Which households are really financially distressed: How MICRO-data could inform the MACRO-prudential policy[1]

P. Bańbuła[**], A. Kotuła[*], J. Przeworska[*], P. Strzelecki [**]

Abstract

We provide a model for calibration of DSTI/DTI limits that allows to account for both the effectiveness and cost of these limits, depending on policy makers preferences regarding type I and type II errors. Based on a seminal wealth survey recently conducted in Poland, the financial position of individual households is assessed. Crucially, the high level of detail in the data allows us to simulate expenditure, income, as well as liquid assets and liabilities. Based on these simulations

and self-assessment of household indebtedness we provide two complementary measures of households' over-indebtedness. By comparing these sets of overindebted households with a set that would arise with commonly used debt-to-income ratios, we assess the desirability of using DSTI and DTI limits in macroprudential policy. We find that that DSTI can be an effective tool in identifying over-indebted households and for a range of plausible preferences regarding type I and type II errors the suggested DSTI limit is in a range of 30%-40%.

Keywords: macroprudential tools, DSTI calibration, households' overindebtedness, financial margin

JEL classification: O50, G21, D12, C81

[1] The views expressed in this paper are solely those of the authors and not necessarily those of the organizations they are affiliated with.

[**] National Bank of Poland, Warsaw School of Economics

[*] National Bank of Poland

1. Introduction

Debt-Service-to-Income (DSTI) and Debt-to-Income (DTI) ratios have been one of the most popular policy tools affecting credit dynamics and resilience of the banking sector for many years in both developed and developing countries (Lim et al., 2011). Their popularity will likely increase as macroprudential policy becomes widespread. However, while the effectiveness of the DSTI/DTI limits in affecting credit dynamics is intuitively clear and confirmed in the literature (Claessens et al., 2014), (Kuttner and Shim, 2013), very little is known about the cost of these measures. As a result, calibration of these tools is usually based on heuristic approach, which fails to properly account for both the effectiveness of the measure in identifying the over-indebted households and their cost related to unwarranted elimination of non-over-indebted households from credit market. In this article we provide an approach that allows to calibrate the DSTI/DTI limits taking into account both these effects and the preferences of the decision maker regarding the cost of type II error (failure to identify overindebted household as indeed over-indebted) and type I error (identification of non-over-indebted household as over-indebted one).

In order to calibrate the DSTI limit one needs to have a measure of over-indebtedness that is not directly related to the DSTI. We use two complementary measures. One uses microsimulation model, which is based on the notion of financial margin – the excess of income and liquid financial assets over consumption and debt-servicing costs. The model includes shocks to employment, interest rate, exchange rate and various adjustments in consumption that household could make in response to these shocks. The data come from a new, rich database on household wealth survey in Poland, which includes detailed information about households characteristics, amount and structure of real and financial assets, amount and structure of debt, income, employment and expenditures. As a complementary tool we use a subjective assessment of over-indebtedness by the households themselves, taken from the same survey. Based on the two approaches, two sets of households for each measure are identified: over-indebted and others. Using these results we first assess the effectiveness of the DSTI/DTI as indicators of over-indebtedness by estimating a logistic regression using the binary variable from both microsimulation model and self-assessment with DSTI/DTI as an explanatory variable. We find that DSTI provides a correct identification of households in 70%-80% of cases. Use of DSTI limit will therefore inevitably produce both type I errors error and type II error. Second, we calibrate the DSTI limit for a set of policy makers preferences regarding the importance of these errors, by estimating the optimal DSTI/DTI limit for a range of weights for both of errors. For a plausible set of preferences the DSTI limits we find are in a range of 30%-40%. Our method is easily applicable to other countries and could improve the quality of information used for DSTI/DTI calibration, making both effectiveness and cost of particular limit explicit to the decision maker.

The article is structured as follows. The first part provides an overview of various approaches to overindebtedness measurement found in the literature. Second part provides description of the data used in the study, including the measure of subjective over-indebtedness. In the third part details of the microsimulation model are presented and the resulting over-indebtedness metric. The last section is dedicated to the calibration of DSTI/DTI, followed by conclusions.

2. Literature review on households overindebtedness

There is no agreement on how to define and measure over-indebtedness. As suggested in the European Commission study, conducted to bring together different views on the matter, it is difficult to find common acceptable definition (Davydoff et al., 2008), (Fondeville et al., 2010). The perception of excessive debt varies across countries. However, analyzing different attitudes is valuable to develop some core features that are important in assessing excessive debt and qualifying vulnerable debtors.

Such variety of proposals to define over-indebtedness result in broad set of indicators to measure the level of household indebtedness. There are two key approaches of over-indebtedness measurement, which bases on objective and subjective (self-assessed) indicators of households' debt position (Keese, 2009). Objective measures discussed in the literature refer frequently to household gearing ratios (DSTI, DTI), the number of credit commitments or the length of credit arrears, with suggested limits above which a household is declared insolvent. Subjective measures stem from individual self-assessment under implicit assumption that households know their financial situation well.

