

CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies



**The Impact of Economic Development on
Asset Poverty: Evidence from Slovakia**

Master's thesis

Author: Bc. Petra Lancuchová

Study program: Economics and Finance

Supervisor: Mgr. Petr Polák, M.Sc.

Year of defense: 2020

Declaration of Authorship

The author hereby declares that she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis in whole or in part and agrees with the thesis being used for study and scientific purposes.

Prague, May 7, 2020

Petra Lancuchová

Abstract

This thesis deals with asset poverty and examines whether current economic development reduces the threat of households falling into asset poverty and whether the gap between poor and rich households is widening. For that purpose, we use data obtained from the Slovak HFSC survey, which took place in 2014. Economic development between 2014 and 2019 is simulated using macroeconomic indicators such as inflation, unemployment rate, and others. Besides the OLS method, which shows the effect of examined independent variables on the average value of household assets, we also employ quantile regression to compare the difference in the influence of independent variables on different values of assets. Regression results suggest that, indeed, recent economic development in Slovakia might reduce the risk of asset poverty; however, this does not apply to all households. Economic development seems to be significant primarily for households with a higher value of assets, which may lead to a growing gap between wealthy and poor households.

JEL Classification C13, D31, I32, O11

Keywords asset poverty, economic development, poverty measurements, wealth

Title The Impact of Economic Development on Asset Poverty: Evidence from Slovakia

Abstrakt

Tato práce se zabývá majetkovou chudobou a zkoumá, zda současný ekonomický vývoj snižuje ohrožení domácností majetkovou chudobou a zda se majetková propast mezi chudými a bohatými domácnostmi ještě více prohlubuje. Za tímto účelem používáme data získaná ze slovenského průzkumu HFSC, který proběhl v roce 2014. Ekonomický vývoj mezi lety 2014 až 2019 je simulován pomocí makroekonomických indikátorů, jako jsou inflace, míra nezaměstnanosti a jiné. Kromě metody nejmenších čtverců, která ukazuje vliv zkoumaných nezávislých proměnných na průměrnou hodnotu majetku domácnosti, používáme i kvantilovou regresi, která slouží k porovnání rozdílu působení nezávislých proměnných na různé hodnoty majetku. Regresní výsledky naznačují, že ekonomický vývoj na Slovensku může snižovat ohrožení majetkovou chudobou, ale neplatí to pro všechny domácnosti. Zdá se, že ekonomický vývoj hraje určitou roli především u domácností s vyšší hodnotou majetku, což může vést k prohlubování propasti mezi majetnými a nemajetnými domácnostmi.

Klasifikace JEL C13, D31, I32, O11

Klíčova slova majetková chudoba, ekonomický vývoj, měření chudoby, blahobyť

Název práce Vliv ekonomického vývoje na majetkovou chudobu: případ Slovenska

Acknowledgments

The author is grateful especially to Mgr. Petr Polák, M.Sc. for all the comments, professional guidance, time and stimulating ideas.

Moreover, the author would like to thank her family and friends for their support and endless patience.

Furthermore, the author would like to express her gratitude and sincere admiration to all the researchers, academics, journalists cited and also to software engineers that dedicated their time to science and helped to enrich human knowledge.

Typeset in L^AT_EX using the IES Thesis Template. The models were produced in RStudio by R Development Core Team (2006). The tables in this thesis were formatted by the package stargazer (Hlavac 2018).

Bibliographic Record

Lancuchová, Petra: *The Impact of Economic Development on Asset Poverty: Evidence from Slovakia*. Master's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2020, pages 97. Advisor: Mgr. Petr Polák, M.Sc.

Contents

List of Tables	viii
List of Figures	ix
Acronyms	x
Thesis Proposal	xi
1 Introduction	1
2 Literature review & Theoretical background	4
2.1 Poverty	4
2.2 Asset poverty	6
2.2.1 What are basic needs?	6
2.2.2 What period of time?	7
2.2.3 What is “wealth”?	7
2.3 Asset poverty measurement	7
2.3.1 Methods	7
2.3.2 Annuitization	9
2.4 Macroeconomics indicators	10
2.4.1 Leading indicators	11
2.4.2 Lagging indicators	11
2.5 Mortgages	14
2.6 Economic development in Slovakia	14
3 Overview of data collection	17
3.1 Data	17
3.2 Imputation of missing values	18
3.3 Description of variables	20
3.3.1 Dependent variables	20

3.3.2	Independent variables	23
4	Detailed description of the research	28
4.1	Empirical research background	28
4.1.1	Cross-sectional data formulation	28
4.1.2	Quantile regression	29
4.1.3	Robust standard errors	30
4.2	Empirical models	31
5	Evaluation of the results	34
5.1	Results obtained by the OLS method	34
5.2	Results obtained by quantile regression	47
6	Conclusion	55
	Bibliography	63
A	Estimation results of quantile regression	I
B	Gauss-Markov assumptions	X
C	Tests	XIV
D	Overview of models	XIX

