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ABSTRACT

Credit capacity of the Hungarian firms is estimated based on a sample of firms. The credit capacity is the maximum level of credit that a firm is ready to take in order to finance its normal business activities, including long term investment projects. This concept of credit capacity refers to unobservable characteristics of firms, therefore a special identification strategy is needed in order to make an estimation. We use financial statement data of 35 thousand firms between 2009 and 2013 in an unbalanced panel setting. The observations show high level of heterogeneity and variability of indebtedness. Comparing it to periods when firms extend existing credit stocks or take new credits, we apply the Heckman selection model to make an estimation of the credit ratio of the firm. The model estimates are used for simulation on how much further credit might be reasonable.

Keywords: credit capacity, debt capacity, Heckman model, Hungarian firms

INTRODUCTION

Recent economic policy in Hungary had to face the question of how to support domestic firms, how to help their development in order to motivate economic growth. This problem has become even more important due to the incoming financial support from the EU. Since 2004 Hungary received a huge amount of support from the EU, a large part of which has been given to firms in the form of non-refundable financial support. These subsidies generally financed investments, acquisition of modern and more efficient tangible assets, education of the labour force, and similar developments. However, the refundable subsidies have also become important lately. These are basically loans to firms with less-than-market interest rates. Their condition is that their targeted firm population differs from the average firms which are financed by private banks.

The subsidized loans were given to firms based on their investment plans. These programs were designed to promote firms' investment in order to generate more economic growth. However, taking a loan to finance a new investment project is – in most cases - a long term commitment and raises risks related to the financial position of the firm. Therefore – even at lower interest rates – these investment opportunities may remain underutilized.

In this paper, we do not address the problem of interest-subsidized loans and how they influence investment decisions of firm – even if this motivates our research – but we focuse only on the bottom line: how much credit a firm is willing to take. We define credit capacity of a firm as the amount of credit that a firm or, more precisely, its managers are willing to take. The credit capacity is expressed in the percentage of the total assets. This forms an upper limit above which the firm leaders are not likely to go.

The idea of credit capacity strongly relates to the more general concept of debt capacity. Debt capacity is generally used in the literature to express how much debt a firm is ready to take. Although credit is only one particular form of debt, we find to use this general concept quite useful in our approach.

Studies show how debt capacity of a firm influences its investment decisions. For example, Vanackert and Manigart (2007) analyse how financing decisions are different in high growth companies, and they use debt capacity as one of their explanatory variables. They do not estimate directly the debt capacity itself, instead they use proxy variable to measure it. The leverage and the cash-flow variables are used as proxies for debt capacity. In their empirical paper, they show that high growth Belgian firms tend to rely more on internal financing even when they underutilized their debt capacity. They point out that firms with large leverage and low cash-flows most often issue external equity to finance investment decisions. Moreover, they discover that firms investing largely in intangible assets prefer to finance it using external equity instead of debt financing. They argue that these firms do not choose external financing instead of debt but they are forced to do it due to the lack of other opportunities.

Similarly to this paper, Pour and Khansalar (2014) analyse how the debt capacity is helpful in solving underinvestment problems. In their empirical paper they investigate the investment and financing decisions of firms in 24 OECD countries. They estimate debt capacity applying the regression results of Lemmon and Zender (2010). Pour and Khansalar (2014) show how leverage and maturity of debt is combined to finance investment decision. According to their results, firms with higher debt capacity and firms that are less constrained consider leverage and maturity as substitutes: they either choose a large leverage – low maturity or a low leverage– large maturity combination. However, firms with less debt capacity – constrained by their financial opportunities – consider leverage and maturity more complementary and often choose a low leverage – low maturity combination to finance their investment decisions.

Following these lines of research, in this paper we wish to address the question of how much credit a firm is ready to take. It seems reasonable to argue that debt capacity can be a useful concept in addressing this question. Modifying the existing methods, we define credit capacity and apply econometric models to estimate it for Hungarian firms. The structure of this paper is the following: we first summarize some influential papers on debt capacity that we found very useful in our approach (see section 1). Based on these results, we describe our estimation methodology and data in section 2. Based on our regression framework we estimate credit capacity of Hungarian firms and outline the next line of research that our results may indicate. These are summarized in section 3.

1. DEBT CAPACITY ESTIMATIONS

The concept of debt capacity has been introduced by Myers (1977) who suggested that it measures the limit above which an additional debt reduces the total market value of the firms' debt. Recently, this concept is more often used as a threshold above which further debt issues are too costly, therefore, companies intend to avoid using it. As of today there is a large body of literature on how a firm decides on its financial structure, what the most important factors that generate financial flexibility are and how financial flexibility influences – in return – the financial structure of the firm. Most of these papers consider the concept of debt capacity, either as an explanatory variable or as a variable to be explained. However, this estimation is not without its own serious challenges. As observed variables only tell us what firms do, it is essential to make assumptions on behaviour in order to estimate intentions, such as credit demand. Each paper has its own interpretation and identification strategy for debt capacity. Without attempting to give a complete overview, we only focus on some of the most recent applications.