2.1 Basic indicators

Over-indebtedness is frequently indicated when the ratio of debt repayments relative to household income exceeds certain limit, commonly set at 30%, 40% or 50% for total debt (Bryan et al., 2010), (Disney et al., 2008), (d'Alessio and Iezzi, 2013), (Persson, 2012), (Betti et al., 2007). It has been relatively well documented that the DSTI/DTI limits indeed do curb credit growth (Claessens et al., 2014), (Kuttner and Shim, 2013). This should not come as a surprise as the DTI limits essentially eliminate some households from the market. To our knowledge very little is known about the cost of these measures – proposed DSTI caps are usually based on heuristics instead of quantitative research and calibration. It has been found that default rate grows with DSTI rate, but is noticeably lower among the most indebted households (Dietsch and Welter-Nicol, 2014). This suggest that the measures are costly, as they fail to correctly identify only truly over-indebted households, yet little is known about the exact nature of these costs.

Another group of commonly used objective indicators refer to the number of credit commitments a household repay or number of months its debt payment is in arrears (Bryan et al., 2010), (Disney et al., 2008), (d'Alessio and Iezzi, 2013). For such measures, over-indebtedness occurs for household with 4 or more credit commitments or 2-3 months being in arrears with debt or/and domestic bill commitments (Disney et al., 2008), (d'Alessio and Iezzi, 2013).

Less frequently used indicators to evaluate over-indebtedness are administrative/legal measures based on credit register information (Haas, 2006), (Persson, 2012), liquidity/illiquidity measures (Disney et al., 2008), debt to assets ratio or consumption to income ratio, which high value may indicate over-indebtedness (Betti et al., 2007) but also a measure to separate households which spending on total borrowing repayments takes them below the poverty line (d'Alessio and Iezzi, 2013). Abovementioned studies suggest, it is impossible to find one statistic to classify households with excessive debt burden, so that there is need to take into account several measures when investigating over-indebtedness (Disney et al., 2008).

2.2 Other measurable indicators

Financial margin is commonly used when assessing households' financial situation, especially its resistance to adverse shocks. Apart from being an excessive debt burden indicator, financial margin, as a multifactorial measure may be used to evaluate households' vulnerability in stress test scenarios considering various type of economic shocks. Indeed, it can include aspects of many basic indicators.

Stress testing is a practical method of evaluating households' vulnerability on micro and macroeconomic shock scenarios and had been used in numerous institutions interested in creditability of borrowers under certain circumstances. Most of researchers consider shocks on unemployment rate and interest rate, but the other possible scenarios are shocks on inflation rate (Hlaváč et al., 2013), real estate price (Froyland and Larsen, 2002), asset prices (Bilston et al., 2015), (Albacete and Fessler, 2010) or exchange rate (Zajaczkowski and, Żochowski , 2007), (Albacete and Fessler, 2010), (Albacete et al., 2014).

Financial margin is usually defined as:

$$FM_i = TI_i - C_i - DS_i + LA_i \tag{1}$$

where TI is i-th household annual net income, C is consumption, DS is debt service and LA are liquid assets.

Financial margin may be defined in various manners, depending on a stress scenario that one aims to examine. For instance (Johansson and Persson, 2006) and (Holló and Papp, 2007) exclude liquid assets and define margin as disposable income reduced by living cost (including debt service cost). However, liquid assets may be an important buffer absorbing a shock, particularly short-lived ones (Vatne, 2006).

An impact of introduced stress factors may vary across countries because of certain credit markets characteristics. In Finland, for instance, interest rate disturbance impacts level of distress significantly more than unemployment rate and exchange rate shocks (Kauko and Herrala, 2007).

2.3 Subjective indicators

Subjective approach assumes that debtors are well-informed about their financial situation. In subjective assessment debtors are categorized as over-indebted when they declare themselves that their borrowing repayments are a 'heavy burden' (d'Alessio and Iezzi, 2013), (Betti et al., 2007), (Haas, 2006), (Disney et al., 2008), (Persson, 2012), (Disney et al., 2008), (Lusardi and Tufano, 2009), (Bryan et al., 2010).

3. Data

We use data from the pilot Study on Household Wealth, which was carried out in 2014 by National Bank of Poland in cooperation with the Central Statistical Office. The study covered representative sample of 3.5 thousand households in Poland. The survey offers ample and detailed information concerning households real and financial assets, level and structure of debt, income, employment and expenditure.

The results of Study on Household Wealth shows that 37% of households in Poland are indebted, including 12.1% holding mortgage loans and 29.4% with non-mortgage (mainly unsecured) debt. Those types of loans accounts for, respectively 81.5% and 18.5% of total household debt in Poland. Polish borrowers hold, on average (median) 2.4 thousand euro of debt, including 25 thousand of mortgage and 1.2 thousand of non-mortgage debt. They spend approximately 10% of their monthly gross income on its service (and 14.1% of their net income).