List of Tables

3.1	Descriptive statistics	26
3.2	Development of macroeconomic indicators in %	26
4.1	Overview of our models	32
5.1	Estimation results of Model1a & Model1b	35
5.2	Estimation results of Model1c & Model1d	37
5.3	Estimation results of Model2a & Model2b	38
5.4	Estimation results of Model2c & Model2d	40
5.5	Estimation results of Model3a & Model3b	41
5.6	Estimation results of Model3c & Model3d	43
5.7	Estimation results of Model4a & Model4b	45
5.8	Estimation results of Model4c & Model4d	46
A.1	Estimation results of quantile regression - Model 1 (2014)	II
A.2	Estimation results of quantile regression - Model 1 (2019)	III
A.3	Estimation results of quantile regression - Model 2 (2014)	IV
A.4	Estimation results of quantile regression - Model 2 (2019)	V
A.5	Estimation results of quantile regression - Model 3 (2014)	VI
A.6	Estimation results of quantile regression - Model 3 (2019)	VII
A.7	Estimation results of quantile regression - Model 4 (2014)	VIII
A.8	Estimation results of quantile regression - Model 4 (2019)	IX
B.1	Correlation matrix	XIII
C.1	Breusch-Pagan test against heteroscedasticity	XV
C.2	Normality testing	XVIII

List of Figures

5.1	Quantile regression plots - Model 1 (2014)	48
5.2	Quantile regression plots - Model 1 (2019)	48
5.3	Quantile regression plots - Model 2 (2014)	50
5.4	Quantile regression plots - Model 2 (2019)	50
5.5	Quantile regression plots - Model 3 (2014)	52
5.6	Quantile regression plots - Model 3 (2019)	52
5.7	Quantile regression plots - Model 4 (2014)	54
5.8	Quantile regression plots - Model 4 (2019)	54

Acronyms

BP	Breusch-Pagan
CPI	Consumer Price Index
ECB	European Central Bank
GDP	Gross domestic product
HFCS	Household Finance and Consumption Survey
MLR	Multiple linear regression
NBS	National Bank of Slovakia
NRC	National Research Council
NW	Net wealth
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
QFAs	Quarterly financial accounts
QR	Quantile regression
SO SR	Statistical Office of the Slovak Republic
US	United States
WB	World Bank

Master's Thesis Proposal

Author	Bc. Petra Lancuchová
Supervisor	Mgr. Petr Polák, M.Sc.
Proposed topic	The Impact of Economic Development on Asset Poverty: Evidence from Slovakia

Motivation The main purpose of this study is to examine if and how asset poverty in Slovakia has changed during the last four years. The measurement of poverty is usually based on income while assets are often ignored. The main reason for ignoring assets is the difficulty of gaining information on assets at an individual level. In this thesis I will use the Slovak macroeconomics indicators (GDP, inflation, employment etc.) to simulate the development of Slovak households in the last four years. Such approach allows to address the main research question: how the current development of economic situation in Slovakia influences the development of asset poverty. In addition, I would like to specify the rate of indebtedness which leads to asset poverty with special attention given to mortgages taken by the households.

Hypotheses

Hypothesis #1: The current development of Slovak economy reduces asset poverty.

Hypothesis #2: Households who took a mortgage four years ago are better off compared to those who did not.

Hypothesis #3: The gap between rich and poor households is widening.

Methodology One of the approaches to the measurement of asset poverty is based on the perception of what the net position of an individual would be if he/she sold all his assets and afterwards lived on the revenues from these assets. As a first step, the current economic situation will be simulated by using the cross-sectional HFCS 2014 microdata from National Bank of Slovakia and macroeconomic fundamentals which include unemployment, GDP, inflation (consumer price indices), interest rates and

fiscal and monetary policy and balance of payments. As a second step, I will construct an econometric model (multiple linear regression) with the variable representing asset as the response variable. Afterwards, the model will be re-estimated separately for households with mortgages and for households without the loans. The estimations will be performed with R software for numerical analysis.

Expected Contribution The main contribution of this thesis relative to the existing literature is the possibility to extend the analysis of measurement of asset poverty based on the development of Slovak economy during the last four years and use simulate “up-to-date” data. Moreover, the research will be enriched by the diversification of households according to their indebtedness. Special attention will be given to mortgages because it is nowadays very discussed public topic and it may increase its significance in connection with poverty and economic development in the following few years.

Outline

1. Introduction of the topic
2. Literature review
3. Overview of the data collection
4. Detailed description of the research
5. Evaluation of the results
6. Conclusion
7. Bibliography

Core bibliography

Brandolini, A., Magri, S., and Smeeding, T. M. (2010). Asset-Based Measurement of Poverty. *Journal of Policy Analysis and Management*, 29(2):267-284.

Caner, A. and Wolff, E. N. (2004). Asset Poverty in the United States, 1984-99: Evidence from the Panel Study of Income Dynamics. *Review of Income and Wealth*, 50(4):493-518.

Haveman, R. and Wolff, E. N. (2001). Who Are the Asset Poor?: Levels, Trends, and Composition, 1983-1998. Institute for Research on Poverty, Discussion Paper no. 1227-01.

