THE EFFECT OF SOCIO-ECONOMIC AND DEMOGRAPHIC FACTORS ON HOUSEHOLD INDEBTEDNESS: EVIDENCE FROM SLOVAKIA

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Abstract: *Lower interest rates and easier access to credit have elevated demand for debt over the last two decades. However, Slovak household indebtedness has increased most significantly among the European Union countries. Therefore, understanding the factors which drive Slovak households to the debt is crucial for policymakers, regulators, and financial institutions. The main goal was to analyse relevant socio-economic and demographic characteristics of indebted and non-indebted Slovak households. This analysis was based on microeconomic data collected through a survey on Household Financing and Consumption in 2017. Firstly, we performed a descriptive analysis which closer identified factors related to household indebtedness. Subsequently, a logistic regression model was tested based on univariate analysis. Then, we illustrated the significant average marginal effects of selected socio-economic and demographic factors on the probability of indebtedness of Slovak households graphically and numerically. After all, the results suggest that the likelihood of household participation in the credit market increases with increasing levels of wealth, while the level of household income does not have a statistically significant effect on debt distribution. Also, households with more members and households with two children are more likely to hold any debt. An opposite effect was observed in households where the reference person was economically inactive, achieved a higher level of education, or was older.*

Keywords: *HFCS, Indebtedness, Slovak households, Socio-economic and demographic factors, Microeconomic data analysis*

JEL Classification: C25, D14, G51

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1 Introduction

Rising living standards contribute to the growing needs of the population. These needs are usually satisfied by consumption. Consumption is, however, limited by one's financial capacity. Households can cover their needs easier and almost instantly by borrowing the additional financial resources through credit market. Lower interest rates and easing the access to the loans steamed demand for the debt over the past two decades. This trend can be seen in both rising small consumer loans as well as in mortgage indebtedness (Autio et al., 2009; Moore and Stockhammer, 2018; Abd Samad et al., 2020). Rising households' indebtedness may thus lead to deterioration of the financial and monetary stability of the economy.

Indebtedness of households can be expressed by the Debt-to-Income ratio (DTI). For the last ten years, DTI ratio in Slovakia doubled from approximately 35% in 2008 to 69% in 2018.[2] Therefore, understanding the factors that drive households into debt is key for policymakers, regulators and financial institutions.

The observed trend in the rapid credit expansion can be explained by households' individual propensity towards indebtedness. Literature explains the households' debt choices according to economic, social and psychological circumstances (Livingstone and Lunt, 1992; Rahman et al., 2020). From the perspective of economic theory, the financial situation of households is mainly connected with socio-economic and demographic factors, such as disposable income, amount of saving, expenditure on basic needs, social status, age structure, educational qualification, family size, etc. (Costa and Farinha, 2012; Flores and Vieira, 2014; Farrar et al., 2019; Baker et al., 2019).

Betti et al. (2007) analysed the consumer over-indebtedness between the member states of the European Union. Interestingly, they found that low income could not be used as evidence of the existence of over-indebtedness. However, in many countries, especially those with more comprehensive access to consumer credit, over-indebtedness of high-income, low-age groups are more likely. Holló and Papp (2007) investigated the main individual driving forces of Hungarian household credit risk. Their study suggests that the primary individual factors affecting household credit risk are disposable income, the income share of monthly debt servicing costs, the number of

[2] Source: Eurostat database, available online at http://appsso.eurostat.ec.europa.eu

dependants, and the employment status of the head of the household. On the other hand, authors Costa and Farinha (2012, p.133) found that *"low income and young households who have taken mortgages are the most vulnerable groups of the population, for which the probability of materialisation of credit risk is higher."* Similarly, Albacete and Lindner (2013) analyzed the indebtedness and vulnerability of households in Austria. Their results show that debt participation and debt levels generally increase with wealth and income, indicating a relatively low risk for the financial sector. They, however, identified as particularly vulnerable low-income and low-wealth households or households with an unemployed reference person. In line with previous studies, Bover et al. (2018) studied the differences in the distribution of household secured debt outcomes across euro-area countries conditional on household characteristics. Their results showed that the age and income level of household members are essential determinants of debt.

The aim of this study is to investigate the debt distribution over Slovak household sector according to selected relevant socio-economic and demographic characteristics. Which of these characteristics increases the probability of indebtedness?

The analysis is based on the data from the latest European Central Bank's (ECB) survey on the financial situation and household consumption (HFCS). The third wave of HFCS was conducted across countries in euro area[3] in 2017. The main objective of the HFCS is gathering structural microeconomic data on households' wealth[4], income and consumption, as well as various economic[5] and demographic information of surveyed individuals (NBS, 2020). This type of information allows us to separately analyse the situation of indebted households and the details behind debt distribution. At the same time, this makes it possible to reveal factors that statistically increase the probability of indebtedness (Costa and Farinha, 2012).

