated by using the estimated parameters (weights) of the logit and network models. As a first step, the 'shocked' debt servicing cost is determined for each household, then it is inserted into the models and the new conditional PDs and debt at risk are calculated. Charts 6 and 7 depict the effects of various financial shock scenarios on debt at risk and on the average default probability. On the charts the effects of only 'single shocks' can be seen. This means that, for instance, when calculating the impact of a 200 basis point CHF interest rate increase, the exchange rate and HUF interest rate are held constant. Tables about the combined effects of financial shocks can be found in Appendix 2 (Tables D and E).

The results suggest that portfolio quality is more sensitive to exchange rate movements and a CHF yield rise than to an increase in HUF interest rates. This is due to the denomination and repricing structure of the household loan portfolio. Regarding the denomination structure, the domestic-foreign currency composition by the end of 2006 was approximately 50-50 per cent. However, in the case of new loans an 80-90 per cent dominance of foreign currency denomination can be observed. As a consequence, the exposure of the portfolio to exchange rate risk is permanently increasing. Regarding the portfolio's repricing structure, as the share of forint loans with fixed interest rates is relatively high, only a small proportion

[31] The households' average shock tolerance period – depending on the size of the shock – is between one and three months. This is the average period under which households eat up their financial savings, provided that their behaviour remains unchanged (i.e. constant consumer preferences, no restructuring of consumption expenditures, unchanged labour supply).

[32] The values of the examined financial shocks are the tails of the historic distributions calculated from the data of the HUF/EUR exchange rate, the 3-month forint yields and the average 3-month Swiss money market rate between January 2001 and May 2007 (in case of the exchange rate 3, 6 and 8 standard deviation, in case of the HUF interest rate 1, 2, 3 standard deviation and in the case of the CHF interest rate 1 and 2 standard deviation). The reason for counting with the effect of a CHF interest rate rise is that approximately 85–90 per cent of total retail FX debt is denominated in Swiss franc.

[33] As all the relevant information was available regarding the loan product of a particular household, the individual APRs are calculated. When the effects of rising interest rates are analysed, the increase of the interest rate is added to the individual APRs, and then the monthly debt servicing costs are recalculated.

[34] The PDs from the parametric approaches were not recalculated, as the equal 10 per cent shift in income does not change the relative positions of the households in the income distribution.

**Chart 6**

**Increase in debt at risk to various financial shock scenarios**

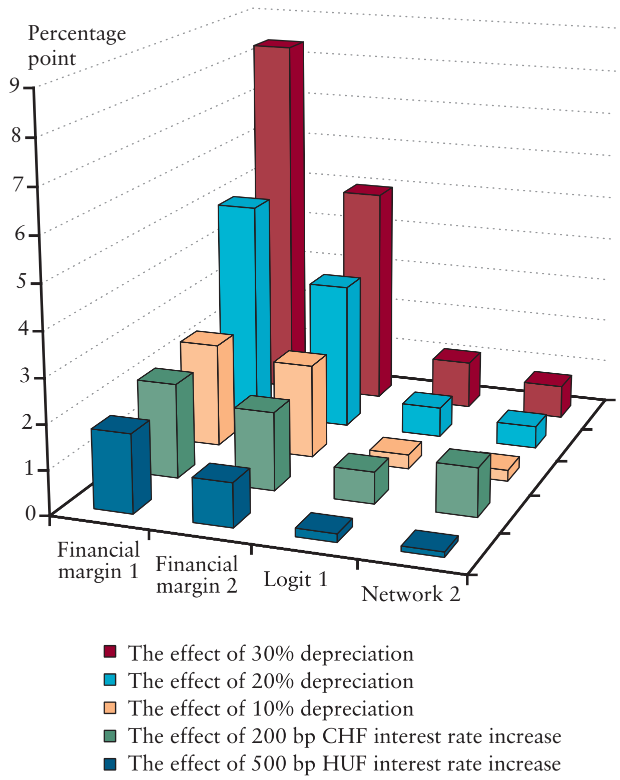
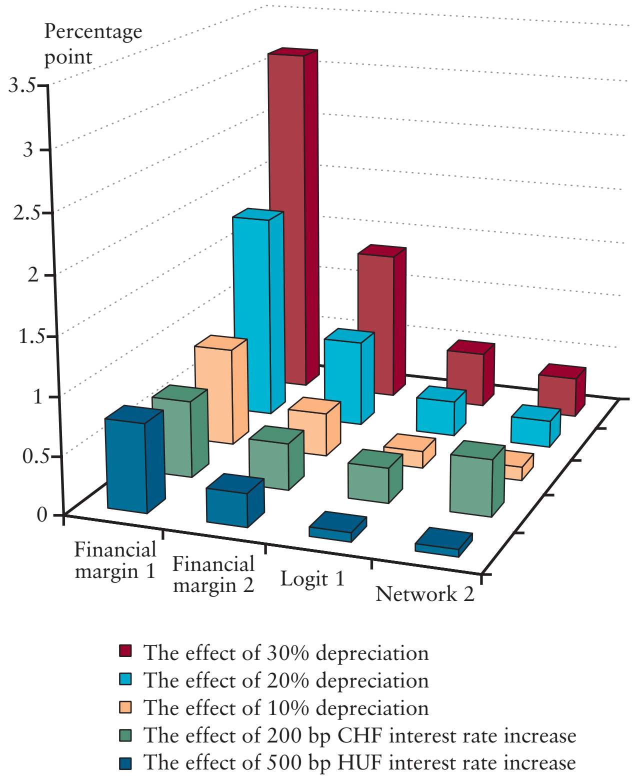



**Chart 7**

**Increase in the average default probability to various financial shock scenarios**




*Notes: The charts depict the single effects of a 10, 20 and 30 per cent exchange rate depreciation and a 500 and 200 basis point HUF and CHF interest rates rise. The baseline values of debt at risk (i.e. no shock case) are the following: 12.9 and 5.7 per cent in the non-parametric approach with original income and with a 10 per cent higher income, 4.8 per cent in the case of the first logit model (Logit 1) and 5.5 per cent in the case of the second network model (Network 2). The baseline values of average default probabilities are the following: 4.2 and 2.2 per cent in the non-parametric approach with original income and with a 10 per cent higher income, 3.4 per cent in the case of the first logit model (Logit 1) and 4.0 per cent in the case of the second network model (Network 2).*

is exposed to HUF interest rate shocks. In contrast, as FX loans involve variable rates with short repricing periods, the role of foreign interest rate risk (especially CHF) is getting even more prevalent.