Nam, Y., Huang, J. and Sherraden M. (2008). Assets, Poverty, and Public Policy: Challenges in Definition and Measurement. Center for Social Development Washington University in Saint Louis, A Report in the Series Poor Finances: Assets and Low-Income Households.

Oliver, M. L. and Shapiro, T. M. (1990). Wealth of a Nation: A Reassessment of Asset Inequality in America Shows at Least One Third of Households Are Asset-Poor. *The American Journal of Economics and Sociology*, 49(2):129-151.

Weisbrod, B. A. and Hansen, W. L. (1968). An Income-Net Worth Approach to Measuring Economic Welfare. *The American Economic Review*, 58(5):1315-1329

Author

Supervisor

Chapter 1

Introduction

Poverty is most often associated with the living conditions of people in developing countries. The term poverty is used for a situation in which people cannot afford a minimum standard of living and to satisfy basic human needs. Although poverty is largely a matter for developing countries, it has a major impact on advanced economies, thus becoming one of the most severe global problems.

There are many ways how to define or measure poverty. However, most official statistics estimating the level of poverty in poor as well as in rich countries are based solely on household income. Numerous contributions have recently remarked the necessity to supplement standard income poverty measures with information on other households attributes in order to obtain a more comprehensive indicator of household welfare (Chakravarty & Silber 2008). We want to take into account the assets and liabilities of an individual or a household when measuring poverty. Those are often ignored because of the difficulty of gaining enough information about an individual's assets. The inclusion of assets in measuring poverty is referred to as measuring asset poverty. Asset poverty can be defined as having insufficient net wealth to cover a certain period of living expenses without any income. Assets can play an essential role in reducing exposure to distress. It can serve as collateral for borrowing, giving families a possibility to move out of poverty and improve their standard of living.

The main purpose of this study is to examine how current economic developments affect asset poverty. In the literature, we could find a considerable amount of researches dealing with asset poverty, its definition and measurement. But we are interested in how asset poverty develops over time from an economic point of view and whether households are more endangered of asset

poverty today than they were a few years ago. In our analysis, we use data obtained from a survey of households in Slovakia conducted in 2014. Our goal is to investigate the differences in the risk of asset poverty over a period of five years. For that purpose, macroeconomics indicators (GDP, inflation, unemployment, etc.) are used to simulate the economic development of Slovakia between 2014 and 2019. Slovakia experienced very positive economic development during that period. Almost all indicators of well-being improved. It could be assumed that households' wealth has become stronger than it was in the past.

In addition to examining the development of asset poverty over time, we focus on how mortgage drawdown affects asset poverty and whether it is a significant determinant influencing the threat of asset poverty. Moreover, we give attention to the question whether economic development in Slovakia widens the gap between poor and rich households in terms of asset poverty.

The primary motivation leading to the elaboration of this work was the curiosity whether the property situation of households has been improving due to the recent economic development. We can often read that governments try to implement various policies to reduce poverty. Policymakers concentrate on people's income before implementing new social policies and overlook their wealth. The government spends hundreds of billions of funds each year to support long term poverty reduction (Kamal 2014). However, they try to minimise only income poverty. There are not many policymakers focused on asset poverty; therefore, we were interested in how these policies aimed at lowering income poverty affect asset poverty. Another motivating factor is the existence of a small number of studies focusing on asset poverty in Central Europe. In recent years, researches on asset poverty have begun to spread slowly, but most of them are being carried out outside of Europe. In our thesis, we would like to slightly expand the small number of studies performed on European data.

We believe that the results of this study can be helpful not only for further research of asset poverty but also for the overall improvement of the situation of households facing the threat of asset poverty. With the rising public awareness of asset poverty, there is an increasing chance that governments will look at poverty not only in terms of income but also in terms of assets. This could initiate the process of finding new ways to reduce asset poverty or prevent the widening of the gap between poor and wealthy households.

The rest of the thesis is organised as follows. The second chapter provides a

theoretical basis for understanding the concept of asset poverty and presents an overview of macroeconomic indicators, mortgages and economic development in Slovakia. The third chapter describes our dataset, while the fourth chapter provides the methodology used for the analysis. In chapter five, we present and evaluate the results of our estimation. The final chapter concludes the thesis with the key findings. Appendix A to D cover tables and additional research information that were not included in the text.

Chapter 2

Literature review & Theoretical background

2.1 Poverty

Poverty is a socio-economic issue. Socio-economic issues are factors that have a negative influence on an individuals' economic activity, including lack of education, cultural and religious discrimination, overpopulation, unemployment, and corruption. In these days, we define poverty as the situation when the individual's incomes fall below the poverty level. However, there are many various methods of how poverty can be described and measured. One of the options is to define poverty as a lack of income to meet basic needs. Poverty is also a variable that determines one's socio-economic status. It means an individual's or group's position within a hierarchical social structure, which depends on a combination of variables, including occupation, education, income, wealth, and place of residence. Scientists increasingly emphasise the need to include assets and liabilities when measuring poverty as it plays a central role in identifying who is poor and who is not.