Based on variables of over-indebtedness suggested in the literature and the limits above which excessive debt is assumed, in Poland there are 8.9% and 4.9% indebted households who allocate more than, respectively, 30% and 40% of their gross income for total debt servicing (16.9% and 10.1% when disposable income is concerned). 22.4% of households declare that their financial margin – the difference between income and liquid financial assets on the one side and expenditures together with debt-servicing costs – is negative. This likely reflects the underreporting of income, documented in various survey around the world (Deaton, 1997), (Bound et al., 2001), (Meyer et al., 2009), (Hurst et al., 2014). We deal with this issue by running simulations on several models, assuming varying degrees of underreporting.

Approximately 23% of indebted judge their debt as a 'heavy burden'. The distribution of answers is presented in Table 1.

Table 1: **The distribution of answers to the question: "Is household over-indebted?"**

	Definetely disagree	Disagree	Maybe	Agree	Definetely agree
% of indebted households	21.5	38.7	16.8	14.1	8.9

Data on unemployment and resulting transition probabilities in the labour market come from the Polish Labour Force Survey (PLFS). PLFS is a quarterly, representative survey of Polish population carried out by Polish Central Statistical Office. In each round it covers over 100 thousand observations since 2010 (before 2010 it was around 50 thousands). This survey is the main source of information about labour market in Poland. Thanks to the standardized questionnaire, the results of the survey are internationally comparable. It is also important that it allows to use standard definitions of labour market indicators (for example the definitions employment, unemployment and inactivity are consistent with International Labour Organization standard). The PLFS is also designed as so called rotated panel. It has longitudinal structure in which the same persons are asked in two consecutive quarters then there is a two quarters break after which persons are once more asked in two consecutive quarters. This feature of the data can be used to calculate probabilities of losing or finding job between two consecutive quarters.

3.1 Simulation

3.1.1 Labour market transition matrix

The labour market simulations are based on the probabilities of transitions between employment (E), unemployment (U) and inactivity on the labour market (N). Including inactivity is important because of the significant changes in labour supply due to the baby boom generations and pension reforms. The two most important probabilities are the transition from employment to unemployment (probability of job separation) and from unemployment to employment (job finding probability). Probabilities of transitions between different labour market states are estimated using quarterly Labour Force Survey panel data that covers in Poland 100 thousand persons every quarter. However only the half of that number is interviewed in every two consecutive quarters. We use the same procedure mentioned below to calculate job finding and job separation probabilities for the whole population and for six groups of individuals defined by educational level (basic, secondary, tertiary) and age (15-34,35-54, 55+). The probability of finding job by unemployed person can be described as:

$$F_t = \frac{n^{UE}_{t \to t+1}}{n^U_t} \quad (2)$$

where $n^{UE}_{t \to t+1}$ means the number of persons unemployed in time t, who find job until $t + 1$ and n^U_t stands for the total number of unemployed in moment t. The probability of separation was calculated as:

$$X_t = \frac{n^{EU}_{t \to t+1}}{n^E_t} \quad (3)$$

The probabilities were estimated quarterly in order to shorten the period before observations and minimise the problem of missed multiple transitions between observations. However, the estimated probabilities need to be seasonally adjusted. Additionally we also use Iterative Proportional Fitting (IPF) procedure in order to correct for panel attrition and have the probabilities consistent with aggregate data published by Polish Central Statistical Office. The negative labour market shocks that increase unemployment results from both: changes in EU and UE probabilities (see Figure 1 and Figure 2). It should be also noticed that volatility of the probability of job separation is mainly a result of the episodes of extremely tight labour market or first quarters of economic slowdown. Beside that short periods, the probability of losing job is relatively stable. However, there are huge differences between age and educational groups (Figure 3). In general probability of job separation is lower for older and better educated persons. It is especially low and immune to economic downturns among persons 35+ with tertiary education. The lower the education, the higher vulnerability for unemployment rate fluctuations.

Figure 1: Unemployment and employment before and after the crisis. *Source: Polish LFS data*

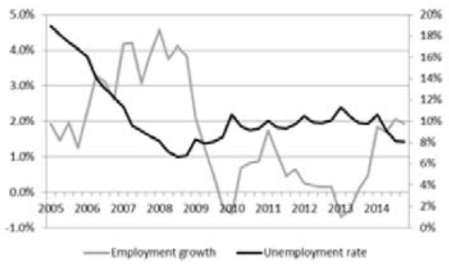


Figure 2: Probabilities of transitions between employment and unemployment. *Source: Polish LFS d*