Based on the results of the ECB's HFCS report (2020), the share of indebted households in the euro area decreased by 0.8 percentage point between 2014 and 2017. However, indebtedness markedly increased across the upper-middle parts of the net wealth distributions. This group consists mainly of the youngest

[3] And some countries outside the euro area: Poland, Hungary, Croatia, Romania, and the Czech Republic.
[4] In the HFCS, the wealth of households is divided into financial assets, real assets and financial liabilities.
[5] For instance, household income, intergenerational transfers, selected categories of consumption and credit constrains, age, education or occupational status of respondents, etc.

households (below 35 years of age), whose mortgage debt rose by 12.7%.[6] On the other hand, due to increases in house prices, indebted homeowners experienced gains in their median wealth (13.9%). Within the comparison of the European Union countries, the indebtedness is most significantly growing in the Slovak Republic. In accordance with the European Commission's country report (2020), the debt of Slovak households reached a record high of 42.8% of GDP in the second quarter of 2019. Main reason was higher mortgages due to rising property prices. It is expected that house prices will grow faster than disposable income. This will reduce affordability mainly for lower-income groups. Despite the rapidly increasing debt of Slovak household, overall indebtedness is still relatively low compared to other OECD countries (Sivák et al., 2018).

The growing risk of financial instability of indebted subjects, especially in a recession, when unemployment and interest rates are rising and investment activity decreasing, may lead to the insolvency or default in the worst-case scenario. Similarly, as in other EU countries, the level of Slovak private debt is growing faster than the corporate one. However, based on an ex-post credit risk analysis since 2008, in the event of an unfavourable phase of the economic cycle, households show better payment discipline compared to enterprises (IFP, 2019). Recent years have been marked by favourable economic emergence within the EU. In Slovak conditions, economic growth was reflected in the net wealth increase of households. Between 2014 and 2017, the median of net wealth increased by approximately 40%. However, this growth is negatively affected by the growth of financial liabilities, and although the share of indebted households did not change significantly (36.6%), the total volume of debt almost doubled (Kucserová and Strachotová, 2019).

In terms of financial stability, it is important to know the socio-economic and demographic characteristics of households participating in credit market. The factors that determine this participation may vary depending on the type of debt. For this reason, performed analysis of general indebtedness is complemented by the characteristics of households that hold mortgages. This paper consists of the descriptive analysis of the relationship between households' indebtedness level and their characteristics. A logistic regression model tested the statistical significance and magnitude of identified potential relationships identified from the univariate analysis.

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[6] Specifically, the average mortgage debt for the youngest households increased from approximately EUR 110,000 (2014) to more than EUR 124,000 in 2017.

The paper is divided into three parts. Section 2 presents the methodology and using variables. Section 3 deals with the description of the demographic and socio-economic characteristics of participants in the credit market. The last section includes main conclusions.

2 Methodology and Variables

The aim of the work is to provide a systematic and comparable overview of the situation of households' participation in the credit market, mainly to analyse the level of household indebtedness in according to some relevant socio-economic and demographic characteristics. The following section presents the results of logistic regressions[7] in which binary dependent variables are the participation in the credit market with separate focus on the mortgage market (equal to 1 if participate, 0 if not). Explanatory variables were selected in relation to the economic Life cycle theory and consumption hypothesis developed by Franco Modigliani and Richard Brumberg (1954; Ando and Modigliani, 1963). The economic decisions regarding consumption as well as investment, and thus also indebtedness, are based on the individual expectation about the level of wealth and lifetime income which consists of the current income and the discounted value of future income achieved within the expected life expectancy. Individual assumptions regarding the future development of income and wealth are related to the achieved level of education, as well as the representation of economic active members of the household, its size and structure.

Based on the above assumptions, in the analysis of households' characteristics influencing indebtedness, we examined the level of income, type of household, number and age distribution of members living in one household, achieved the level of education and work status of the reference person.[8]

Adjustments made to explanatory variables are partly in accordance with the HFCS analysis performed by Sónia Costa and Luisa Farinha (2012). In the analysis households' income was used as the sum of regular income received

[7] For more information about the methodology see, for example, O'Donnell et al. (2007) or Long and Freese (2006).
[8] The term reference person is used to refer to a person with financial information about a household – the head of the family.

by all household members,[9] and the value of real assets[10]. Each of the selected variables is divided into subcategories according to their specification.[11] Subsequently, from these adjusted variables were created new artificial variables (dummies).

In the analysis we used data from the latest ECB survey on the financial situation and consumption of Slovak households. The HFCS dataset[12] is a probability sample of households. For this reason, all the results in this paper were obtained, taking into account the final sample weights. The study is based on the analysis of 10,895 interviews with Slovak households.

3 Demographic and Socio-Economic Characteristics

This section of the paper presents a descriptive analysis of the characteristics of the indebted Slovak households. In the analysis, the subjects are divided mainly into two groups according to their indebtedness status, namely indebted (Any debt) and non-indebted (No debt). Indebted households are then examined in terms of mortgage liabilities. The first part of this section includes a descriptive analysis of the percentage of households that participated in the credit market in relation to the relevant characteristics.

The second part of this section presents the results of logistic regression. This approach was used to estimate the probability of households entering to debt market based on the socio-economic and demographic characteristics of households.

3.1 Univariate analysis

Table 1 presents selected characteristics of households participating in the credit market in 2017. Based on data from the latest HFCS, more than 36% of Slovak households hold at least one financial liability and less than 21% of households repay a mortgage for housing.