Poverty is a problem on a global scale. In each country, some people can be characterised according to the criteria of that given country as poor individuals. People living in poverty are, therefore, in both developing and developed countries. Poverty regulation is one of the traditional topics in the social sciences, and especially economists believe that increased attention should be given to poverty. The main path to its reduction should be economic growth, which in many cases reduces the number of people below the poverty line and their share in the total population (Novotný & Nosek 2009). According to the World

Bank (WB) estimates, about 1.4 billion people are currently living below the poverty line. In the European Union is this amount about 85 million people (Eurostat 2019). The WB set the poverty line at \$1.90 per day using 2011 prices. As the world gets wealthier and extreme poverty becomes more concentrated, there were legitimate questions over whether this line is appropriate for more developed regions. In 2017, the WB set new standards at \$3.20 a day for people in “lower-middle-income” countries, such as Egypt or India, and \$5.50 a day for “upper-middle-income” countries, such as Jamaica or South Africa. The WB also released a third standard for high-income countries, like the US, at \$21.70 a day. These new poverty lines are designed to complement the old \$1.90 international poverty line. Jolliffe *et al.* (2018) state in their book that the rapid gains against extreme poverty have not been matched by reductions in the number of people living below these higher levels of income. In 2015, more than 25% of the world’s population survived with \$3.20 per day, and nearly 50% of the world still lived with less than \$5.50 per day.

We currently distinguish more types of poverty. When measuring poverty, the chosen type depends on the aspects we want to emphasise. We divide poverty into subjective and objective poverty. Subjective poverty is a self-assessment of the life situation. This assessment is usually conducted by questionnaire surveys of households. We can say that it is a probe into the living conditions showing the minds of individuals about their conditions (Durlauf & Blume 2008). Objective poverty is based on a set of socio-economic analyses of a given society. It is obtained, for example, as the average per capita household income relative to the country’s poverty line (Eurostat 2013).

Another of the divisions of poverty that we introduce is the division into relative and absolute poverty. According to Jäntti (1993), absolute poverty is defined by the failure to meet basic needs, and the level of income is adequately addressed to the basic needs. The absolute type is mainly used for measuring poverty in developing countries; in developed countries, this type is nowadays used less. Poverty from a relative view is defined depending on the existing standards in society. This type of poverty allows people to meet basic life needs, but their resources are small, and these people are excluded from the minimum acceptable way of life in that society (Žák 2002). Abdelkrim & Duclos (2006) wrote that the relative poverty line might change over time, but this change does not have to indicate a change in the situation of the poor.

2.2 Asset poverty

We define an individual or a household as asset poor if their access to resources is not sufficient to meet basic needs for a limited period. Wolff & Haveman (2001) described asset poverty in their book as a lack of assets that imprisoned the family in inferior economic and social conditions. According to Brandolini *et al.* (2010), an individual is considered asset poor if ownership of property is not sufficient to protect the socially predetermined minimum standard of living in a short period of time. There are trends in the development of asset poverty over time, and there exist several factors that cause the inclusion of certain groups among asset poor more easily than the inclusion of other groups. Changes in these factors have occurred over the years, but asset poverty remains higher than other forms of poverty, such as income poverty. The reason for the difference is that asset poverty represents the total wealth of households and not just the current income level (Wolff & Caner 2004). If we want to develop a measurement of asset poverty correctly, we need to focus on and review the following three questions.

2.2.1 What are basic needs?

Let us assume that household needs can be satisfied if we have access to financial resources. There is not a commonly accepted standard that would determine the minimum amount of required financial resources to meet basic needs. Team working for the National Research Council (NRC) in the US has proposed a poverty line conditioned by the size of the family as an alternative to long-term official poverty thresholds. The threshold amount should include food expenditure, expenses for clothing, housing, and a small additional amount for the other regular everyday needs (such as things needed for personal care or travelling expenses except for commuting). By using the Consumer Expenditure Survey data, a threshold for a reference family consisting of two adults and two children was suggested. The threshold values of this reference families were subsequently adapted to reflect the needs of different types of families and geographical differences in the costs of living. These thresholds proceed from a three-parameter equivalent scale that reflects the needs of families of different sizes and structures (Wolff & Haveman 2001).

2.2.2 What period of time?

Authors writing about asset poverty have different opinions about a period in which some stock of resources will remain in the household to meet basic needs provided that no additional resources are available. For example, Wolff & Caner (2004) or Wolff & Haveman (2005) consider as a reasonable norm the situation when families have a financial cushion that will allow them to satisfy basic needs for three months if no additional resources were available. Contrary to them, Gornick *et al.* (2009) used a reference period longer than three months.

2.2.3 What is “wealth”?

In almost every book dealing with the issue of poverty, we can find a definition that says income is a flow quantity, while wealth is a state quantity. Income is a cash gain over a certain amount of time, usually within one year. It can be used as a good benchmark for a certain type of asset within a very short time (Oliver & Shapiro 1990). Previous income does not necessarily reflect what resources we have available right now. This is because we can spend our income very quickly. Wealth has a form of savings, investments, homes, and land. It is precisely the notion of wealth that includes the savings and investments that can be used in tough times. In comparison with income, wealth is a more stable indicator of position in society and represents a stockpiled purchase strength. Unlike income, wealth is accumulated throughout life, and it is only exceptionally subject to rapid changes, except for inheritance or serious economic crises.