Most recently, Lemmon and Zender (2010) use rating data to estimate debt capacity. In their approach they define debt capacity as probability that a firm has access to public debt. They find that firms' characteristics, such as their size, profitability, ratio of tangible assets, market to book ratio, age, leverage, standard deviation of stock returns have a significant impact on having access to public debt. They interpret high- and low debt capacity firms depending on the predicted value of the probit regression. They use their estimation to test the pecking order theory and they find that firms with high debt capacity tend to rely on external debt financing more than firms with lower debt capacity.

We find particularly important and influential the paper of Hess and Immenkötter (2014), in which they similarly use observations on firms' credit ratings to estimate the debt capacity. They basically assume that firms' behaviour is governed by the goal of avoiding degrade in their credit rating. As pure credit rating data is negatively correlated with debt ratios, it is a reasonable starting point for their estimation. In their approach they assume that when a firm is close to its debt capacity, it is more likely to rely on internal financing. Their work also discusses how the concept of debt capacity relates to financial decisions of the firm and how financial flexibility drives these decisions.

[2] The approach is described in Shyam-Sunder L and Myers S C (1999), "Testing Static Trade-Off Against Pecking Order Models of Capital Structure", Journal of Financial Economics, Vol. 51, No. 2, pp.219–244 as cited by Sinha and Gosh (2013).

In their approach they used corporate credit ratings to identify the critical debt ratio that triggers a downgrade. They used the annual database of Standard and Poor's long-term credit issuer ratings between 1980 and 2012 excluding the financial firms, which generally have very different leverage ratios and are very differently regulated. They estimated credit ratings as a function of the debt ratio and other firm characteristics where the debt ratio was defined as the book debt over the market value of assets. Other explanatory variables are the size of the firm, its profitability, its liquidity and tangibility. These variables proved to be important in our estimation as well. Our econometric model follows their approach; however, we have no information on credit ratings and the market value of assets, therefore, we apply a modified method (see next section about the details of our approach).

Their credit score regression showed a negative coefficient on the debt ratio indicating that an increasing amount of debt makes it more likely that a firm loses its current rating. According to their results, large and profitable firms tend to have higher ratings and liquidity also has a positive effect on the firm's credit rating. The age of the firm and its industrial affiliation also proved to be significant factors in terms of the credit score.

Financial flexibility of firms stems from unused debt capacity, which makes it possible to issue further debt without risking a downgrade. When firms get closer to their debt capacity they repay debt or rely more on internal financing when investment is made. Therefore, as they point out, when a firm makes a financial decision, it is much more about deciding on or restoring financial flexibility. For quantifying this concept, they define debt buffer as the difference between debt capacity and actual debt ratio. Using the concept of debt buffer, they show that firms without debt constraints generally utilize a higher share of their investment opportunities.

However, the estimated value of debt capacity depends on how the debt capacity is defined and what identification strategy is used. For example, in their study, Eisfeldt and Rampini (2007) show that debt capacity is usually larger when a firm takes leasing instead of a secured loan. The advantages of leasing compared to secured loans come from the lower costs of the repossession of the assets. On the other hand, agency costs are usually higher when it comes to leasing due to the separation of management and ownership. In their paper, Eisfeldt and Rampini (2007) show that firms close to their debt capacity can benefit from leasing because its benefits outweigh its costs.

In their early paper, Shleifer and Vishny (1991) offer an explanation on why debt capacity might be so diverse in different industries. In their theoretical paper, they argue that more liquid assets can be useful in periods of financial distress, thus firms are ready to take more debt in this case. Liquidating an asset is always costly, just as restructuring the financial structure of a firm, so in case of temporary illiquidity firms usually choose the less costly solution. A firm with less liquid assets should chose restructuring, so that they do not have as much debt as firms with more liquid assets. Assuming that assets liquidity can be quite different in certain industries (depending on the nature of their technology and the level of leveraged buy-outs) it is reasonable to conclude that debt capacity might be different across industries.

Another example is the paper of Sinha and Ghosh (2013), in which they analyse how the composition of debt influences the debt capacity itself and this way explains why the debt capacity itself can change in time. They adapt the approach[2] of Shyam-Sunder and Myers by defining debt capacity as a limit, below which a firm only issue low-risk debt. Going beyond this threshold debt is of high risk, which is issued only occasionally. Using their theoretical and empirical framework, they show how the debt capacity changes as the firms extend their utilization of secured debt capacities and turn towards less secure debt. Furthermore, they show that the level of debt capacity depends on the market valuation of firms as firms with higher market value tend to depend more on internal financing.

A frequent approach is to connect cash flows to debt capacity. For example, in their paper, Chen, Harford and Lin (2017) apply this approach and analyse how the collateral value influences debt capacity. They interpret debt capacity as the change in the cash of the firm. In their econometric approach they control for the change in the value of collateral (real estate prices) and also firm characteristics like, for example, logarithm of size, leverage, market to book value, industry and year effect. Using instrumental variable approach, they address the endogeneity issue of the regression framework.