It has to be mentioned that the potential increase in credit risks are mitigated by the high reserves built into the prices and by the fact that a significant proportion of the debt at risk is comprised of mortgage loans. The risks can be further diminished to some extent by loan constructions with fixed instalment payments, where any drop in the relevant exchange rate affects the maturity of the loan instead of increasing the instalment payment. However, these types of loans are not yet widely used.

## 3.3.2. The effect of declining employment on portfolio quality

Unemployment directly affects a household's disposable income and, as a result, its payment ability. In the simulations a 3 and a 5 per cent decline in employment are considered, which affects only indebted households.[35] Beyond the above mentioned assumptions (i.e. unchanged consumption, labour supply, no bank reaction) we include some additional simplifications. First, we presume that unemployment risk does not depend on individual factors such as age, qualification, etc., so each employee has an equal probability of becoming unemployed. Second, only one household member looses his or her job and the worker in question will not find new employment in a one year period. Finally, each employee is equally contributing to the household income.

[35] The average employment rate between 1998 and 2006 was 56 per cent with 1.12 per cent standard deviation. So a 3 and 5 per cent employment decline is equal to an approximately 3 and 4 standard deviation shock.

The effects of declining employment are analysed in several different scenarios.[36] We checked how layoffs affect debt at risk within the entire portfolio, by selecting the unemployed workers randomly from the total sample, while in the second instance we assumed that layoffs affect a given sector (services, agriculture, industry, trade). The relevance of this latter scenario is provided on the one hand by the fact that, the exposure of individual sectors to cyclical fluctuations of the economy may differ significantly, and as a result the developments of employment also show sectoral fluctuations and may be more dominant in certain sectors. On the other hand, there may be differences between sectors in terms of the composition of loan portfolio extended to those working in the given sector, which may also affect the developments in losses considerably.

For the 'selected households' the new disposable income after unemployment has to be calculated. When each employee equally contributes to the household income, then the new income is calculated as follows: [37]

$$yn^i = \left(\frac{y^i}{n^i}\right)\left(n^i - 1\right) + unemp\_aid \tag{3.1}$$

where *yn* is the new income, *n* is the number of employees of household *i*, and *unemp_aid* is the dole.

For deriving the distributions of the probability of default and debt at risk, unemployed households are randomly drawn 2000 times then the new income, income share of debt servicing cost and unemployment (i.e. unemployment dummy) data is inserted into the models and the average PDs and debt at risk are recalculated. In the case of the non-parametric approach the debt of those households whose income reserve becomes negative after the shock is added to the risky loan portfolio. If the margin of a selected household was already negative, then its debt outstanding was not added again to the risky loan portfolio. Charts 8 and 9 depict the density functions of the increase in the risky loan portfolio, when unemployment is not sector specific.

The results indicate that the expected increase in debt at risk is lower in the case of the parametric approaches than in the non-parametric ones. The reason for this lies in the different ways default probabilities are assigned to households in various models. In the financial margin approach the consequence of unemployment is default by assumption, so the 'weight' of unemployed household's debt outstanding added to the risky loan portfolio is 1, while in the logit and network models these 'weights' (i.e. default probabilities) vary between 0 and 1.

**Chart 8**

**The effect of a 3 per cent decline in employment on the share of the risky portfolio (debt at risk)**

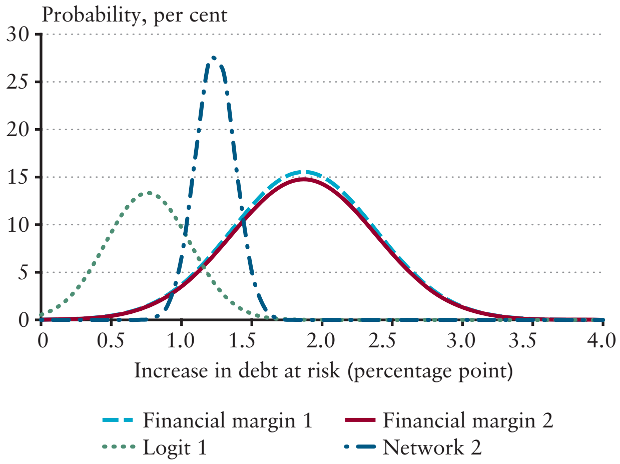
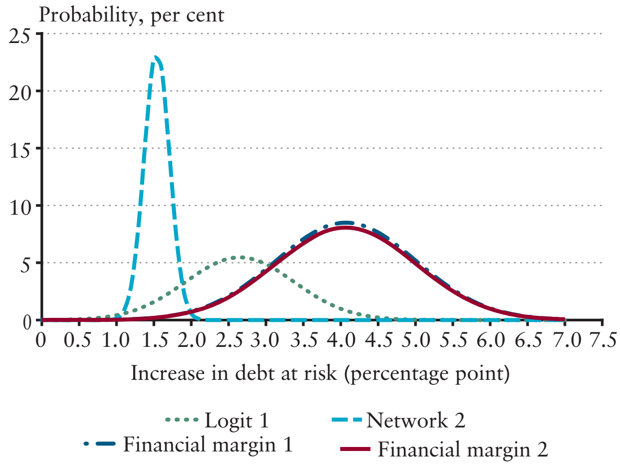



**Chart 9**

**The effect of a 5 per cent decline in employment on the share of the risky portfolio (debt at risk)**




*Notes: As debt at risk in the baseline case (i.e. without shocks) differs across methods, only the increases relative to the baseline are depicted. The baseline values of debt at risk are the following: 12.9 and 5.7 per cent in the non-parametric approach with original income and with a 10 per cent higher income, 4.8 per cent in the case of the first logit model (Logit 1) and 5.5 in the case of the second network model (Network 2).*

[36] The sectors analysed are the following: agriculture, commerce, industry, services.