2.3 Asset poverty measurement

2.3.1 Methods

The main criterion when measuring wealth is how easily and how much assets the household can use for consumption when current income falls. As a basic unit of wealth, we define the market value of wealth as the present value of all tradable or exchangeable assets reduced by the current value of the debt. Thus, the net value of wealth is the difference in the value between total assets and total liabilities. Wolff & Haveman (2001) concerned us that the NW (net

wealth) concept is the primary measure of wealth because it reflects wealth as a value keeper, therefore, as a source of potential consumption.

Most of the existing studies include various variables representing the market values of wealth. The reason for this is that topic of the research and the data availability are slightly different. We can frequently find following six items in the studies: net financial assets (values in current and savings accounts, funds money market, bond certificates, bonds, stocks, net unsecured debt), the net value of domestic capital, the net value of other real estates, net trading capital, the value of individual pension assets and the net value of the vehicle.

The other two estimates of asset poverty are based on two more restrictive definitions and consist of the net value of wealth reduced by domestic capital (NW - HE) and liquid assets (LIQ). In the first case, we assume that it would be inappropriate to require the household to sell its home to secure the financial resources necessary to overcome the period without income. In the latter case, we have an even more restrictive definition, which includes only cash or financial asset, which are easy to convert into money, excluding individual pension accounts and pension assets.

Citro & Michael (1995) wrote in their paper the information that the NRC proposed not to include asset values as family resources in the official poverty measurement for which the measurement period is one year. Families with lower income usually own only a small fraction of assets, so financial assets will prevent them from falling into poverty for only a short period of time. The NRC recommended the inclusion of income from assets (such as interest or rent) when calculating the financial resources available to the household (Nam *et al.* 2008).

Wolff (1990) came up with a slightly different approach to measuring asset poverty. He focused on financial resources easily available to individuals. Furthermore, he did not assume the use of wealth at the time of death. In his study, he used the interchangeable value of net wealth instead of the total net assets to calculate a common measure of economic well-being. Its definition of interchangeable wealth includes domestic capital, liquid assets (e.g. savings deposits), business capital, and investment property, but excludes durable goods and household stocks (Nam *et al.* 2008). Wolff (1990) developed an alternative measure of poverty. According to his measurement of financial resources, a family is considered poor if the value of its financial resources is less than the official poverty threshold defined by the Census Bureau. Wolff's measurement

reduces the poverty line by about 10% compared to the official poverty line.

2.3.2 Annuitization

Weisbrod & Hansen (1968) were the first authors who tried to measure poverty by the concept of asset poverty. In their analysis, income data are supplemented by the net assets of the surveyed entity. The analysis is based on the assumption that current income and current net assets are not the only determinants of an individual/household economic position. They suggested that the economic situation of an individual/household is better captured if the income from the net asset in year t is replaced by the value of the net wealth of the n -year annuity:

$$AY_t = Y_t + \left[\frac{\rho}{1 - (1 + \rho)^{-n}} \right] NW_{t-1}, \quad (2.1)$$

where Y_t is the current annual income, NW_{t-1} is the net asset, n is the annuity length and ρ is interest rate of the annuity.

In the equation, net assets are converted to a constant income flow discounted at an interest rate of n years. Weisbrod & Hansen (1968) suggested that n should be equal to the number of expected remaining years of an individual, provided that no wealth is left at man's death, although this formula would easily allow us to count with inheritance.

This approach to measuring poverty was criticised by Projector & Weiss (1969). They believed that choice n is arbitrary, as there is no way to assess the appropriate time span during which net assets should be evenly distributed while allowing the end of life. They saw another problem in comparing units of different age groups. The formula ignores the life cycle of savings and consumption and does not take into account potential higher savings of young people (Brandolini *et al.* 2009). When using this method, older people will perform on average much better than they would if only a one-dimensional income concept were used. On the other hand, the performance of children would worsen. Thus, the annual annuity will increase with increasing property value and decreasing life expectancy (Želinský 2014).

As the last authors using the annuitization approach, we would like to mention Short & Ruggles (2005). Annuitization is the process of converting an asset into a series of periodic income payments. Annuities may be annuitized for a specific period or the life of the annuitant. The result of their work is a slight modification of the method proposed by Weisbrod & Hansen (1968). The

difference is in adjusting the annuity for the head of the household for its whole life. In the study of these authors, a household is defined as poor if the sum of the net asset value and family income is below the poverty line. Compared to Wolff (1990), Short & Ruggles (2005) have different treatment of financial assets, and their poverty rate estimates are higher than the poverty rate based on a traditional measurement that includes only income.