Debt capacity is defined differently in these papers, and the econometric methods are also different. One common thing in these applications is the application of probit regression to calculate probabilities of certain actions (either access to public funds or downgrading). This similarity in methodologies comes from the fact that many firms do not have access to public financing; therefore, there is a selection in any sample of firms. An other important similarity is that the control variables in these regression equations capture the characteristics of the firms, thus these lists often overlap each other: most authors control for the size of the firms (in logarithm), profitability, market to book ratios, leverage. These firms' characteristics highly correlate with the probabilities that a firm have access to market (private) debt. We intend to follow this standard solution.

The most remarkable difference in these papers is how the dependent variable is chosen. The exact definition of debt capacity differs in these papers as authors use different identification strategies to quantify them. In our application we wish to focus on a very different measurement: a special segment of indebtedness, namely private credits only. Our approach addresses the issues of selection in a more explicit way, using the Heckman model to control for unobservable managerial attitudes.

2. ESTIMATION METHODOLOGY AND DATA

2.1. ESTIMATION STRATEGY

In estimating the credit capacity, the focus is on how much new loan a firm is ready to take. However, taking a loan is a complex process along which many decisions are made, not only by the managers of the firms but also at other institutions, such as banks. Our data shows that firms having similar characteristics with regard to their financial measures have different loan rates. This is largely because management decisions are driven by factors hard to observe. Therefore, these unobservable managerial decisions lead to very different indebtedness.

We assume that financial statements contain all necessarily information about the credit riskiness of a firm, thus the firms' ability to get a loan highly depends on the management decision. This is not an innocent assumption, however, given our approach, it is a necessarily one. Thus in our estimation we control for the size of the firms, their profitability, liquidity and most of all, their tangibility. These measures capture a large part of the variation of the observed differences in indebtedness.

It is also important to note that the primary goal of this paper is to estimate the credit ratio a firm is ready to take. However, this cannot be observed directly, only how much they actually take. Therefore, we need an identification strategy to quantify this unobservable measure. Unlike in Hess and Immenkötter (2014), we do not have information on the risk rate of these firms; moreover, most of them have never been rated by any agencies. Therefore, we need a different identification strategy.

We assume that in those periods when a firm takes on a new loan, it gets closer to its credit capacity limit compared to those periods when the debt is basically non-increasing. However, we cannot be sure that in these periods they are actually at the boundaries, but assuming they are closer, we may estimate this boundary. Our estimation strategy relies on differentiating between those periods when a firm takes on a new loan and when the credits are non-increasing.

But still, even if the assumptions are strong enough to identify the relationship we still face serious problems. There are firms that do not have a loan in our sample at all, and there are others with credits in all periods. The cross section variation in the credits of firms is basically far from random: it is the result of a complex selection procedure. The selection comes from two sources: on the one hand, the management decides if they want to take a loan or not, and on the other hand the bank decides if the firm may have a loan or not. This selection makes it difficult for estimating the credits of a firm.

Controlling for selection in the estimation is crucial, therefore, we apply the Heckman selection model for this problem. We estimate the credit ratio of the firm based on control variables of riskiness of the firm and measures of new loans taken, taken into account the selection process. The regression equation is

$$CREDIT\ RATIO_{it} = X_{it}\beta + Y_{it}\delta + u1_{it}$$

and the selection equation is

$$Z_{it}\gamma + W_{it}\omega + u2_{it} > 0$$

where X_{it} are observable variables controlling for credit worthiness of a firm (size, profitability, liquidity, tangibility), Y_{it} and W_{it} variables are measures related to taking a new loan and Z_{it} variables are controlling for selection. It is important to note that selection occurs both on the supply and demand side of a loan contract, therefore in our estimation, Z_{it} is basically a subset of X_{it}.

2.2. THE DATA SET

Our sample is a panel data set of Hungarian firms between 2009 and 2013 with information obtained from their financial statements. Data of financial and insurance companies (NACE 64, 65 and 66) are excluded from our sample. The dataset is basically an unbalanced panel; however, we do not utilize the panel characteristics. The estimation is carried out as a pooled cross section regression. As some variables uses lagged data, the estimation basically covers four years. There are a total of 35602 firms in the sample with average 1.9 observations.

Table 1. Number of firms in the sample according to observations and years

by number of observations		by years of observation	
no. of obs.	no. of firms	year	no. of firms
1	17876	2010	23640
2	9588	2011	13824
3	2828	2012	13874
4	5310	2013	15338
total	35602	total	66776

The dependent variable of the regression equation is the credit ratio, which is the sum of short term credit and investment credit of the firm as a share of its total assets:

$$CREDIT\ RATIO_{it} = \frac{CREDITSTOCK_{it}}{ASSETS_{it}}$$

where CREDITSTOCK is the sum of investment and development credits and other short term loans as it is indicated in the financial statements of the firms.[3] All these information are from the financial statements of the firms whenever these pieces of information are available. As for the smallest firms, it is allowed to submit a simplified financial statement as for those firms, data for the nominator is simply not available. This basically excludes most of the firms from the regression; however, the remaining sample contains the most relevant sample for our estimation.