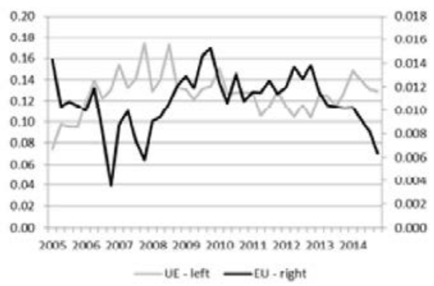
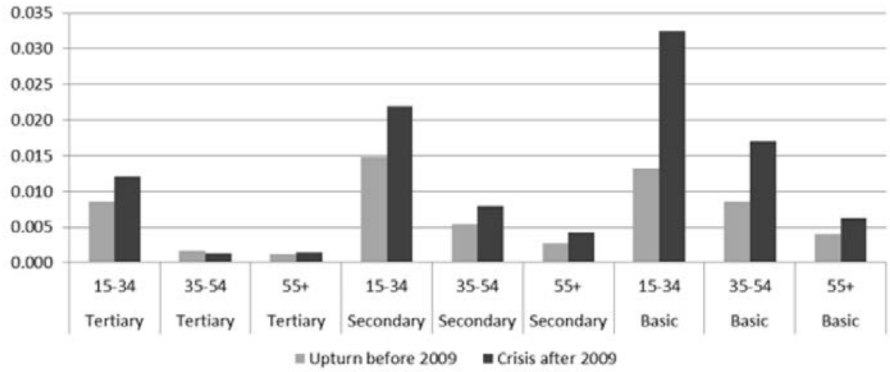


Figure 3: Probabilities of transition E→U (job separation) by education and age groups. *Source: Polish LFS data*



3.1.2 Model description

Stress test of polish households is based on microsimulation model for the financial margin for each individual household (see Equation 1). We allow for shocks in unemployment, credit costs and various responses of the expenditures to these shocks. Given that, negative financial margin is declared by almost one quarter of households even before any shock and this is likely due to underreporting of income. We account for it by identifying over-indebtedness under three different levels of financial margin: lower than zero, lower than -10% of income and lower than -20% of income.

Unemployment, interest rate and exchange rate shocks are all considered in a simultaneous stress test that is based on the highest historical annual growth of stress factors in the last 20 years. In Poland it was 2.7 percentage points for unemployment rate, 3.5 percentage points for interest rate and 17 percentage points for exchange rate.

Unemployment probability had been computed for every individual in the survey with respect to age and education level. Details of the procedure are presented in section describing labour market transitions matrix. Employees are drawn from the sample proportionally to their risk of being unemployed until the increase in unemployment is equal to the one assumed in the shock scenario. To absorb a shock of income fall, unemployment benefits and severance pay have been introduced to the model and they are assigned according to polish employment law. Severance pay in Poland depends on professional experience in one company and varies between 100% of monthly salary for employees with less than 8 years of experience and 300% after 20 years of work. Unemployment benefit depends on overall work experience (amount of benefit) and unemployment rate in a district (number of months a benefit is being paid). As can be seen in Equation 1, employment shock has an influence on households' income and perhaps indirectly on consumption.

$$FM_i = TI_i - C_i - DS_i + LA_i \quad (1)$$

Exchange rate and interest rate shocks, influencing monthly credit commitment, may expose households' vulnerability to particular type of disturbance. Six possible types of credit instalments are considered (various combinations of fixed or variable interest rate, foreign or domestic currency and equal or decreasing instalment) and only one of them is invulnerable to any type of stress scenario (fixed interest rate and domestic currency).

We allow for four responses of consumption to these shocks: unchanged consumption pattern, decrease by 25%, decrease by 50% and finally, reduction to social minimum. Financial margin includes liquid assets, which are assumed shock-invariant. Our simulation implicitly assumes that shocks last for a year. The results of assumed shock scenario are presented in Table 2.

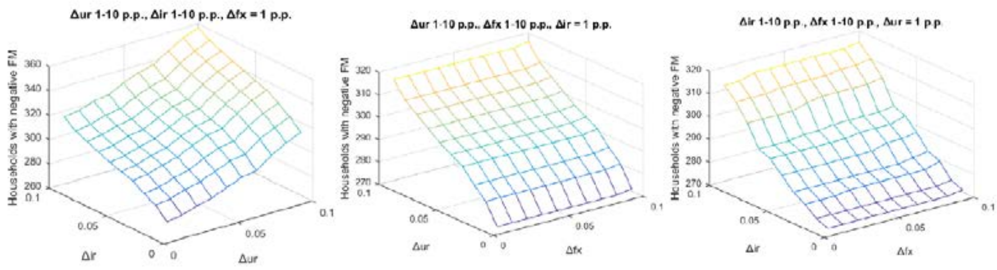
Table 2: Households with negative financial margin before and after stress scenario with possible consumption adjustments

	$FM < 0$		$FM < -0.1TI$		$FM < -0.2TI$	
Consumption adjustment	Before	After	Before	After	Before	After
Without reduction	247	289	175	214	121	150
Reduction by 25%		285		207		144
Reduction by 50%		282		205		140
Reduction to social minimum		194		144		103

As a result of introduced shock, number of households with negative uncorrected financial margin grows by 15.4% and comprises 25.8% of indebted households (3.4 percentage points more than before disturbance). What is more, shock absorption by consumption cut seems to be ineffectual. Once a household falls below over-indebtedness line, it usually cannot adjust its lifestyle to be in the black again, what can identify a serious problem for overindebted households. In other words, relatively few households are affected by introduced shocks, but the affected ones usually cannot take an action to deal with the crisis without financial support.