[37] We also analyse the sensitivity of our results, when the equal income contribution assumption is loosened. We consider a 50 and a 60 per cent contribution of each person hit by unemployment to the household's disposable income. In the case of the 50 per cent contribution the results remain almost the same, while in the case of the 60 per cent contribution a moderate rise in the debt at risk can be observed relative to the equal contribution case.

From the charts it is also apparent that two graphs (i.e. financial margin 1 and 2) show a strong congruence, which at first glance seems surprising. However, the reason is rather simple. The positive effect of a 10 per cent rise in disposable income on the financial margin is more than offset by the job loss of a wage earner, which might result in a 25 to 100 per cent[38] decline in a household's disposable income depending on the number of wage earners in the household.

In Chart 10 and Chart 11 the density functions of the average default probabilities are depicted.

**Chart 10**

**Distribution of average default probabilities (Logit 1)**

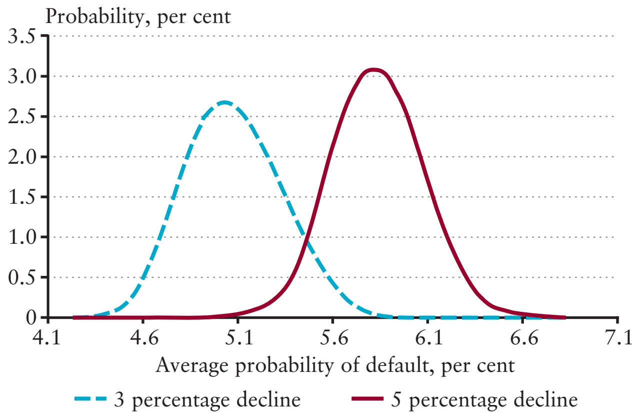
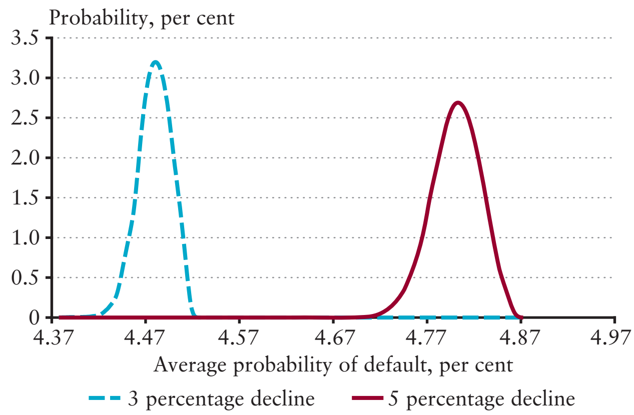



**Chart 11**

**Distribution of average default probabilities (Network 2)**




*Notes: The results of the non-parametric approach are not depicted, as the average PD (i.e. the share of households with negative margin) of a given employment shock is the same. The baseline average default probability is 3.4 per cent in the logit model case and 4.0 per cent in the network case, respectively.*

Regarding the sectoral concentration of unemployment, the portfolio quality is most sensitive to the layoff of workers in the services, followed by industry, commerce and agriculture. In the case of the service industry, the expected increase in debt at risk as a result of a 5 per cent decline in employment is 0.97, 1.75 and 3.36 percentage points, regarding the logit, the network and the financial margin approaches, respectively. It should be noted that the range of products offered by banks grew in 2006 with the appearance of home loans combined with insurance. In the case of unemployment, this insurance provides coverage for payment of instalments for a predetermined period (typically one year) to prevent any interruption in the continuity of payments while in search of a job. If these types of loans gain popularity, the impact of any shock in the labour market on the portfolio could drop.

### 3.3.3. Analysing the shock-absorbing capacity of the banking system

In this chapter, based on the results of the most severe financial and employment stress scenarios, the shock-absorbing capacity of the banking system, proxied by the capital adequacy ratio, is analysed.

In the calculation of the capital adequacy ratio we carried out the following steps. First, we determined the actual capital adequacy ratio of the banking sector. Then the potential loss based on the most severe stress scenarios was calculated (debt at risk) by using the four models. From our perspective not the average probability of default but the banking sector's exposure to risky households determines directly the amount of possible losses (debt at risk). As our debt at risk definition can be considered as a weighted average default probability, we think that it is able to better capture the risks than the average default probability, since it takes into account both the differences among individual household PDs and debt outstanding. In the calculation, debt at risk, equal for all banks, was multiplied by the single bank's exposure and then weighted with the LGDs (loss given default). From the received values the loan loss provisions were deducted. The profitability and the capital

[38] The maximum number of wage earners in a household within the sample was 4.

strength of the banks are influenced by the stress event only in those cases when the losses exceeded the size of the loss provisions. Finally the new capital adequacy ratios of the sector were built as a weighted average of the individual banks' ratios (the weights were the individual banks market share). The calculations were based on year-end data of 2006 and any potential income that might be generated after 31st December 2006 was not taken into account.