The selection equation is estimated by adding a dummy variable to the dataset. The dependent variable of the selection equation is

$$CREDITDUM_{IT} = \begin{cases} 1, \text{if } CREDITRATIO > 0 \\ \quad 0, \quad \text{otherwise} \end{cases}$$

The control variables for both the regression and selection equations measure the credit capabilities of the firm. These variables have been chosen following the paper of Hess and Immenkötter (2014). Even though in this paper we use a very different country and time period, we find it important that these measures fit the framework very well. The relevant variables in the debt capacity estimations are those that measures profitability, liquidity, tangibility and the size of the firms. Moreover, we controlled for the sector of the firm, creating 20 categories after excluding financial and insurance companies from the sample. The financial measures of the firms were calculated according to the following formulas:

$$SIZE_{it} = log(SALES_{i,t-1})$$

Basically, the size of a firm is measured by its previous year's sales revenue. The profitability of the firm is a variation of ROA measure:

$$PROFITABILITY_{it} = EBITDA_{i,t-1}/ASSETS_{it}$$

The liquidity conditions of the firm are measured by the following variables:

$$LIQUIDITY1 = WORKING\ CAPITAL_{it}/ASSETS_{it}$$

$$LIQUIDITY2 = RETAINED\ EARNINGS_{it}/ASSETS_{it}$$

A measure of the asset structure has become an important variable in estimating indebtedness, which is defined as

$$TANGIBILITY = PROPERTY, PLANT\ AND\ EQUIPMENT_{it}/ASSETS_{it}$$

3 The data we use stem for the financial statements of Hungarian firms. The accounting rules and the structure of the balance sheet is described in detail in the Schedule No. 1 to Act C of 2000 and can be accessed here: http://www.8cld.eu/Lists/Country/Attachments/13/1%20-%20Hungary%20Act%20C%20of%202000%20on%20Accounting%20-%20EN%20vs.pdf.

There is one very important variable in our estimation. The dependent variable measures how much credit a firm has; however, this is not the only source of debt for a firm. It is reasonable to assume that if a firm has higher leverage, it is less likely to get or have credits. Therefore, we add another control variable that measures the indebtedness of the firm in general:

$$DEBTRATIO_{it} = LIABILITIES_{it}/ASSETS_{it}$$

The identification strategy stems from the idea that when firms are taking loans, they get much closer to their debt limits than would otherwise. However, it is reasonable to assume that they are heterogeneous in how much they can take on and, therefore, how much it will influence their credit ratio. Thus, without formally modelling how much new credit they take, we use interaction variables to capture this effect. The basis of these interaction variables is a dummy which indicates if a firm has taken a new loan or it has extended its existing stock in the given period:

$$LOANTAKE_{it} = \begin{cases} 1, if\ CREDITRATIO_{it} > CREDITRATIO_{i,t-1} \\ 0\ otherwise \end{cases}$$

Based on this dummy variable we create the following interaction variables:

$$TAKESIZE_{it} = LOANTAKE_{it} \cdot SIZE_{it}$$

$$TAKEDEBT_{it} = LOANTAKE_{it} \cdot DEBTRATIO_{it}$$

$$TAKETANGIBILITY_{it} = LOANTAKE_{it} \cdot TANGIBILITY_{it}$$

These variables form matrix W and Y. These variables are used for simulation on how to change the credit ratio of firms if they take on new loans. The dependent and the independent variable take on values in a very wide range as can be seen in Table 2.

Table 2. **Descriptive statistics of the estimation database**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Debt ratio	66,776	0.499	0.263	0	1
Size	66,776	10.88	2.107	0	19.66
Profitability	66,776	0.136	0.183	-1.603	1.990
Liquidity 1	66,776	0.175	0.335	-0.980	1
Liquidity 2	66,776	0.219	0.304	-1.949	2.328
Tangibility	66,776	0.413	0.300	0	1
Creditdum	66,776	0.747	0.435	0	1
Credit ratio	49,878	0.264	0.208	2.22e-07	0.996
New_credit	66,776	0.335	0.472	0	1
New_credit * Debtratio	66,776	0.194	0.304	0	0.999
New_credit * Size	66,776	3.818	5.488	0	18.40
New_credit * Tangibility	66,776	0.151	0.269	0	1.000

The original database stems from a corporate tax administration database. The numerically problematic records have been excluded, just like those firms who had no assets, no sales revenue or negative capital. After excluding outliers, the final database resulted in approx. 250,000 companies. However, in the case of most of them we had no information about their credit stocks. The final sample contains those firms who submitted all relevant information in their tax statements.

3. RESULTS

3.1. ESTIMATION

The estimation of the Heckman model has been carried out by both the twostep and the ML procedure. The results of the twostep estimation are presented in the appendix. The ML estimation has been converged to the following results. In each case, sector dummies have been applied as well. The estimation was carried out in STATA using the Heckman command.