[9] The sum of employee income, income from self-employment, income from businesses and income from the social security system.
[10] The sum of the value of real estate, motor vehicles, self-employment businesses, and other valuables.
[11] We divided financial indicators into five subcategories (quintiles) depending on the amount of household income or the value of real assets *(Real wealth)*. The purpose of categorizing other variables *(Work status, Education, Age, Household size,and type, Children,and Gender)* was to simplify analysis of the results.
[12] Analysed data from the HFCS were provided by the National Bank of Slovakia.

The results in Table 1 point to a common development between growing household income and mortgage indebtedness. The percentage of indebted households increases with household income. This phenomenon can be explained both by a better access to loans due to better financial stability as well as by the expectations of individuals that their incomes will grow over time.

Table 1: Univariate analysis, HFCS 2017

PERCENTAGE OF HOUSEHOLDS HOLDING DEBT IN 2017 As a percentage of the number of households in each class				
Household characteristics	**% of households**	**No debt**	**Any debt**	**Mortgages**
Total	**100.00**	**63.36**	**36.65**	**20.68**
Income percentile*				
Less than 20	12.58	10.47	2.11	0.54
Between 20 and 40	14.70	11.03	3,67	1,68
Between 40 and 60	18.78	12.47	6,31	3,87
Between 60 and 80	24.03	13.72	10,32	5,78
More than 80	29.91	15.67	14,24	8,81
Real wealth percentile*				
Less than 20	18.00	12.75	5.25	1.52
Between 20 and 40	17.63	11.43	6,20	3.27
Between 40 and 60	19.16	11.97	7,19	4,53
Between 60 and 80	21.82	13.18	8,64	5,50
More than 80	23.39	13.68	9.71	6.82
Work status				
Employee	47.23	22.79	24.44	15.15
Self-employed	12.11	6.96	5.15	3.67
Unemployed	3.32	2.15	1.18	0.36
Retired	34.63	29.88	4.75	1.11
Other	2.71	1.59	1.12	0.40
Education				
Below secondary	0.57	0.30	0.27	0.03
Secondary	78.08	50.19	27.89	15.17
Tertiary	21.35	12.87	8.48	5.50
Age				
Under 35	9.57	3.50	6.08	4.07
35-44	22.04	8.73	13.31	8.42
45-54	19.22	10.10	9.12	5.80
55-64	22.06	16.95	5.11	1.56
65-74	17.39	15.05	2.33	0.63
75 and over	9.71	9.03	0.68	0.21

Household size				
One	17.66	14.29	3.38	1.57
Two	29.71	23.00	6.71	3.56
Three	21.68	11.47	10.21	6.49
Four	19.34	8.57	10.77	6.06
Five or more	11.61	6.04	5.57	3.01
Household type				
One adult	17.66	14.29	3.38	1.57
Several adults	42.24	31.28	10.96	5.16
Adult(s) and child(ren)	40.10	17.79	22.30	13.96
Children				
None	59.9	45.6	14.33	6.7
One	20.7	9.7	11.01	7.1
Two	14.6	6.1	8.52	5.0
Three or more	4.8	2.0	2.78	1.9
Gender				
Male	66.2	40.5	25.72	15.5
Female	33.8	22.9	10.92	5.2

Source: Own calculations based on the Household Finance and Consumption Survey 2017

Notes: *Table 1 presents the results of a survey of Slovak households conducted by the ECB (N = 10,895 observations = 100% of households). Table 1 is divided into several sectors according to categorized variables. The first two parts of the table assess the financial situation of households, especially in terms of total household income and assets. The rest of the table presents the relevant social and demographic characteristics in relation to the tendency of households to enter the credit market.*

** For the sake of representativeness of the observations, we used the final sample weight in our analysis. Due to weights, the number of observations at each income/wealth level (quintile) varies (we used analytic type of weights).*

The distribution of wealth among households seems to have a similar effect on their level of indebtedness. The positive relationship is likely to be explained by the higher value of real assets owned by wealthier households, and therefore there is a higher demand for debt financing. However, debt growth is smoother between sub-categories compared to income distribution. The distribution of wealth in the sample is relatively balanced.

Regarding the work status of the reference person (RP), if the RP is economically active they have a higher share in the debt market, while the employed RP (24% and 15% for mortgage debts) has the highest share. This group also dominates over other subcategories of the employment status (almost half of all RP are employed). The lower participation in the debt market for the other households is likely to be explained by poorer creditworthiness due to lower financial stability.

The level of education attained also seems to be a significant predictor of household indebtedness. RPs most often achieve secondary education (78%) and at the same time, their households have the highest share in the debt market (~ 28% and 15%). The second fastest indebted group are university graduates (~ 8% and 6%).

The impact of the age structure of RPs on indebtedness suggests that the share of households in the mortgage market is declining with age. A similar trend can be observed in the frequency of total household debt. This profile confirms Modigliani and Brumberg's hypothesis about the impact of the life cycle on individual consumption, where younger households have a greater need to finance their higher expenditures through debt, especially households in the second age category. This age is commonly associated with the acquisition of the first residence.

In terms of household size, the most frequently indebted households are three- and four-member households (~ 10% and 6%). Household composition is probably linked to the level of household consumption. HFCS results suggest that these households could have one or two children.

Relatively interesting results were obtained by comparing the probability of indebtedness within gender, which suggests that if the head of the family (RP) is a woman, the probability of indebtedness is more than 50% lower compared to a situation where the reference person is a man (at the mortgage debt this probability is threefold lower). However, this significant difference in results may be due to the more frequent enforcement of man as head of the family (66%).