2.4 Macroeconomics indicators

Macroeconomic indicators are statistics or data readings that reflect the economic circumstances of a particular country, region, or sector. The aim of all economies in the world is their positive economic development. Macroeconomic indicators are used by analysts and governments to assess the current and future health of the economy and financial markets. By comparison of macroeconomic indicators, we can determine the overall position of the national economy. Macroeconomic indicators will vary in their meaning and the impact that they have on the economy, but broadly speaking, there are two main types of indicators:

1. *Leading indicators*, which forecast where an economy might be heading. They are often used by governments to implement policies because they represent the first phase of a new economic cycle. These include the yield curve, interest rates, and share prices.
2. *Lagging indicators*, which reflect an economy's historical performance and only change after a trend has been established. They are used to confirm that a trend is underway. These contain the gross domestic product (GDP), inflation, and employment figures.

Macroeconomic indicators are important because they can have a significant influence on market movements. Therefore, the most fundamental analysis will incorporate macroeconomic indicators. The goal of macroeconomic indicators is to ensure the economic stability of the country. There is no way to be sure that these indicators are reliable on their own, but they do have a role in shaping the economy. In the following section, we describe some indicators that will be used to simulate data for our estimation.

2.4.1 Leading indicators

House prices

The housing market is widely considered a leading indicator because the information can notify the state of the economy months in advance. A decline in housing prices suggests that the number of houses exceeds the number of people looking to buy. This could be because prices are inflated, or people simply cannot afford to buy. When the housing sector weakens, the entire economy feels it. The decline can have an impact on homeowner wealth, jobs in the construction sector, and taxes. It can also force homeowners into foreclosure - the process of lenders seeking to recover the mortgage loans from borrowers.

The number of building permits can be a leading indicator of economic health because companies will apply for these permits at least six months before they start construction. If new projects start, this is seen as an indication that these companies expect demand for homes to rise. If house construction starts to fall, then builders are more pessimistic about the future of the market.

2.4.2 Lagging indicators

GDP growth rates

Gross domestic product (GDP) is the monetary value of all goods and services produced in a country within one year and legally sold on the market. According to Helisek (2002), gross domestic product is the result of the functioning of production factors located in the given country, regardless of who is their owner. Products are converted to monetary value because it is not possible to add all final products in their physical form.

GDP is widely used to compare the differences between the two economies and forecast their growth. The economic indicator of GDP per capita is often used when monitoring the standard of living in the country. The rate of GDP growth is mostly given as a percentage, so it can reach both positive and negative variables. For the comparability of GDP with other countries, the resulting product must be converted from national currency to a common currency unit. For this conversion, purchasing power parity is used. Kadeřábková & kolektiv (2005) stated that purchasing power parity is a unit of currency conversion, which expresses the price ratio of the same goods and services in national currency to its price in the currency unit of the comparable country. The four components of GDP are personal consumption, business investment,

government spending, and net exports. However, the GDP indicator neglects the reality of the shadow and black economy, which represents a large part of the economic activity of all countries. This is the part of the economy which is not controlled by governments and is not taxable. The GDP indicator can be put on this base as inaccurate.

When GDP increases, it can have a knock-on effect on other macroeconomic indicators, such as employment rates, as companies take on more employees and increase manufacturing. If a country has a consistent GDP growth rate, it is a good sign that the economy is stable. However, rapidly growing GDP rates are often met with criticism. Some analysts argue that it is only too easy to manipulate GDP figures, with programmes such as quantitative easing or excessive government spending.

The Consumer Price Index and inflation

Inflation is the sustained increase in the price of goods and services in a country. Jurečka & Jánošíková (2004) defined inflation as a disturbance of the balance of basic macroeconomic variables, which is most evident in the rise in prices. It is a lagging indicator, as it is the result of economic growth or decline.

During periods of economic growth, there is likely to be an increase in inflation. A high rate of inflation can have a severe impact on the price of a country's currency, decreasing its purchasing power and making it more expensive for consumers to buy products – at least nominally. It can also have an impact on other macroeconomic indicators, as it can lead to decreases in employment and GDP growth. High inflation rates lead to rising interest rates, as governments attempt to get prices under control.

During periods of economic downturn, there can be declining levels of inflation or even 'deflation' - when inflation falls below 0%. This might sound positive, but it is confirmation that consumers have reduced their spending. This is often accompanied by reduced money supply, declining retail sales, and rising unemployment rates.

Inflation is measured by price indices. The best known and most used index is the Consumer Price Index (CPI), which monitors changes in prices of selected products and services in the consumer basket, such as transportation, food, and medical care. It is calculated by taking price changes for each item in the predetermined basket of goods and averaging them. Consumer basket inspections are carried out at intervals of 5 years, and this revision takes up to

3 years in some European Union countries. The CPI is calculated as *Cost of the market basket in a given year/Cost of the market basket at base X 100*.

Labour market statistics

Perhaps the most useful lagging indicator is the unemployment rate. It is one of the most important macroeconomic indicators with broad economic impacts and is closely related to GDP development. If the unemployment rate increases month-on-month over some time, it tends to indicate that the overall economy has been declining in health. If unemployment falls, it means that the country does not produce at the limit of its production possibilities. If employment rates fall, it means that businesses have finally given up hope that the situation will improve and have started to lay off their workers. Even once the economy is back on track, unemployment rates might not decline, because employers will always wait until they are sure the economy is growing before starting to employ new workers.