The selection equation shows that the main role of tangible assets is that they are the first choice as collateral, thus having more tangible assets is highly correlated with having more credits. The coefficient of profitability is positive in the credit ratio equation; however, it is negative in the selection equation. As the firm is more profitable it is less dependent on foreign sources, thus they are less likely to take a credit. Nevertheless, if a highly profitable firm decides to take on a credit, it can get more resulting higher credit ratio. Liquidity has positive effect on the credit as well, and we see that their coefficient is larger in the selection equation. As in both equations the dependent variable is of the same scale (between 0 and 1) it is reasonable to say that more liquid firms can have better access to loans, although it is less influential on how much they take.

Table 3. **Estimation results of the Heckman model using ML algorithm**

VARIABLES	(1) creditratio	(2) creditdum	(3) athrho	(4) lnsigma
Debt ratio	0.578***	2.813***		
	(0.00831)	(0.0745)		
Size	0.000404	0.140***		
	(0.00101)	(0.0113)		
Profitability	0.0169***	-0.170***		
	(0.00560)	(0.0354)		
Liquidity 1	0.203***	0.884***		
	(0.00791)	(0.0590)		
Liquidity 2	0.0225***	0.280***		
	(0.00448)	(0.0272)		
Tangibility	0.412***	2.279***		
	(0.00749)	(0.0522)		
New_credit * Debtratio	0.181***	8.247***		
	(0.00808)	(0.855)		
New_credit * Size	0.00236***	0.901***		
	(0.000304)	(0.118)		
New_credit * Tangibility		4.501***		
		(0.573)		
Constant	-0.366***	-3.225***	2.084***	-1.759***
	(0.0160)	(0.103)	(0.133)	(0.00810)
significance of industry dummies	14 out of 19	17 out of 19		
significance of year dummies	3 out of 3	2 out of 3		
Observations	66,776	66,776	66,776	66,776

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient on the interaction variables are all positive, indicating that when a firm takes on a new loan or extends existing loans, its credit ratio increases. Additionally, in the selection equation their coefficient is positive, indicating that it means a higher chance of taking and getting a new loan.

The correlation coefficient of the residuals of the two equations is 0.9694, which indicates that selection is really relevant so estimating separately the selection and the credit ratio would lead to biased results. A crude check of the appropriateness of fit of the equation is to see how well the selection equation shows the change of being selected. We predicted the selected equation. Using the predicted value of being selected, we calculated the threshold above which we believe the firm is selected, and below which it is not. The threshold had been chosen to show the aggregate share of selection our sample. Using this method, the threshold proved to be 0.5883, and those correctly predicted count a total of 85% of the total sample.

Table 4. Prediction precision of the selection equation

		predicted selection		
		0	1	total
observed selection	0	11987	4911	16898
	1	4911	44967	49878
	total	16898	49878	66776

3.2. SIMULATION

In our simulation experiment we calculated how the credit ratio of each firm and its aggregate value would have changed assuming that each firm had taken on a new loan. This means that we carried out a calculation based on the previous model estimation. We assumed that LOANTAKE = 1 for each firm in each period. Needless to say, this is a highly speculative scenario. However, by recalculating the interaction variables and using the estimated coefficients of the Heckman model, it is possible to calculate what value the credit ratio could take.

In order to correct for selection, we introduced the following concepts. Let us call the following variable "probability weighted credit":

$$PCREDIT = CREDITRATIO \cdot PROBABILITY\ OF\ BEING\ SELECTED$$

PCREDIT is the multiplication of the credit ratio and the probability of being selected. The latter has been calculated from the selection equation. This measure shows both the selection and the change in the credit ratio.