In summary, the lowest share of household in debt market is in the lowest income and wealth sub-categories as well as in older households with a basic educated RPs who are not economically active and have three or more children.

3.2 Regressions analysis

The following subsection presents the results of the logistic regression. The dependent variable is the probability of household indebtedness. Compared to a univariate analysis, this approach is more appropriate for differentiating the characteristics of indebted and non-indebted households. The first two columns of Table 2 show the results of the probability and percentage change in odds that Slovak households will have any type of debt, and the second two columns show the probability and percentage change in odds that they will hold a mortgage debt.

These dependent variables (Any debt; Mortgages) are binary (1 if the household has the debt, 0 if not). The explanatory variables remain the same as in the previous subsection. Household income did not have a statistically significant effect on the probability of holding any type of debt. Therefore, the estimated coefficients as well as the percentage changes in odds for this category are not given in Table 2.

Table 2: Regression analysis, HFCS 2017

REGRESSION RESULTS FOR THE PROBABILITY OF HAVING DEBT						
	Any debt			Mortgages		
	Logit coef	*RSE*	change in odds (%)	Logit coef	*RSE*	change in odds (%)
Real wealth percentile						
Between 20 and 40	0.664***	*(0.109)*	94.32%	1.477***	*(0.158)*	338.08%
Between 40 and 60	0.513***	*(0.112)*	67.00%	1.543***	*(0.153)*	368.03%
Between 60 and 80	0.582***	*(0.108)*	78.89%	1.697***	*(0.151)*	445.60%
More than 80	0.479***	*(0.111)*	61.44%	1.753***	*(0.153)*	476.99%
Work status						
Self-employed	-0.286**	*(0.0925)*	-24.85%	-0.196	*(0.102)*	-17.78%
Unemployed	-0.723***	*(0.164)*	-51.49%	-0.997***	*(0.199)*	-63.12%
Retired	-0.157	*(0.128)*	-14.51%	-0.916***	*(0.157)*	-59.99%
Other	-0.382	*(0.206)*	-31.72%	-0.660*	*(0.270)*	-48.34%
Education						
Secondary	-1.121**	*(0.402)*	-67.42%	0.550	*(0.481)*	73.39%
Tertiary	-1.194**	*(0.407)*	-69.71%	0.520	*(0.489)*	68.23%
Age						
35-44	-0.283*	*(0.117)*	-24.67%	-0.472***	*(0.121)*	-37.59%
45-54	-0.879***	*(0.119)*	-58.49%	-0.903***	*(0.128)*	-59.45%
55-64	-1.914***	*(0.134)*	-85.25%	-2.403***	*(0.166)*	-90.95%
65-74	-2.313***	*(0.179)*	-90.10%	-2.386***	*(0.235)*	-90.80%
75 and over	-2.861***	*(0.224)*	-94.28%	-2.559***	*(0.347)*	-92.26%
Household size						
Two	0.296	*(0.242)*	34.45%	1.187***	*(0.307)*	227.64%
Three	0.831***	*(0.242)*	129.58%	1.414***	*(0.293)*	311.26%
Four	1.098***	*(0.225)*	199.82%	1.303***	*(0.269)*	268.17%
Five or more	0.999***	*(0.165)*	171.58%	0.964***	*(0.189)*	162.13%
Household type						
Several adults	0.0210	*(0.237)*	2.12%	-0.805**	*(0.298)*	-55.31%

Children						
One	0.0131	*(0.217)*	1.32%	-0.457	*(0.273)*	-36.66%
Two	-0.220	*(0.187)*	-19.74%	-0.789***	*(0.237)*	-54.57%
Gender						
Female	0.287***	*(0.072)*	33.24%	-0.0116	*(0.091)*	-1.15%
Constant	0.655	*(0.427)*	92.58%	-2.599***	*(0.498)*	-92.56%
Observations	10225			10225		

Source: Own calculations based on the Household Finance and Consumption Survey 2017

Note: *The results from the regression must be interpreted against the omitted categories of explanatory variables used in this logit model. These omitted categories correspond to households with real wealth below the 20th percentile, with only one household member and zero children, whose reference person is male, is less than 35 years old, is employed and has an education level corresponding to basic education. The percent change in the odds, as well as coefficients represented in the table, are the results of regression, the magnitude of which cannot be interpreted as the marginal effect of the explanatory variables on the dependent variables (indebtedness). In the logit model marginal effects have the same sign and significance of the estimated coefficients but vary in the values of the regressors. Robust Standard Errors (RSE) in parentheses* p < 0.05, ** p < 0.01, *** p < 0.001, calculated from weighted data (we used analytic type of weights).*

The results of the regression of financial variables (households' income and wealth) did not confirm the expected effect of these variables on indebtedness from the previous analysis. None of the income subcategory was statistically significant ($p > 0.05$).