Shock effect is not stronger for financial margin lower than -10% of income and lower than -20% of income (growth by 22.3% and 24% of overindebted households respectively). Consumption adjustments are also ineffectual when margin corrections are considered. The results show that shock and possible reaction in the form of consumption adjustment are almost equal regardless of assumed attitude to financial margin.

Figure 4: Concomitant changes in stress factors (1-10 percentage points).



The charts in Figure 4. present an impact of introduced stress factors on the number of households with negative financial margin. Simultaneous disturbances in 2 out of 3 parameters were introduced (1 to 10 percentage points), with the change of third parameter fixed at the level of 1 percentage point. It is apparent that concomitant changes in unemployment rate and interest rate are the most influential on the number of overindebted families. Assuming 10 percentage points change of both factors and 1 percentage point change of exchange rate, 355 households are said to be overindebted. Exchange rate change seems to have less significant influence on over-indebtedness problem. In conclusion, Polish households are believed to be more vulnerable to disturbances on labour market and interest rates shock.

3.2 DSTI calibration

In the last part, the problem of DSTI limit calibration is discussed. We first use two previously computed measures of over-indebtedness – from microsimulation and self-assessed – to evaluate the effectiveness of the DSTI/DTI ratio in identifying financial stress. Second, we calculate DSTI limits consistent with type I error and type II error trade-offs to present approximate regulations effects. The final choice is the exclusive responsibility of decision makers and depends on one's preferences regarding false positive and false negative ratios importance. Our approach allows to explicitly account for these preferences.

A calibration technique bases on logistic regression model, where a dependent variable is one of over-indebtedness measures and an independent variable is DSTI. Logistic regression estimates for available over-indebtedness measures are presented in Table 3.

As can be seen, 1 percentage point change in DSTI ratio increases odds ratio of being over-indebted in comparison with being solvent by 1.67 to 6.25 percentage points, depending on over-indebtedness indicator assumed.

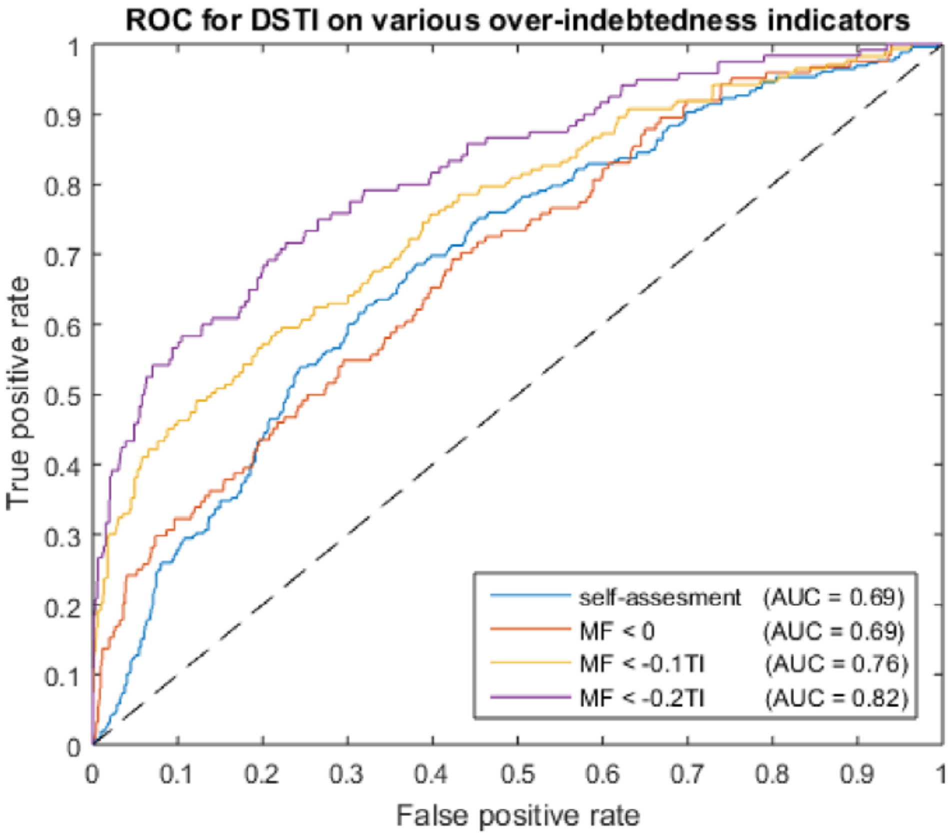
However, margin-based estimates are relatively consistent and there is a significant difference in comparison with self-assessment estimates.