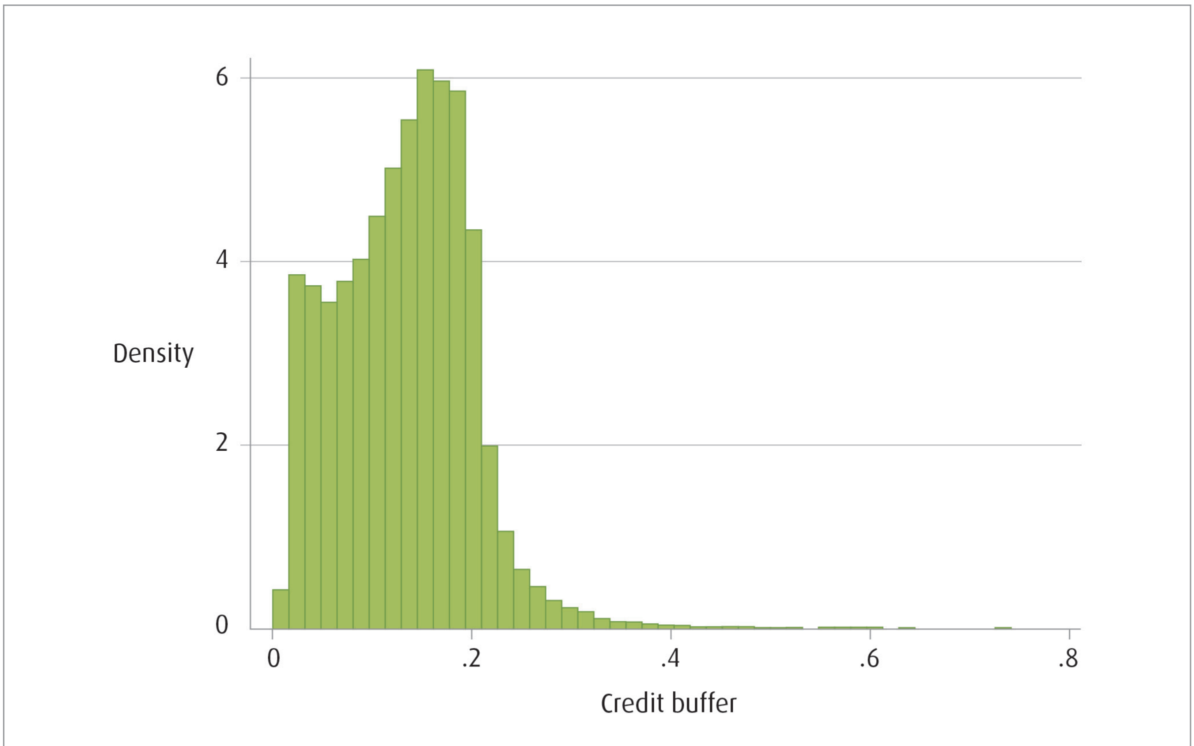
The probability of being selected was predicted using the selection equation. In the original scenario it was 75% to be selected on average, whereas in the simulation scenario it increased to 99%. Using the same threshold, still 12 out of 66776 observations would not be selected, nonetheless, all the others were. Using the coefficients of the regression equations, we calculated the new credit ratios.

Variable	Obs	Mean	Std.Dev.	Min	Max
Observed	66776	.7543521	.2831863	.0017935	1
Counterfactual	66776	.9997707	.0100326	.0110671	1

We define credit buffer of the firms as the difference in the value of PCREDIT between the two scenarios. By definition, the credit buffer takes on nonnegative values. For observations where there were new credits, its value is zero. However, for other observation it gains positive values. The simulation shows that credit buffer takes value between zero and 0.7422, however, the distribution is highly asymmetric. The mean of the estimated credit buffer is 0.0877, with the standard deviation of 0.0825 (in the whole sample, including observations with zero credit buffer).

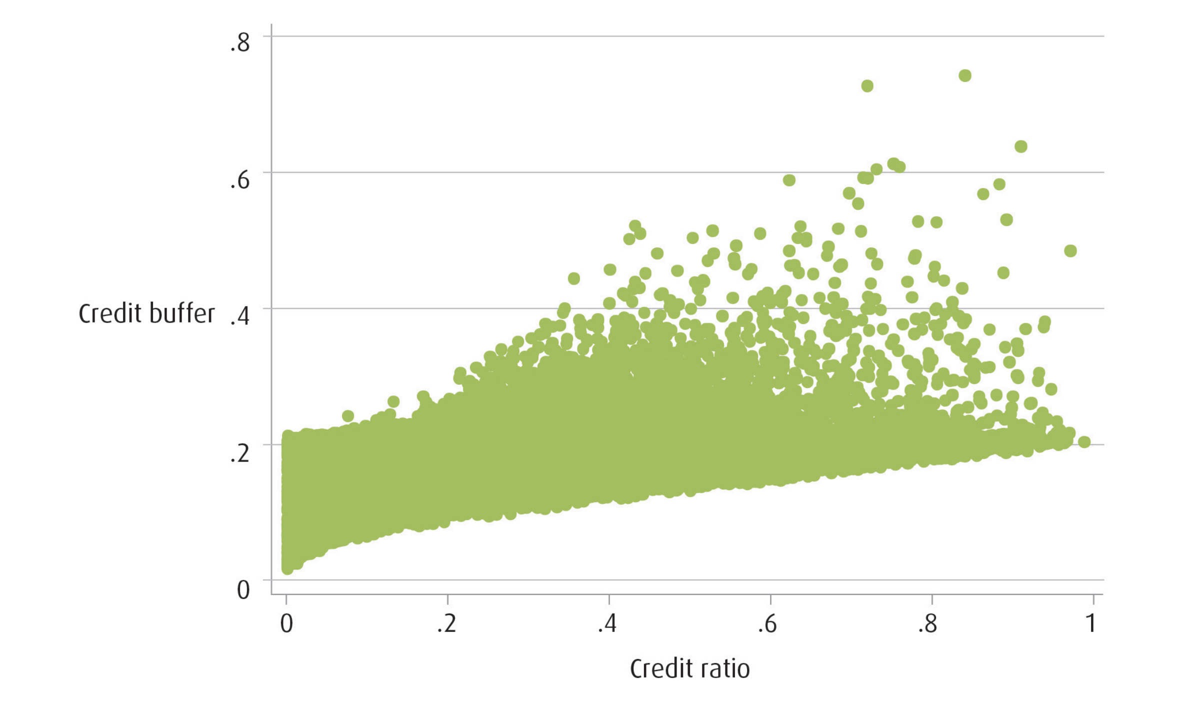
In the following analysis we will focus on the positive values of credit buffer. These are the values calculated in the counterfactual scenarios. The histogram of the positive estimated credit buffer can be seen in the following graph. For most observations the credit buffer is below 20% and only in 100 out of 44382 cases it is above 40%.