In the calculations we had to adopt some simplifying assumptions. First, we assumed that banks' client structures from a quality point of view are similar. This means that the probability of default and debt at risk are the same for all banks. Second, we also admitted that these indicators are uniform for all loan types. Banks' portfolio composition and the product-specific LGD assumptions imply the only differences among individual institutions. Due to lack of reliable Hungarian data about the stream of recoveries, workout costs and an appropriate spread for the risk of the recovery, the computation of recovery rates was not possible. Therefore, we considered a varying loss given default for mortgages[39] and fix 50 and 90 per cent LGD for vehicle and unsecured loans, respectively.

The LGD numbers of vehicle and unsecured loans compared to the international practice were considered to be more conservative. There were three main reasons for using varying mortgage LGDs. First, the share of mortgage loans within baking retail portfolios is constantly increasing and, as a result, the banking sector's exposure to real estate market movements is gradually rising. Second, the development in losses calculated alongside the various shock scenarios might be sensitive to LGD assumptions in general, and as the literature suggests – Schuermann (2004), for instance – during economic downturns not only does the volume of risky exposures rise, but the value of collaterals decline. Therefore, neglecting the 'LGD effect' might result in the substantial underestimation of losses. Third, due to the lack of information about the value of stress mortgage LGDs, we tried to handle this problem by sensitivity analysis.

In the loss calculation we count with the most severe financial and employment shock scenarios. In the financial shock's case, the effect of a 30 per cent HUF exchange rate depreciation, 500 basis points HUF interest rate and 200 basis points CHF interest rate rises were analysed, while in the employment shock the 99th percentile values of the risky portfolio distributions were reckoned, when indebted households are hit by a 5 per cent employment decline (depicted on Chart 9). Charts 12 and 13 portray the capital adequacy ratio of the banking sector in relation to the most severe shock scenarios as a function of mortgage LGD.

**Chart 12**

**The effect of the largest financial shocks on the capital adequacy ratio of the banking sector**

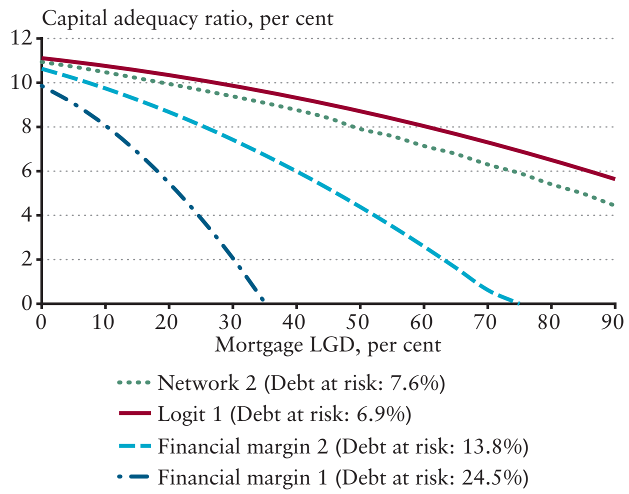
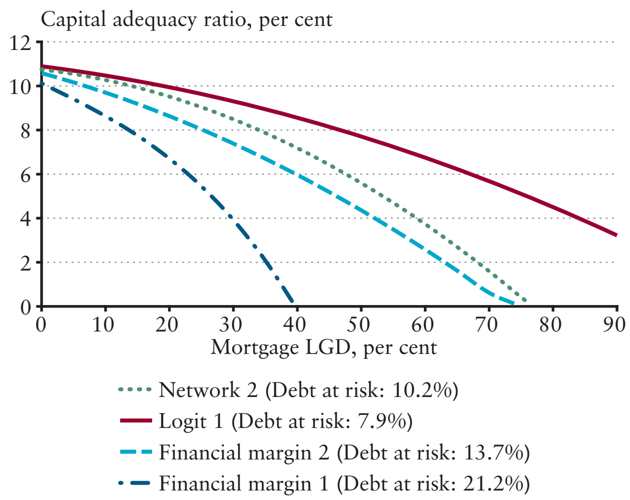



**Chart 13**

**The effect of the 5 per cent employment decline on the capital adequacy ratio of the banking sector**




*Note: In the case of the employment shock, the baseline values of debt at risk were added to the distribution of increments depicted in Chart 9 and then the 99th percentiles were calculated.*

[39] For a study of how to estimate LGDs for mortgages, see Calem and Lacour-Little (2004).

The results indicate that the conclusion regarding the shock-absorbing capacity of individual banks as well as the banking sector is sensitive to the LGD assumptions taken. Up to 10 per cent of mortgage LGD all the models used give robust conclusions about the capital strength of the sector. Furthermore three models (financial margin 2, logit 1 and network 2) suggest that up to 30 per cent of mortgage LGD, the capital adequacy ratio does not fall below the current regulatory minimum of 8 per cent. If we consider the 10 per cent loss rate as the LGD in normal times, then the latter 20-25 percentage point decline in the recoveries (increase in the loss rate to 30 per cent) can be thought as a stress event, and this assumption is consistent with the calculations of Frye (2000) who estimated that in depressed periods the LGD of high-quality loans rise by about the same measure.

When evaluating the shock-absorbing capacity, one has to keep two further issues in mind. First, as was mentioned above, the financial margin calculation has a lot of shortcomings, but the main weakness is its excess sensitivity to income and consumption data uncertainty. Therefore, the results based on the non-parametric approach have to be handled carefully. Second, in the loss calculations we neglect to measure how the shock propagation affects other sectors in the economy. However this latter might induce substantial deterioration in the quality of other banking portfolios and can substantially push the capital adequacy ratio below the regulatory minimum.

# 4. Summary and conclusion

By using three different types of credit risk measurement techniques (financial margin, logit and neural network approaches) this paper investigated the main idiosyncratic determinants of household credit risk, examined whether the current state of indebtedness threatens financial stability, and by employing stress tests it analysed the shock-absorbing capacity of the banking system.