Table 3: DSTI odds ratio estimates in logit models (endogenous variables in the first row). Standard error in parenthesis.

	Self-assesment	$MF < 0$	$MF < -0.1TI$	$MF < -0.2TI$
DSTI odds ratio	1.0167 (.003)	1.0466 (.005)	1.054 (.005)	1.0625 (.005)

Receiver operating characteristic (ROC) curves of estimated models are presented in Figure 5.

Figure 5: ROC curves for estimated logit models



The most significant part of the chart in terms of benefit to cost ratio of imposed caps is the first 10% of false positive rate (higher costs would probably be rejected by policy maker). Financial margin corrections (10% and 20% of total income below 0) seem to be significantly better classified by DSTI ratio than the other indicators, especially when low calibration cost is assumed. Uncorrected financial margin and self-assessment are comparably efficient indicators, but the first one seems to be better in the area of interest. Area under the curve varies between 0.69 and 0.82, what is a satisfying result whereas DSTI is an only regressor.

The results of DSTI calibration based on various over-indebtedness indicators are presented in Table 4. (in the model positive means overindebted). There is not an obvious answer to the question about the best DSTI level and a final decision should be taken by a governing body. However, on the basis of presented results some solutions may be proposed. The core function of the tool is to eliminate as much overindebted as possible (TP - true positive rate). Nonetheless, there is always a side effect, which is rejection of credible debtors (FP - false positive rate). 20% limit causes rejection of a significant fraction of credible households, regardless of over-indebtedness indicator assumed. Application of 30% limit allows to reject a significant share of potentially insolvent debtors, but costs of such decision may also be relatively high (12.2% to 15.5% false positive rate). Limit of 40% DSTI allows to reject from 19.8% to 47.5% of overindebted (depending on assumed over-indebtedness indicator) with relatively low cost (5% to 7.5% false positive rate). However, none of possible DSTI limits can be used as an only tool. Even after imposition of DSTI limit, commercial banks should have an obligation to verify customers' creditability.

Table 4: DSTI limits. True positive (TP) and false positive(FP) classifications with various over-indebtedness indicators. Type I error and type II error trade-offs for every DSTI cap in parenthesis

	DSTI = 20%		DSTI = 30%		DSTI = 40%		DSTI = 50%	
	TP	FP	TP	FP	TP	FP	TP	FP
Self-assesment	56.2%	27.6%	32.2%	13.7%	19.8%	7.1%	12%	4.5%
	(1/1.6)		(1/4.9)		(1/11.3)		(1/19.6)	
$FM < 0$	54.8%	31.6%	37.9%	15.5%	29.8%	7.5%	24.2%	4%
	(1/1.4)		(1/4)		(1/9.4)		(1/19)	
$FM < -0.1TI$	63%	29.1%	49.1%	12.2%	37.6%	5%	30%	1.8%
	(1/1.3)		(1/4.2)		(1/12.5)		(1/38.9)	
$FM < -0.2TI$	75.8%	29.4%	60%	12.9%	47.5%	5.5%	39.2%	2.2%
	(1/0.8)		(1/3.1)		(1/9.5)		(1/27.6)	

Notes: True positive rate describes effectiveness in classification of overindebted households. False positive rate equals costs of introduced limits (rejection of credible debtors). Trade-offs in parenthesis represent relation of type I error and type II error (FP/(1-TP)). Relation 1/10 means, that decision-maker considers type I error (unjustified rejection) 10 times more harmfull than type II error.

Table 5. includes various false positive and false negative trade-offs with corresponding DSTI limits. Considering policymakers' preferences and possible weights assigned to false positive and false negative values, it is important to highlight DSTI levels consistent with various trade-offs. Trade-off 1/1 describes symmetric preferences of a decision-maker. In other words, if one treats rejection of credible debtors and acceptance of potentially insolvent ones as equal problems, trade-off 1/1 and 20% DSTI limit should be applied. If, however, costs of credible debtors rejection are considered more harmful than costs of ineffective exclusion, a governing body would choose 1/2, 1/5 (DSTI = 30%) or 1/10 (DSTI = 40%) trade-offs, depending on individual preferences. Trade-off 1/10 means, that cost of unjustified rejection is 10 times more harmful than cost of false negative classification. Commercial banks are obliged to verify debtors credibility and therefore double check whether the households who pass the DSTI test are indeed creditworthy. However, households above the DSTI limit are automatically eliminated from the credit market. This suggests that the cost of type I error is higher than of the type II error as type II error can always be corrected by the commercial bank.

Table 5: DSTI caps for various false positive and false negative (type I error and type II error) trade-offs.