Figure 1. **Histogram of credit buffer (excluding zero predicted values)**



The following graph shows the estimated credit buffer and the observed credit ratio of the firms. The graph only shows those observations where the credit buffer is positive, meaning only those where there were new loans in the simulation scenario. The graph indicates that the credit capacities of the firms are quite heterogeneous and they are seemingly increasing in the credit ratio. This result comes from the way we defined PCREDIT.

Figure 2. Credit buffer and credit ratio in the simulation scenario



The credit buffer is the probability weighted credit of a firm. Using the previous formula, the buffer can be calculated as

credit buffer=CREDITRATIO·ΔPROB+NEWLOAN·PROB2

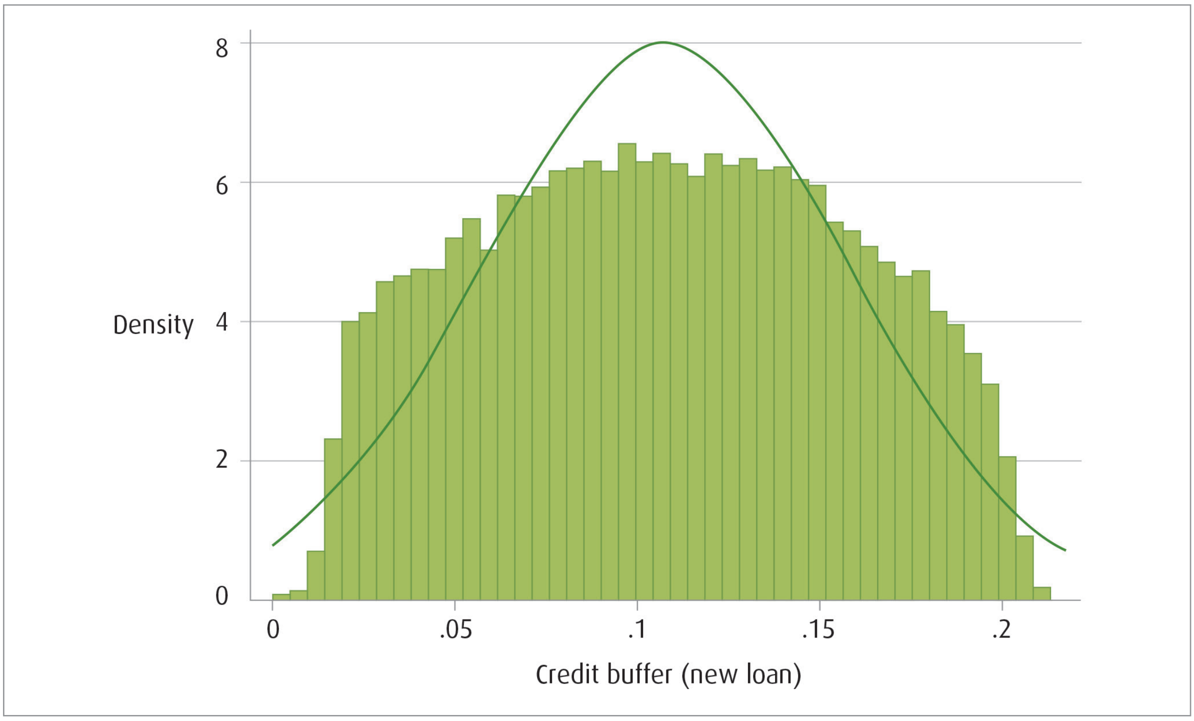
where PROB2 is the predicted probability of the selection in the counterfactual scenario, and PROB1 in the basic (observation) scenario. ΔPROB is the difference between PROB2 and PROB1. This expression shows that credit buffer can be split into two different measures: one that captures the higher chance of having a new loan (selection) and the other which captures the size of the new loan. The summary statistics of these components are shown in the following table.

Table 6. Descriptive statistics of the components of credit buffer (simulation scenario)

Variable	Obs	Mean	Std.Dev.	Min	Max
Credit buffer	44382	.1320658	.0664048	.0000181	.7422747
Credit buffer (newloan)	44382	.1080357	.0500784	.0000181	.2184961
Credit buffer (selection)	44382	.0240301	.0381839	0	.5632913