Estimation results show that the most important idiosyncratic factors of credit risk are the disposable income, the number of dependants, the share of monthly debt servicing costs and the employment status of the head of the household. Empirical evidence suggests that effects of unemployment and income on the probability of default monotonically increase with the number of dependants and the income share of monthly debt servicing costs, that is, these effects are stronger among those households where the number of dependants or the share of monthly debt servicing costs are originally high. The results also suggest that debt payment problems are most likely to occur among households living in less developed regions (i.e. North-Eastern Hungary, the Northern and Southern Plain), where the main wage earner has a low qualification and the household disposable income is in the 1st income quintile. The results also indicate that a substantial part of the loan portfolio is owed by potentially risky households, which is unfavourable from a financial stability point of view. However risks are somewhat mitigated by the fact that a substantial part of risky debt is comprised of mortgage loans, which are able to provide considerable security for banks in the case of default.

Regarding the stress test results of the financial shocks, we find that portfolio quality is more sensitive to exchange rate and CHF interest rate movements than to a forint yield rise, due to the denomination and repricing structure of the household loan portfolio. In the case of the employment shock, the results suggest that employment decline has considerable effects on the size of the risky loan portfolio. Regarding the sectoral concentration of unemployment the portfolio quality is most sensitive to the layoff of workers in services, which is followed by industry, commerce and agriculture. Finally, our findings reveal that the shock-absorbing capacity of the banking sector as well as individual banks is sufficient under the given loss rate (LGD) assumptions, that is the capital adequacy ratio would not fall below the current regulatory minimum of 8 per cent even if the most extreme stress scenarios were to occur.

There are, however, some limitations. In this regard the static assumptions about the behaviour of households and banks, the presumption of homogenous portfolio quality, the separate shock analysis (i.e. separate analysis of real and financial shocks) on banks capital adequacy and the fact that we neglect to measure how the shock propagation affects other economic sectors should be mentioned. The results provide the first set of microeconomic insights into household credit risk. Drawing on these, further investigations, including the extension of the above analysis by using panel data and an integrated analysis of household and corporate sector credit risk, will be aimed at drawing a more refined picture of credit risk and the shock-absorbing capacity of the banking system.

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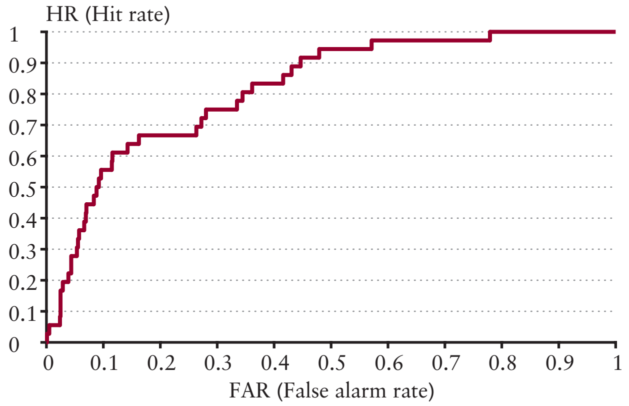
# Appendix 1: charts