	1/1 DSTI	1/2 DSTI	1/5 DSTI	1/10 DSTI
Self-assesment	16.7%	21.9%	30.4%	37.7%
$FM < 0$	17.5%	22.9%	33.1%	41.2%
$FM < -0.1TI$	18.2%	23.7%	32.4%	37.8%
$FM < -0.2TI$	21.2%	26.4%	34.5%	40.1%

To verify robustness of results, DSTI calibration has also been performed after introduced shock scenario. The results of calibration with possible consumption adjustments are presented in Table 6. As can be seen, DSTI limits for every trade-off increase slightly and the growth is more significant for higher consumption adjustments. However, the results seem to be relatively stable and introduced shock causes increase in optimal level of DSTI limits up to 5 percentage points to 35% for 1/5 trade-off and 45% for 1/10 trade-off.

Table 6: DSTI caps for various false positive and false negative (type I error and type II error) trade-offs calibrated after introduced shock scenario with possible consumption adjusments.

	1/1 DSTI	1/2 DSTI	1/5 DSTI	1/10 DSTI
No consumption adjustment				
$FM < 0$	18.5%	24.5%	34.6%	41.1%
$FM < -0.1TI$	20.1%	27%	35.9%	43.2%
$FM < -0.2TI$	22.5%	29.5%	38.9%	46.1%
Consumption -25%				
$FM < 0$	18.6%	24.6%	34.7%	41.1%
$FM < -0.1TI$	20.3%	27.2%	36.2%	43.2%
$FM < -0.2TI$	22.9%	30%	38.9%	47%
Consumption -50%				
$FM < 0$	18.6%	24.6%	34.9%	41.5%
$FM < -0.1TI$	20.3%	27.2%	36.3%	43.2%
$FM < -0.2TI$	22.9%	30.3%	39%	47.1%
Consumption to social minimum				
$FM < 0$	20.2%	27.2%	36.8%	43.7%
$FM < -0.1TI$	21.9%	30.3%	38.9%	46.5%
$FM < -0.2TI$	26.1%	33.1%	42.3%	49.4%

When it comes to DTI caps, there is also possible to perform separate analysis. However, logit-based calibration allows to handle only one variable in the same time. Therefore, a joint DSTI and DTI caps estimation may be a possible extension of this research. The results of DTI calibration are presented in Table 7.

Table 7: DTI limits. True positive (TP) and false negative(FN) calsifications with various overindebtedness indicators.

	DTI = 150%		DTI = 200%		DTI = 250%		DTI = 300%		DTI = 350%	
	TP	FP	TP	FP	TP	FP	TP	FP	TP	FP
Self-assesment	33%	19%	27.5%	14.8%	22.5%	11.2%	18.2%	8.6%	14.3%	6.7%
$FM < 0$	26.5%	20.7%	24.1%	15.9%	20.8%	11.9%	16.7%	9.2%	14.7%	6.9%
$FM < -0.1TI$	29.5%	20.6%	26.6%	16.1%	24.3%	11.9%	19.1%	9.3%	15.6%	7.2%
$FM < -0.2TI$	34.2%	20.5%	31.7%	16%	28.3%	12.1%	21.7%	9.5%	18.3%	7.3%

At first sight, classification's efficiency is noticeably lower than in case of model for DSTI. The only acceptable limits in terms of false positive rate (DTI = 350% for every over-indebtedness indicator) are ineffective in rejection of overindebted households. On the basis of the results it is not possible to recommend any reasonable DTI limit.

4. Conclusions

In this article we have analysed the usefulness of the DSTI limits as indicators of over-indebtedness. Our model not only provide the information on the effectiveness of the measure, but also on its costs, on which the literature has been largely silent. As a result we allow for explicit calibration of the DSTI limits in a way that takes into account both the desire to limit the access to credit for the over-indebted households and the costs related to the unwarranted penalty imposed on non-over-indebted households. DSTI limits turns out to be relatively good indicators of financial stress and correctly categorizes households in 70-80% of cases, as measured with both objective measures of indebtedness based on microsimulations and subjective measures based on self-assessment. The use of complementary measures of over-indebtedness (objective and self-assessed) increases the robustness of our results. As an indicator DSTI is still far from perfect, its application entails two types of cost – failure to correctly identify truly over-indebted households (false negative, type II error) and identification of non-over-indebted households as over-indebted (false positive, type I error). Based on a logistic regression that have been used to assess the quality of the DSTI limit as an over-indebtedness measure, we can account for decision-makers preferences regarding the importance of these two type of errors. Assuming that both type of errors are of equal importance, the DSTI limit should be set at a level of 20%. In principal however, the type I error is more severe, as it is both, unjustified and final decision that a household will not be granted a loan, whereas type II error can still be corrected by the banks who have the obligation to double-check whether households who do pass the DSTI limit are indeed creditworthy. Assuming that type I error is 5 to 10 times more severe, the resulting DSTI limits are in a range of 30-40%.

References

Albacete, N., J. Eidenberger, G. Krenn, P. Lindner, and M. Sigmund (2014): "Risk-bearing capacity of Households – linking Micro-level Data to the Macroprudential toolkit," *Oesterreichische Nationalbank, Financial Stability Report 27*.

Albacete, N. and P. Fessler (2010): "Stress Testing Austrian Households," *Oesterreichische Nationalbank, Financial Stability Report 19*, 72 – 91.