Although the estimated effect on the distribution of wealth is statistically significant for each quintile ($p < 0.01$), the effect of wealth is slightly opposite compared to the univariate analysis. With increasing levels of wealth, the probability of indebtedness decreases relatively to the omitted category (the 1st quintile of wealth). In terms of percentage change of odds, the households in the second quintile of wealth have significantly increased odds of indebtedness by 94% compare to the households in the 1st quintile of real wealth, holding all other variables constant. The second highest increase in the odds of indebtedness compared to the 1st quintile has households from the 4th quintile of real wealth (by 79%). Wald tests confirm that the effect of real household wealth in the 2nd and 4th quintiles is equal on the household debt status ($X^2 = 0.71$, $df = 1$, $p = 0.40$).

Conversely, in the case of mortgages, the coefficients reflect the results obtained in the previous analysis. Wealthier households are more likely to have mortgage debt. At the same time, the results of the regression suggest that the wealthier households have the significantly higher odds (from 338% to 477%) of holding mortgage debt compared to households in the first quintile of real wealth. These differences in the effect on household indebtedness between households in the 1st and following quintiles of real wealth are not significantly equal ($X^2 = 149$, $df = 4$, $p < 0.01$).

Coefficients from logistic regression associated with working status shows that self-employed and unemployed RPs have a statistically significantly lower probability of holding any type of debt compared to employed RPs. The differences between these categories of working status and omitted category are significantly different at the 0.01 level ($X^2 = 27$, $df = 2$). For households with RPs who is on retirement, the odds of holding the mortgage debt are decreased by 60% compare to households with employed RPs, keeping other variables constant. We observe a similar effect in households where RPs are unemployed (decrease in the odds of holding the mortgage debt by 63%).

Surprisingly, in terms of the level of education attained, households with higher education are less likely to participate in the debt market compared to households in which RPs have only basic education. This effect of education on significantly lower odds of household indebtedness (~ by 70% lower odds) is similar both for RPs who have completed secondary education and for reference persons with completed tertiary education, compare to the omitted category. The effect of education was not statistically significant for any category when assessing the probability of holding mortgage debt.

Due to the age structure of households, older RPs are less likely to hold any debt as well as mortgages. For example, seniors aged 75 and over have by 94% lower odds of holding any type of debt compared to the younger RPs under the age limit of 34, if other variables are constant. A similar magnitude of this effect can be observed at RPs aged between 55–74 years and in the situation of holding the mortgage debt. Households where the reference person is 45–54 years old have an almost 60% lower odds of indebtedness compared to the reference group with RPs under the age of 35 years. If the age of the reference person of the household is less than 35 years, the odds of indebtedness is 1 649% higher ($b = 2.861$, $p < 0.01$) compared to households where the RP is older than 75 years, while the other variables are constant. At the same time, difference in the effect between each age category and reference category of RPs under 35 years is statistically significant at the 0.01 level ($X^2 = 305$, $df = 5$).

In line with results of the univariate analysis, there is a higher and statistically significant probability of indebtedness of three and more household members.

The highest odds of indebtedness have four-member households (by 200% higher than one-member households), keeping other variables constant. From the point of view of mortgage indebtedness, three-member households have the significantly highest odds of indebtedness (by 311% higher than one-member households), with other variables unchanged.

However, if households have two children, as opposed to households without, the odds of participation in the mortgage market have decreased significantly by 55%, holding other variables constant.

The last predictor of indebtedness was the gender of the reference person. The predicted coefficient of the impact of gender on household indebtedness is at odds with the direction of the effect supported in the previous analysis. The odds of the household indebtedness have increased significantly by 33% if the reference person is a female, compared to male RPs, holding other variables constant.

The results of the regression generally suggest that the likelihood of holding the mortgage debt increasing with increasing levels of wealth, while the level of household income does not have a statistically significant effect on debt distribution. The probability of indebtedness (of any debt) also increases in three- and four-member households as well as with women as RP. On the other hand, economic inactivity and higher educated RPs reduce the likelihood of households holding any debt. The age of RP has a similar effect on household indebtedness. The older the RPs are, the less likely households participate in the debt market.

3.3 Marginal Effects

The next part presents the results of the calculated marginal effects from the previous logistic regression analysis. Marginal effects are particularly useful for the interpretation of parameter estimates after nonlinear regression models, such as logistic regression.[13]

According to Pampel (2020, p. 27), *"marginal effects refer to the influence of independent variables on a dependent variable. A marginal effect is defined in general terms as the change in the expected value of a dependent variable associated with a change in an independent variable, holding other*

[13] For more information about the applied methodology see, for example, Williams (2012).