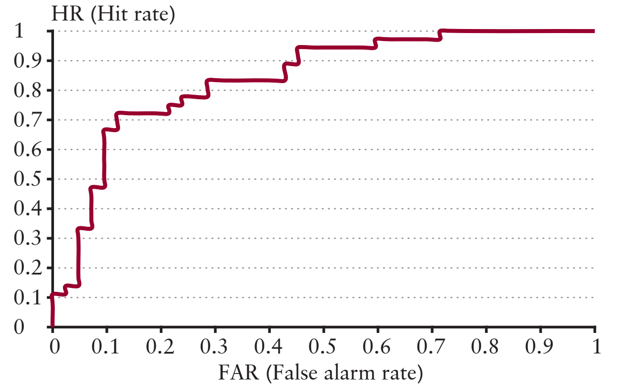
## Chart 1a

### ROC curve of the first logit model (Logit 1)



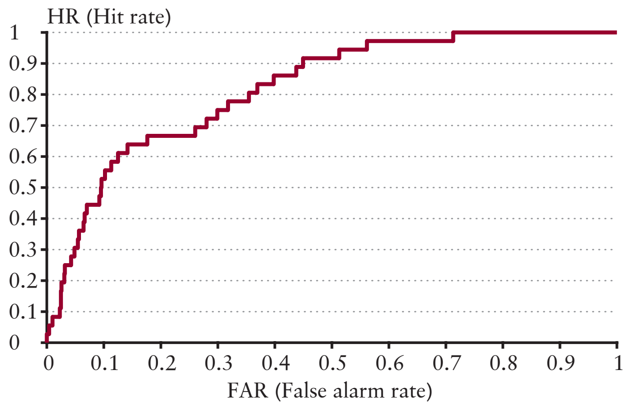

## Chart 2a

### ROC curve of the second logit model (Logit 2)



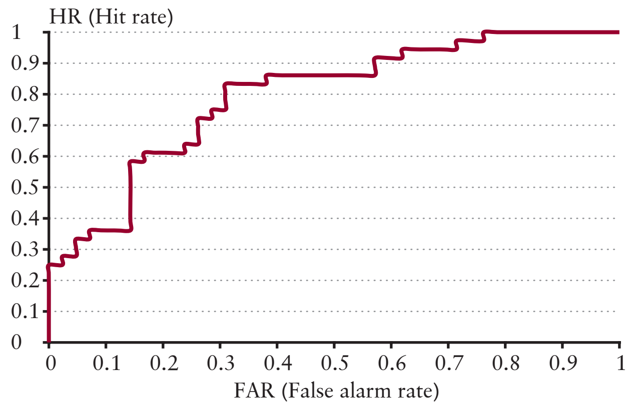

## Chart 3a

### ROC curve of the first neural network model (Network 1)




## Chart 4a

### ROC curve of the second neural network model (Network 2)



# Appendix 2: tables

## Table A

### Descriptive statistics of some selected variables

| Variable | Mean | Median | Standard deviation | Composition of loans by denomination | | |
|---|---|---|---|---|---|---|
| | | | | HUF | CHF | EUR |
| **Debt** | | | | | | |
| *Mortgage Loans (HUF)* | 4,059,049 | 3,000,000 | 3,393,147 | 62% | 33% | 5% |
| *Maturity of Mortgage Loans (Month)* | 150 | 144 | 86 | | | |
| *Reported LTV* | 48% | 45% | 22% | | | |
| *Car Purchase Loans (HUF)* | 1,628,867 | 1,500,000 | 851,931 | 31% | 60% | 8% |
| *Maturity of Car Purchase Loans (Month)* | 48 | 40 | 30 | | | |
| *Unsecured Loans (HUF)* | 408,349 | 200,000 | 712,000 | 92% | 1% | 7% |
| *Maturity of Unsecured Loans (Month)* | 39 | 27 | 15 | | | |
| *Number of loan contracts* | 1.50 | 1.00 | 0.81 | | | |
| **Income and wealth** | | | | | | |
| *Disposable Income (HUF)* | 170,144 | 160,483 | 65,245 | | | |
| *Financial Saving (HUF)* | 139,484 | 0 | 521,678 | | | |
| *Number of own cars* | 0.70 | 1.00 | 0.77 | | | |
| *Reported value of own cars (HUF)* | 835,335 | 220,250 | 1,673,700 | | | |
| *Number of own dwellings* | 0.94 | 1.00 | 0.53 | | | |
| *Reported value of own dwellings (HUF)* | 10,962,715 | 10,000,000 | 9,103,317 | | | |
| **Expenditures** | | | | | | |
| *Montly Loan Installment (HUF)* | 29,695 | 23,000 | 25,765 | | | |
| *Reported income share of monthly loan installment* | 22% | 15% | 13% | | | |
| *Calculated income share of monthly loan installment* | 18% | 15% | 14% | | | |
| *Consumption expenditure (HUF)* | 64,664 | 60,866 | 24,436 | | | |
| *Overhead expenditure (HUF)* | 32,118 | 30,265 | 11,812 | | | |
| **Other household characteristics** | | | | | | |
| *Number of dependants* | 1.31 | 1.00 | 1.29 | | | |
| *Age of the head of the household* | 43 | 45 | 12 | | | |

## Table B

### Explanatory variable set

| | Dummy | Continuous | Comment/Calculation |
|---|---|---|---|
| Job status of the head of the household | | | |
| *Employee* | X | | |
| *Private entrepreneur* | X | | |
| *Unemployed* | X | | |
| *Other inactive* | | | |
| Qualification of the head of the household | | | |
| *Low* | X | | |
| *Medium* | X | | |
| *High* | X | | |
| Age of the head of the household | | | |
| -30 | X | | |
| *31-39* | X | | |
| *40-49* | X | | |
| *50-59* | X | | |
| *60-* | X | | |
| Gender of the head of the household | | | |
| *Male* | X | | |
| *Female* | X | | |
| Number of dependants | | X | |
| Region of residence | | | |
| *Central Transdanubium* | X | | Counties: Fejér, Komárom-Esztergom, Veszprém |
| *Western Transdanubium* | X | | Counties: Győr-Moson-Sopron, Vas, Zala |
| *Southern Transdanubium* | X | | Counties: Baranya, Somogy, Tolna |
| *Northeastern Hungary* | X | | Counties: Borsod-Abaúj-Zemplén, Heves, Nógrád |
| *Northern Plain* | X | | Counties: Hajdú-Bihar, Szabolcs-Szatmár-Bereg, Jász-Nagykun-Szolnok |
| *Southern Plain* | X | | Counties: Bács-Kiskun, Békés, Csongrád |
| *Central Hungary* | X | | Pest county and Budapest |
| Disposable income | | | Upper quintile limits |
| *Quintile 1* | X | | HUF 110946 |
| *Quintile 2* | X | | HUF 148597 |
| *Quintile 3* | X | | HUF 179149 |
| *Quintile 4* | X | | HUF 218790 |
| *Quintile 5* | X | | |
| Financial Saving | | X | Reported value of total financial savings |
| Real wealth | | X | Reported value of own cars and dwellings |
| Share of monthly loan inst. | | X | Monthly debt servicing cost/monthly disposable income |
| Debt to income | | X | Debt/Yearly disposable income |
| Number of loans | | X | |
| Loan type | X | | |
| *Foreign (FX)* | X | | |
| *Domestic (HUF)* | X | | |
| *Foreign and domestic* | X | | |