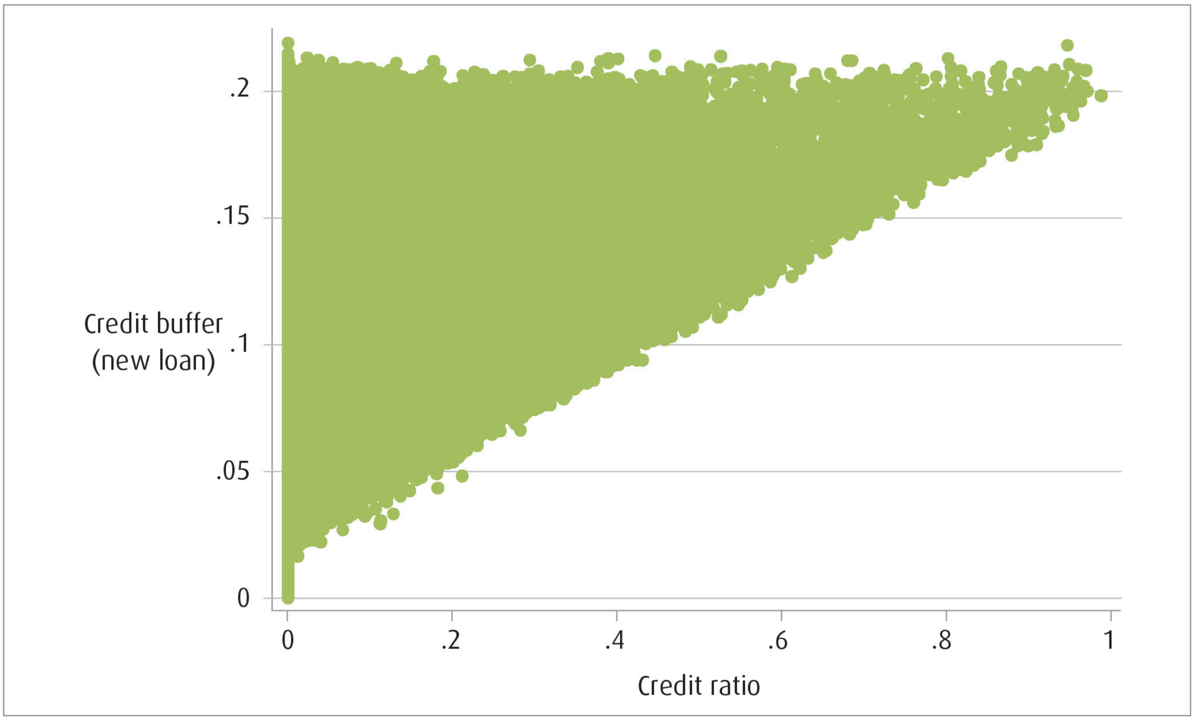
The new loans firm take has a size between 0 and 20% of the total assets. Also, this is highly symmetric in the distribution; however, compared to the normal distribution, which is indicated with the solid line in the graph, it has a lower kurtosis than the normal distribution, thus it has thinner tails.

Figure 3. The histogram of the new loan component of the credit buffer



The scatter graph of new loans and the credit ratio shows that this component of the credit buffer is increasing in the credit ratio (see Figure 4). Basically, this component is the reason why the credit buffer is increasing in the credit ratio. The graph indicates that there is large heterogeneity, especially when the observed credit ratio takes low values. At a very low level of the credit ratio, the size of the new loan is between zero and 20%; however, at higher rates the range is narrower.

Figure 4. Credit buffer (new loan) and credit ratio



CONCLUSION

The credit capacity of Hungarian firms has been estimated. Controlling for firms' characteristics and taking into account the selection that is present in this setting, we applied the Heckman model to estimate the credit capacity of firms. The idea for identifying credit capacity is that firms get closer to their credit limits in periods when they take on new loans. Using the estimated Heckman model, we generally find that firms with larger fixed assets are more likely to have credits. Furthermore, more liquid firms are easier to get a new credit.

Based on our estimated Heckman model, we made a counterfactual simulation assuming that all firms took on loans in every period. Based on this highly speculative assumption, we estimated what their indebtedness would be. In order to estimate their credit buffer, we used a modified measure to control for the probability of being selected. The simulation results show that firms' credit buffer is between 0 and 20% due to the new loan.

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Table 7. The Heckman model estimation results using twostep procedure

VARIABLES	(1) creditratio	(2) creditdum	(3) mills
Debt ratio	0.547***	1.990***	
	(0.00516)	(0.0436)	
Size	-0.0122***	0.258***	
	(0.000445)	(0.00405)	
Profitability	0.0209***	-0.188***	
	(0.00494)	(0.0361)	
Liquidity 1	0.198***	0.570***	
	(0.00397)	(0.0410)	
Liquidity 2	-0.00556*	0.355***	
	(0.00325)	(0.0254)	
Tangibility	0.319***	2.330***	
	(0.00402)	(0.0405)	
New_credit * Debtratio	0.129***	47,808	
	(0.00542)	(0)	
New_credit * Size	-0.000129	1,097	
	(0.000307)	(0)	
New_credit * Tangibility		6,219	
		(0)	
lambda			0.0238***
			(0.00342)
Constant	-0.111***	-3.861***	
	(0.00804)	(0.0707)	
significance if industry dummies	13 out of 19	19 out of 19	
significance of year dummies	3 out of 3	2 out of 3	
Observations	66,776	66,776	66,776

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1