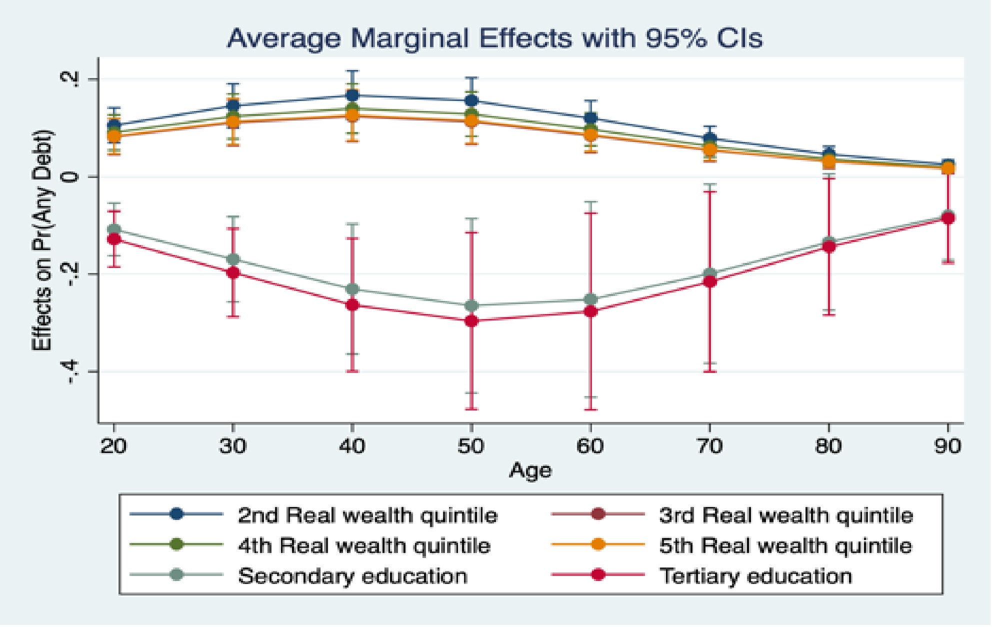
independent variables constant at specified values. (...) In logistic regression the marginal effect on probabilities varies."

Because we use dummy (categorical) independent variables in the regression logistics model, we used average marginal effects and marginal effects at representative values as the most appropriate approaches to our model. At the same time, due to the discrete nature of the regressors, the presented marginal effects relate to a discrete change in the independent variable rather than a marginal change (Williams, 2012). All presented average marginal effects (Table 3, part of the appendix) for factor levels are interpreted as a discrete change from the baseline level (omitted baseline category).

- The marginal effects at representative values (Age)

The marginal effects of the independent variables, which were statistically significant at the 0.05 level, are shown in Figures 1 to 4. The marginal effects are expressed as discrete changes in the distribution of wealth, educational attainment, working status, and gender across the distribution by age (in ten-year increments).

Figure 1: Average marginal effects of Real Wealth and Education at values of age from logistic regression model of indebtedness (Any Debt), HFCS 2017

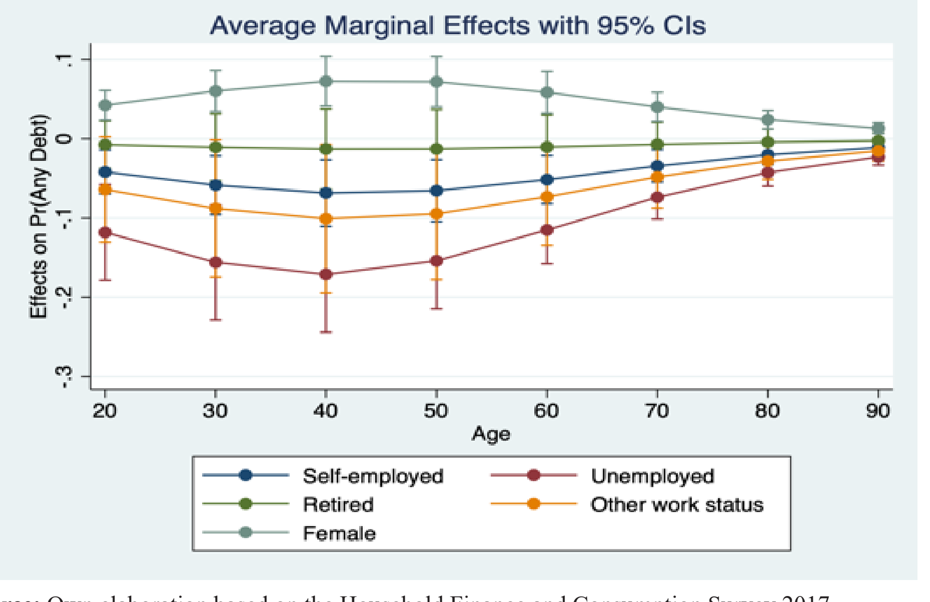


Source: Own elaboration based on the Household Finance and Consumption Survey 2017

Figure 1 shows that the estimated marginal effects of wealth distribution have a similar effect on the likelihood of household indebtedness. However, in terms of age distribution, the effect of household wealth on debt varies slightly. The probability of indebtedness is highest in households from the 2nd to the 5th quintile, where RP is around 40 years old (17 percentage points, 2nd quintile). In general, average household from the 2nd quintile of real wealth have by 12 percentage points higher probability to be indebted than average household from 1st quintile (Table 3). The probabilities of indebtedness of other quintiles are similar, but slightly lower.

From the point of view of educational attainment and its impact on the probability of indebtedness, with higher educational attainment (secondary and tertiary) the probability of indebtedness for households decreases by ~ 22 percentage points, compared to the average household, where RP achieved only basic education (Table 3). At the same time, households where the RP has achieved secondary or tertiary education are least likely to be in debt if the reference person is around 50 years old, compare to the households where RP has a basic education. Before and after this age cut point, the relative probability of indebtedness increases, but is still negative compared to the reference category.