## Table C

### Distribution of the probability of default and debt at risk

*(mean values)*

| | Debt at risk | | | | Probablity of default | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Dimension/Model** | **Financial margin1** | **Financial margin 2** | **Logit 1** | **Network 2** | **Financial margin1** | **Financial margin 2** | **Logit 1** | | **Network 2** | |
| **Region** | | | | | | | **Mean** | **Stdev.** | **Mean** | **Stdev.** |
| *Central Hungary* | 7.1% | 4.1% | 3.7% | 4.6% | 2.0% | 1.2% | 2.3% | 3.5% | 2.8% | 3.3% |
| *Central Transdanubium* | 12.1% | 6.8% | 3.7% | 4.6% | 3.3% | 2.2% | 2.5% | 3.5% | 3.1% | 3.1% |
| *Western Transdanubium* | 10.8% | | 4.7% | 5.2% | 2.4% | | 2.8% | 4.5% | 3.4% | 3.3% |
| *Southern Transdanubium* | 6.8% | 2.0% | 4.7% | 5.4% | 2.9% | 1.0% | 3.7% | 4.1% | 4.5% | 4.3% |
| *Northeastern Hungary* | 22.0% | 18.2% | 5.7% | 5.9% | 7.2% | 5.8% | 4.1% | 5.5% | 4.4% | 4.5% |
| *Northern Plain* | 19.6% | 6.0% | 5.0% | 5.9% | 7.4% | 3.2% | 4.3% | 5.1% | 5.1% | 4.5% |
| *Southern Plain* | 8.1% | 3.5% | 5.2% | 5.9% | 4.1% | 2.0% | 4.7% | 7.5% | 5.1% | 5.5% |
| **Income** | | | | | | | | | | |
| *Quintile 1* | 24.2% | 19.0% | 11.7% | 10.0% | 8.6% | 6.2% | 7.6% | 8.0% | 7.8% | 5.4% |
| *Quintile 2* | 25.9% | 14.6% | 6.0% | 6.5% | 6.2% | 3.3% | 3.3% | 3.8% | 3.7% | 4.1% |
| *Quintile 3* | 7.3% | 4.6% | 4.9% | 5.3% | 2.4% | 1.4% | 2.9% | 3.5% | 3.1% | 3.1% |
| *Quintile 4* | 8.6% | | 5.0% | 5.3% | 2.4% | | 2.9% | 3.1% | 3.2% | 3.2% |
| *Quintile 5* | 8.1% | | 0.8% | 3.2% | 1.4% | | 0.5% | 0.5% | 2.1% | 1.8% |
| **Qualification** | | | | | | | | | | |
| *Low* | 10.3% | 6.2% | 7.3% | 7.7% | 4.5% | 1.8% | 6.2% | 8.4% | 6.7% | 6.4% |
| *Medium* | 12.4% | 6.9% | 5.3% | 5.7% | 4.4% | 2.6% | 3.4% | 4.6% | 3.9% | 4.0% |
| *High* | 15.5% | 1.4% | 2.2% | 4.1% | 3.1% | 0.6% | 1.8% | 2.2% | 2.8% | 2.2% |
| **Age** | | | | | | | | | | |
| *-30* | 18.4% | 6.8% | 5.2% | 5.6% | 3.0% | 0.7% | 3.6% | 4.3% | 4.3% | 4.8% |
| *31-39* | 11.1% | 5.5% | 5.1% | 5.7% | 4.8% | 2.9% | 4.0% | 5.7% | 4.5% | 4.3% |
| *40-49* | 14.2% | 5.1% | 4.8% | 5.7% | 4.6% | 2.1% | 3.8% | 5.8% | 4.4% | 4.7% |
| *50-59* | 14.2% | 6.9% | 4.0% | 4.8% | 5.0% | 2.7% | 2.8% | 4.1% | 3.3% | 3.6% |
| *60-* | 2.1% | 2.1% | 2.9% | 4.0% | 1.1% | 1.1% | 1.8% | 1.8% | 2.6% | 2.1% |

*Notes: Central Transdanubium includes the following counties: Fejér, Komárom-Esztergom, Veszprém; Western Transdanubium includes the following counties: Győr-Moson-Sopron, Vas, Zala; Southern Transdanubium includes the following counties: Baranya, Somogy, Tolna; Northeastern Hungary includes the following counties: Borsod-Abaúj-Zemplén, Heves, Nógrád; Northern Plain includes the following counties: Hajdú-Bihar, Szabolcs-Szatmár-Bereg, Jász-Nagykun-Szolnok; Southern Plain includes the following counties: Bács-Kiskun, Békés, Csongrád; Central Hungary includes the following: Pest county and Budapest. Upper quintile limits are the following: 1. quintile: HUF 110,946, 2. quintile: HUF 148,597, 3. quintile: HUF 179,149, 4. quintile: HUF 218,790.*

## Table D

### Average default probabilities by various financial shock scenarios and model specifications

*(one year horizon)*

| Average unconditional probability of default (non-parametric approach) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Original income | | | | Original income plus 10 per cent | | | |
| CHF interest rate shock: 0 | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 4.2% | 5.1% | 6.0% | 7.4% | 2.2% | 2.6% | 3.0% | 3.5% |
| 100 bp | 4.2% | 5.1% | 6.0% | 7.4% | 2.2% | 2.6% | 3.0% | 3.5% |
| 250 bp | 4.5% | 5.4% | 6.3% | 7.6% | 2.2% | 2.6% | 3.0% | 3.5% |
| 500 bp | 5.0% | 5.8% | 6.8% | 8.1% | 2.5% | 2.9% | 3.3% | 3.8% |
| CHF interest rate shock: 100 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 4.4% | 5.4% | 6.8% | 7.5% | 2.3% | 2.7% | 3.2% | 3.9% |
| 100 bp | 4.4% | 5.4% | 6.8% | 7.5% | 2.3% | 2.7% | 3.2% | 3.9% |
| 250 bp | 4.7% | 5.7% | 7.1% | 7.7% | 2.3% | 2.7% | 3.2% | 3.9% |
| 500 bp | 5.2% | 6.2% | 7.6% | 8.2% | 2.6% | 3.0% | 3.4% | 4.2% |
| CHF interest rate shock: 200 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 4.7% | 5.8% | 7.1% | 7.7% | 2.4% | 2.8% | 3.5% | 4.2% |
| 100 bp | 4.7% | 5.8% | 7.1% | 7.7% | 2.4% | 2.8% | 3.5% | 4.2% |
| 250 bp | 5.0% | 6.1% | 7.4% | 8.0% | 2.4% | 2.8% | 3.5% | 4.2% |
| 500 bp | 5.4% | 6.6% | 7.8% | 8.5% | 2.7% | 3.1% | 3.8% | 4.5% |
| **Average conditional probability of default (parametric approach)** | | | | | | | | |
| | Logit 1 | | | | Network 2 | | | |
| CHF interest rate shock: 0 | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 3.4% | 3.6% | 3.8% | 3.9% | 4.0% | 4.2% | 4.3% | 4.4% |
| 100 bp | 3.5% | 3.6% | 3.8% | 4.0% | 4.0% | 4.2% | 4.3% | 4.4% |
| 250 bp | 3.5% | 3.6% | 3.8% | 4.0% | 4.1% | 4.2% | 4.3% | 4.4% |
| 500 bp | 3.5% | 3.7% | 3.8% | 4.0% | 4.1% | 4.2% | 4.3% | 4.5% |
| CHF interest rate shock: 100 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 3.6% | 3.8% | 4.0% | 4.3% | 4.3% | 4.4% | 4.5% | 4.7% |
| 100 bp | 3.6% | 3.8% | 4.1% | 4.3% | 4.3% | 4.4% | 4.6% | 4.7% |
| 250 bp | 3.7% | 3.9% | 4.1% | 4.3% | 4.3% | 4.4% | 4.6% | 4.7% |
| 500 bp | 3.7% | 3.9% | 4.1% | 4.4% | 4.3% | 4.5% | 4.6% | 4.7% |
| CHF interest rate shock: 200 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 3.7% | 3.9% | 4.1% | 4.3% | 4.5% | 4.6% | 4.8% | 4.9% |
| 100 bp | 3.7% | 3.9% | 4.1% | 4.3% | 4.5% | 4.6% | 4.8% | 5.0% |
| 250 bp | 3.7% | 3.9% | 4.1% | 4.4% | 4.5% | 4.6% | 4.8% | 5.0% |
| 500 bp | 3.7% | 3.9% | 4.2% | 4.4% | 4.5% | 4.7% | 4.8% | 5.0% |