From a macroeconomic point of view, employment is divided into two groups. There is an economically active and economically inactive population. The economically inactive population includes people who do not seek work and are not even employed. This type of unemployment is often referred to as hidden unemployment. This group includes people who have lost interest in work, students, or householders. The economically active population includes people in working age, employed or actively looking for a job. Due to this division, we can determine the development of the labour market. This development is calculated as the number of the unemployed population divided by the economically active population.

All countries in the world are facing unemployment. The ideal labour market is one where there are no surpluses or shortages of labour. Unemployment is also closely linked to an increase in crime. The number of offences increases with the decreasing standard of living of the population, which is associated with loss of work. Unemployment also has social impacts. For unemployment longer than one year, there is a loss of human capital. It is associated with the loss of ability, experience, and practical and theoretical knowledge.

2.5 Mortgages

Ownership of an apartment or house is a dream of many people. They are often attracted by the vision that something belongs to them. Prices of houses and apartments are in millions. People must, therefore, count on a high one-off investment, which will return sooner or later in the form of acquired real estate. If we want to get our housing and we do not have the necessary finance, we have several options on how to get them. The most common option is a mortgage loan. The mortgage is a long-term loan, or lending of funds, the repayment of which is secured by collateral. Long-term character means the maturity from four to thirty years. In the report by OECD (2019b) is stated that mortgages are often over 25 years in Slovakia. Hence, borrowers are vulnerable to shocks, such as interest rate rises or loss of employment over a long period. The purpose for which the mortgage loan is granted is the acquisition of domestic real estate in the form of purchase, construction, and reconstruction (Revenda *et al.* 2017). The mortgage market is constantly expanding; the importance of mortgages is growing. Not only are young people interested in mortgages, but in recent years older people started to be interested in this type of loan too.

The availability of mortgage loans from the client's point of view is conditioned mainly by macroeconomic factors. The most important macroeconomic factors include unemployment rate, monthly income, real estate price, and interest rates. The volume of mortgage loans provided is influenced by GDP in the long term. The positive GDP coefficient confirms the view that economic growth has a positive effect on expected income and profits and thus on the overall financial situation of households. They can thus afford the greater debt. Equally, rising inflation causes an increase in demand for loans. The expected rise in prices leads the population to increase its propensity to consume and reduce its propensity to save.

2.6 Economic development in Slovakia

Slovakia's accession to the EU provided a positive impulse for further economic development. Slovakia has experienced record economic growth between 2014 and 2019, which is the result of reform measures from previous years, as well as a favourable development of the global economy, thanks to which investors are looking for other opportunities to invest in Slovakia. The economic development of Slovakia is affected by global economic developments, especially in the

EU and the euro area, the USA, and China. Not only is Slovakia benefiting from strong links with the world economy, but it has also been catching up with higher-income countries.

From 2014 to 2019, Slovakia's GDP performance has been strong; it grew on average by around 3.4% each year. Dudic *et al.* (2019) stated in their paper that the GDP growth was driven mainly by an increase in the production capacity of the economy, especially in sectors with inflows of foreign direct investment, which have helped develop a competitive export-led manufacturing industry, with a strong specialisation in the automotive and electronics sectors. The investment comes primarily from Austria, the Czech Republic, and Luxembourg. According to the European Commission, GDP grows mainly due to an increase in real wages, further increases in employment, and increased private consumption and consumer demand. Economic activity is supported by the automotive sector, which belongs to key industries in Slovakia.

Achieved economic growth positively influenced the labour market. Since 2014, favourable labour market developments have continued in the form of a decreasing unemployment rate that fell from 13.2% in 2014 to 5.8% in 2019. The value in 2019 was the lowest measured value of the unemployment rate since the Statistical Office of the Slovak Republic (SO SR) started to perform the survey. The decline in unemployment was so sharp that many employers had difficulty filling vacancies. According to Dudic *et al.* (2019), the sectors with the highest average increase in employment are information and communication activities, transport, storage, sales and repair of motor vehicles, selected market services, restaurant and catering activities and accommodation. For the period 2014 to 2019, the average wage increased on average by 5% every year. The national minimum wage per month in Slovakia went up by €168, from €352 in 2014 to €520 in 2019. Wages have been growing fast, and inflation has increased due to rising demand pressure and higher food and electricity prices. From 2014 to 2019, the average inflation rate in Slovakia was about 1.1% (2.66% in 2019).

The household loan market is slowly becoming saturated. Strong loan growth in recent years has led to an increase in the proportion of indebted people. In the most important age cohorts, more than 70% of people in employment have a loan (NBS 2019). About 80% of outstanding loans to households were for house purchase. The share of households with mortgages has increased in the medium- and high-income categories. While the share of households with mortgages grew fastest in the highest income decile in the past, this share also

rose for most medium- and low-income households between 2014 and 2019. House prices have risen in line with fundamentals, annually by around 5.3% between 2014 and 2019. Household credit growth has been fuelled by rising incomes and a fall in the cost of borrowing. These costs were quite significantly above the euro-area average until 2014 but have since fallen sharply to a level somewhat below the average (OECD 2019b). The saving rate increases with increasing income; therefore, the distribution of money savings remains unequal. The highest saving rates were recorded in the ninth and the tenth income deciles. In the other income deciles, they were much lower and below the overall rate. Slovakia's fiscal position is relatively powerful. General government debt has continued to decrease since 2014, and the budget deficit has shrunk to a historically low level (0.8% of GDP) due to strong growth and significant consolidation in 2017.