Figure 2: Average marginal effects of Work status and Gender at values of age from logistic regression model of indebtedness (Any Debt), HFCS 2017

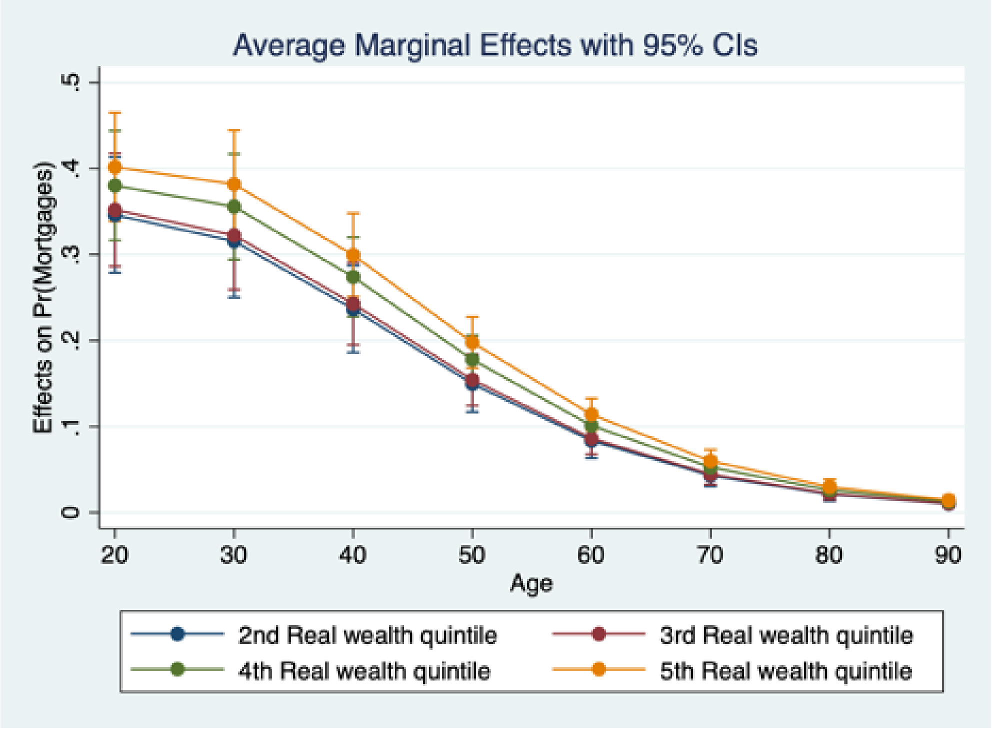


Source: Own elaboration based on the Household Finance and Consumption Survey 2017

Figure 2 shows the marginal effects of working status and gender at representative values of the age distribution. The lowest probability of indebtedness is in average households where RP is unemployed (13 percentage points lower than in average households where RP is employed, Table 3). This effect is highest in households where the reference person is approximately 40 years old and unemployed (*dy/dx* = -0.171).

In terms of gender, on average females' probability of having any debt is 5 percentage points higher than it is for males (Table 3). From view of the effect of gender across age distribution, the likelihood of debt increases most in women aged 40.

Figure 3: Average marginal effects of Real Wealth at values of age from logistic regression model of indebtedness (Mortgages), HFCS 2017

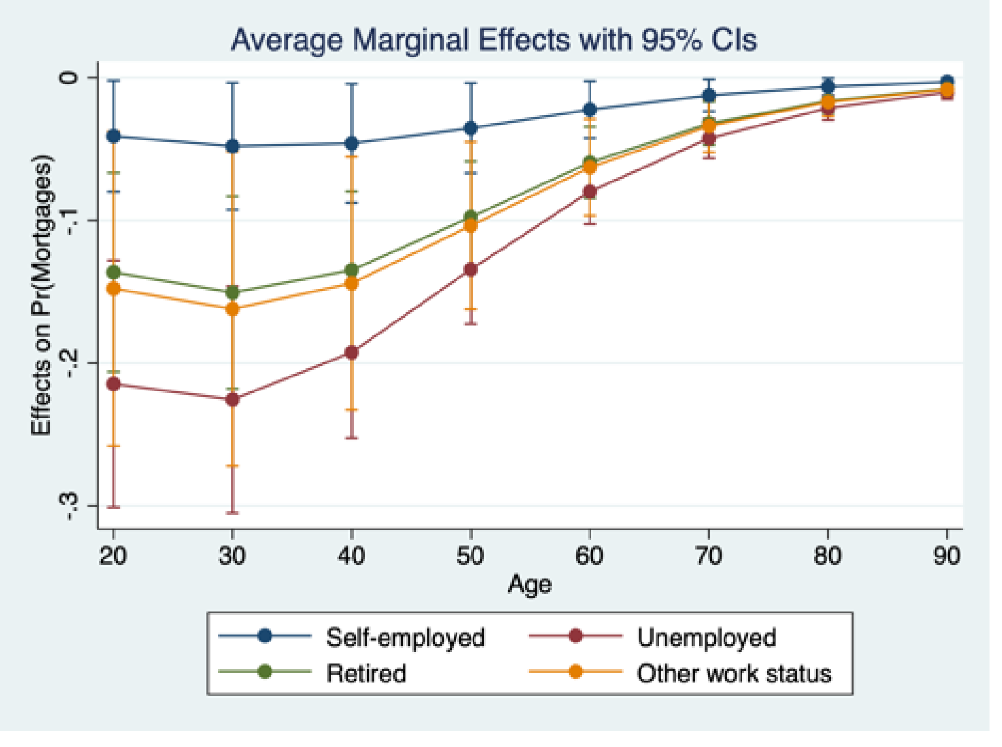


Source: Own elaboration based on the Household Finance and Consumption Survey 2017

Figures 3 and 4 below show the effects of the real wealth (Figure 3) and the work status (Figure 4) on the probability of mortgage indebtedness of Slovak households within the age distribution of their reference persons.