## Table E

### Debt at risk by various financial shock scenarios and model specifications

*(one year horizon)*

| Debt at risk (non-parametric approach) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Original income | | | | Original income plus 10 per cent | | | |
| CHF interest rate shock: 0 | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 12.9% | 15.5% | 18.1% | 21.5% | 5.7% | 7.8% | 9.0% | 10.6% |
| 100 bp | 13.2% | 15.5% | 18.1% | 21.5% | 5.7% | 7.8% | 9.0% | 10.6% |
| 250 bp | 14.1% | 16.4% | 19.0% | 22.4% | 5.7% | 7.8% | 9.0% | 10.6% |
| 500 bp | 14.9% | 17.2% | 19.8% | 23.2% | 6.6% | 8.8% | 10.0% | 11.6% |
| CHF interest rate shock: 100 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 13.4% | 16.8% | 20.6% | 21.7% | 6.8% | 8.5% | 9.6% | 12.1% |
| 100 bp | 13.7% | 16.8% | 20.6% | 21.7% | 6.8% | 8.5% | 9.6% | 12.1% |
| 250 bp | 14.6% | 17.8% | 21.6% | 22.6% | 6.8% | 8.5% | 9.6% | 12.1% |
| 500 bp | 15.4% | 18.5% | 22.6% | 23.4% | 7.8% | 9.5% | 10.6% | 13.1% |
| CHF interest rate shock: 200 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 14.3% | 17.9% | 21.6% | 22.8% | 7.2% | 8.8% | 11.3% | 12.8% |
| 100 bp | 14.6% | 17.9% | 21.6% | 22.8% | 7.2% | 8.8% | 11.3% | 12.8% |
| 250 bp | 15.5% | 18.8% | 22.5% | 23.7% | 7.2% | 8.8% | 11.3% | 12.8% |
| 500 bp | 16.3% | 19.6% | 23.3% | 24.5% | 8.2% | 9.8% | 12.3% | 13.8% |
| Debt at risk (parametric approach) | | | | | | | | |
| | Logit 1 | | | | Network 2 | | | |
| CHF interest rate shock: 0 | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 3.4% | 3.6% | 3.8% | 3.9% | 4.0% | 4.2% | 4.3% | 4.4% |
| 100 bp | 3.5% | 3.6% | 3.8% | 4.0% | 4.0% | 4.2% | 4.3% | 4.4% |
| 250 bp | 3.5% | 3.6% | 3.8% | 4.0% | 4.1% | 4.2% | 4.3% | 4.4% |
| 500 bp | 3.5% | 3.7% | 3.8% | 4.0% | 4.1% | 4.2% | 4.3% | 4.5% |
| CHF interest rate shock: 100 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 5.2% | 5.6% | 6.1% | 6.6% | 6.0% | 6.3% | 6.6% | 6.9% |
| 100 bp | 5.2% | 5.6% | 6.1% | 6.6% | 6.0% | 6.4% | 6.7% | 7.0% |
| 250 bp | 5.3% | 5.7% | 6.2% | 6.7% | 6.1% | 6.4% | 6.7% | 7.0% |
| 500 bp | 5.4% | 5.8% | 6.3% | 6.8% | 6.1% | 6.4% | 6.7% | 7.1% |
| CHF interest rate shock: 200 bp | | | | | | | | |
| HUF Interest rate shock/HUF depreciation | 0 | 10% | 20% | 30% | 0 | 10% | 20% | 30% |
| 0 | 5.3% | 5.7% | 6.2% | 6.8% | 6.5% | 6.8% | 7.1% | 7.5% |
| 100 bp | 5.3% | 5.7% | 6.2% | 6.8% | 6.5% | 6.8% | 7.2% | 7.5% |
| 250 bp | 5.4% | 5.8% | 6.3% | 6.8% | 6.5% | 6.9% | 7.2% | 7.6% |
| 500 bp | 5.5% | 5.9% | 6.4% | 6.9% | 6.6% | 6.9% | 7.3% | 7.6% |

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