Betti, G., N. Dourmashkin, M. Rossi, and Y. P. Yin (2007): "Consumer over-indebtedness in the EU: measurement and characteristics," *Journal of Economic Studies, 34(2), 136-156*.

Bilston, T., R. Johnson, and M. Read (2015): "Stress Testing the Australian Household Sector Using the HILDA Survey," *Reserve Bank of Australia, Research Discussion Paper 2015-01*.

Bound, J., C. Brown, and N. Mathiowetz (2001): "'Measurement error in survey data," *Handbook of econometrics, 5, 3705-3843*.

Bryan, M., M. Taylor, and M. Veliziotis (2010): "Over-Indebtedness in Great Britain: An Analysis Using the Wealth and Assets Survey and Household Annual Debtors Survey," *University of Essex, Institute for Social and Economic Research*.

Claessens, S., S. Ghosh, and R. Mihet (2014): "'Macro-Prudential Policies to Mitigate Financial System Vulnerabilities," *IMF WP/14/155*.

d'Alessio, G. and S. Iezzi (2013): "Household over-indebtedness: definition and measurement with Italian data," *Bank of Italy Occasional Paper, (149)*.

Davydoff, D., G. Naacke, E. Dessart, N. Jentzsch, F. Figueira, M. Rothemund, W. Mueller, E. Kempson, A. Atkinson, and A. Finney (2008): "Towards a common operational European definition of over-indebtedness (Vol. 11)," *European Commission, Directorate-General for Employment, Social Affairs, & Equal Opportunities*.

Deaton, A. (1997): "The analysis of household surveys: a microeconometric approach to development policy," *World Bank Publications*.

Dietsch, M. and C. Welter-Nicol (2014): "Do LTV and DSTI caps make banks more resilient?" *Banque de France, D´ebats ´economiques et financiers No 13*.

Disney, R., S. Bridges, and J. Gathergood (2008): "Drivers of Over-indebtedness," *Centre for Policy Evaluation, Report to the Department for Business, Enterprise and Regulatory Reform*.

Fondeville, N., E. Ozdemir, and T. Ward˝ (2010): "Over-indebtedness: New evidence from the EUSILC special module," *European Commission, Research note 4/2010*.

Froyland, E. and K. Larsen (2002): "How vulnerable are financial institutions to macroeconomic changes? An analysis based on stress testing," *Norges Bank. Economic Bulletin*, 92 – 98.

Haas, O. (2006): "Over-indebtedness in Germany," *Employment Section (No. 44). Social Finance Program Working Paper*.

Hlava´ c, P., P. Jakubˇ ´ık, and K. Galuˇscˇ ak´ (2013): "Household stress tests using microdata," *Czech National Bank / Financial Stability Report 2012/2013*, 113 – 119.

Hollo, D. and M. Papp´ (2007): "Assessing household credit risk: Evidence from a household survey," *Magyar Nemzeti Bank, Occasional Papers, No. 70*.

Hurst, E., G. Li, and B. Pugsley (2014): "'Are household surveys like tax forms? Evidence from income underreporting of the self-employed," *Review of economics and statistics, 96(1), 19-33.*

Johansson, M. W. and M. Persson (2006): "Swedish households' indebtedness and ability to pay – a household level study," *Penning- och Valutapolitik 3/06. Sveriges Riksbank*, 24 – 41.

Kauko, K. and R. Herrala (2007): "Household Loan Loss Risk in Finland – Estimations and Simulations with Micro Data," *Bank of Finland Research Discussion Papers, No. 5/2007*.

Keese, M. (2009): "Triggers and determinants of severe household indebtedness in Germany," . Kuttner, K. and I. Shim (2013): "'Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies (No. w19723)," *National Bureau of Economic Research.*

Lim, C., F. Columba, A. Costa, P. Kongsamut, M. A.Otani, T.Wezel, and X.Wu (2011): "'Macroprudential Policy: What Instruments and How to Use Them? Lessons from Country Experiences," *IMF WP/11/238*.

Lusardi, A. and P. Tufano (2009): "Debt literacy, financial experiences, and overindebtedness (No. w14808)," *National Bureau of Economic Research*.

Meyer, B. D., W. K. Mok, and J. X. Sullivan (2009): "The under-reporting of transfers in household surveys: its nature and consequences (No. w15181)," *National Bureau of Economic Research*.

Persson, A. (2012): "Study on the over-indebtedness of the European households: updated mapping of the situation, nature, and causes, effects and initiatives for alleviating its impact,".

Vatne, B. H. (2006): "How large are the financial margins of Norwegian households? An analysis of micro data for the period 1987–2004," *Penning- och Valutapolitik 3/06. Sveriges Riksbank*, 173 – 180.

Zajączkowski, S. and D., Żochowski (2007): "Housing loans growth, foreign currency risk and supervisory response: the Polish case," *National Bank of Poland*.