In terms of the distribution of wealth, the magnitude of the probability of holding a mortgage debt in each age category is quite similar. However, the effect of the real wealth of the household varies greatly according to the age of the reference person. The probability of holding mortgage debt is between 35 and 40 percentage points for twenty years old RP and then decreases with increasing age up to almost 0 percentage point for those aged ninety. In general, average household from the fifth quintile of real wealth have by 19 percentage points higher probability to hold mortgage debt than average household from 1st quintile (Table 3).

Figure 4: Average marginal effects of Work status at values of age from logistic regression model of indebtedness (Mortgages), HFCS 2017



Source: Own elaboration based on the Household Finance and Consumption Survey 2017

Figure 4 shows the effect of RPs work status on indebtedness within the age distribution of reference persons. The effect is similar to the effect we observed in Figure 2, but with a slightly larger magnitude and a shifted cut point at age (ten years less).The lowest probability of holding mortgage debt is in average households where RP is unemployed (12 percentage points lower than in average households where RP is employed, Table 3). This effect is highest in households where the reference person is approximately thirty years old and unemployed (*dy/dx* = -0.226).

4 Conclusion

The increase in indebtedness of Slovak households is one of the most significant among the countries of the European Union. The favourable economic situation, the reduction of the unemployment rate to historically low, rising wage levels, and the expansionary monetary policy of the European Central Bank create suitable conditions for increasing household debt. More affordable loans today can lead to the financial instability of indebted households in the future. Therefore, understanding the factors that drive households into debt is key for policymakers, regulators, and financial institutions.

This article analyses the tendency of households to participate in credit market. Presented analysis is based on microeconomic data collected through the Household Financing and Consumption Survey in 2017. The HFCS dataset provides relevant information on the economic, social and demographic characteristics of households that are representative of the country's population. The main goal was to find statistically significant factors that indicate the indebtedness of households.

Univariate analysis revealed a potential relationship between the subset of selected socio-economic and demographic characteristics and the households' indebtedness. Subsequently, the logistic regression model was used to examine identified relationships and estimate the probability of being indebted.

The debt of households should be considered together with the wealth of households. The results suggest that the likelihood of household participation in the credit market increases with increasing levels of wealth, while the level of household income does not have a statistically significant effect on debt distribution. Also, households with a larger number of members are more likely to hold any debt. Conversely, households with two children are less likely to participate in mortgage market than households without children. Similarly, the negative effect was observed in households where the reference person was economically inactive or achieved a higher level of education. Furthermore, the increasing age of the reference person has also a negative impact on participation in debt market. This finding is consistent with Modigliani and Brumberg's hypothesis about the life cycle of households' consumption and investment decisions.

Acknowledgment

Thanks to anonymous reviewers for all their helpful comments and suggestions. This research was financially supported by VEGA grant No. 1/0827/18) "Experimental investigation of factors influencing the decision-making of economic subjects".

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Appendix

Table 3: Average Marginal Effects (AME) from Regression analysis, HFCS 2017

REGRESSION RESULTS FOR THE PROBABILITY OF HAVING DEBT		
	Any debt AME	**Mortgages AME**
Real wealth percentile		
Between 20 and 40	0.117***	0.149***
	(0.019)	(0.015)
Between 40 and 60	0.090***	0.159***
	(0.019)	(0.015)
Between 60 and 80	0.102***	0.180***
	(0.019)	(0.014)
More than 80	0.083***	0.188***
	(0.019)	(0.014)
Work status		
Self-employed	-0.052**	-0.028
	(0.017)	(0.014)
Unemployed	-0.126***	-0.120***
	(0.027)	(0.020)
Retired	-0.029	-0.113***
	(0.024)	(0.018)
Other	-0.069	-0.086**
	(0.036)	(0.031)
Education		
Secondary	-0.208**	0.065
	(0.073)	(0.051)
Tertiary	-0.221**	0.061
	(0.074)	(0.052)
Age		
35-44	-0.063*	-0.095***
	(0.026)	(0.024)
45-54	-0.202***	-0.173***
	(0.026)	(0.025)
55-64	-0.414***	-0.344***
	(0.028)	(0.027)
65-74	-0.474***	-0.343***
	(0.032)	(0.029)
75 and over	-0.535***	-0.354***
	(0.032)	(0.033)

Household size Two Three Four Five or more	(not estimable)	
Household type Several adults	(not estimable)	
Children One Two	(not estimable)	
Gender Female	0.052*** (0.013)	-0.001 (0.012)
Observations	10225	10225

Source: Own calculations based on the Household Finance and Consumption Survey 2017

Note: *The average marginal effects must be interpreted as the discrete change from the omitted base categories of independent variables used in the previous logistic regression model. These omitted categories correspond to households with real wealth below the 20th percentile, whose reference person is male, is under 35 years old, is employed and have completed basic education. Robust standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001, calculated from weighted data (we used analytic type of weights).*