To sum it up, the economy is in a phase of strong, broad-based expansion. Nearly all indicators of well-being have been improving over the past five years. The growth in household income is being reflected in an increase in consumption and indebtedness and is being accompanied by a decline in the gross saving rate. Household incomes have risen in all income groups. Household net wealth has increased mainly due to growth in financial assets. Investment in housing has also risen amid growth in property prices. Household financial and non-financial assets grew at a higher rate than their financial liabilities. A similar trend in household net financial wealth can be observed in the euro area.

Based on the described positive economic development in Slovakia in the last five years, we assume that the asset position of households in our research has improved over this period. With an improved financial position, the risk of asset poverty could be reduced. Whether this is, indeed, the case will be explored in the following sections of this thesis.

Chapter 3

Overview of data collection

3.1 Data

In the analysis, the data from the Household Finance and Consumption Survey in Slovakia (HFCS) are used. These data were obtained under the European project HFCS which is coordinated by the ECB. The HFCS collects household-level data on households' finances and consumption. In terms of households, the survey covers private households that reside in the respective national territory, irrespective of the citizenship of their members, at the time the data are collected. Persons living in collective households and institutions are excluded from the target population.

The fieldwork for the first survey took place in late 2010/early 2011 in most countries of the Eurozone (except for Ireland and Estonia) and the second wave was implemented during 2014. Anonymised microdata from the first wave was made available to the researchers in 2013 whereas data from the second wave were released in 2016. The HFCS is primarily focused on gathering structural microeconomic data on household wealth and its components - financial assets, real assets, and liabilities. The survey also collects other information to analyse the economic decisions taken by households (e.g. household income, intergenerational transfers, selected categories of consumption and credit constraints, as well as demographic characteristics of surveyed individuals such as age, education, or occupational status). The survey aims to obtain reliable and comparable figures about the current economic situation of households in the Eurozone. The gained data are intended to help central banks with making important decisions on the monetary policy and the financial stability of the Eurosystem. The interest of central banks is also the increasing range of in-

debtedness of households, its distribution, and the impact of indebtedness on the economic situation and consumer spending of households.

The collection of the data in Slovakia was carried out by the Statistical Office of the Slovak Republic in collaboration with the National Bank of Slovakia (NBS). In the second wave of HFCS survey, 2,135 households participated out of a total of 4,200 households addressed. The main element of the survey is a household defined as a person living alone or a group of individuals sharing common expenses. According to Cupák & Strachotová (2015), the household may have more members but is characterised by a reference person. The reference member is described as the head of the family, which in this case is equal to the person with the financial information about the household. The survey was conducted in the form of personal interviews in respondents' homes. The interviews lasted one hour on average, and their length was based on the number of household members and the extent of their real and financial assets and liabilities. Households were chosen based on probability selection so that the sample of households is representative not only for Slovakia but also at the regional level.

The limitation of the study is the fact that the survey covers only private households and information on household wealth is based on self-assessment of respondents. Other limitations are missing data values. We will discuss this in the following section.

3.2 Imputation of missing values

The issue of missing values can be found in almost all datasets. In R, missing values are indicated by NA's. Missing values arise in data files for various reasons. The reason why we need to be concerned with missing values is the imperfection of used statistical programs when these programs assume a complete rectangular matrix. If any values are missing in a matrix, missing units are usually ignored, resulting in loss of information and distorted results.

In classical regression, R automatically excludes all cases in which any of the inputs are missing; this can limit the amount of information available in the analysis, especially if the model includes many inputs with potential missingness. This approach is called a complete-case analysis. There are various kinds of missing values, such as unrecorded, unknown or irrelevant, and various techniques to handle them.

We distinguish three main approaches on how to deal with missing values.

Nisbet *et al.* (2009) reported that one option on how to get rid of missing values is to exclude all incomplete records. However, the disadvantage of this approach is the generation of distorted (misleading) estimates that can occur in the case of a correlation between the missing data and the target variable. Pejčoch (2011) advises to perform data deletion only if we have a relatively low number of missing values with a maximum limit of 5% of the relative frequency for a given variable. The second possible approach is to process incomplete data with special methods. Nisbet *et al.* (2009) suggests replacing the missing data in justified cases rather than leaving the data blank. The third option is the replacement (imputation) of missing data and the subsequent processing of already complete data. This is the procedure where the missing values of one or more variables are filled in with substitute values.

We divide the imputation method into simple and multiple. For a simple imputation, we will replace each missing value with one generated value. Multiple imputation provides a useful strategy for dealing with data sets with missing values. Instead of filling in a single value for each missing value, Rubin (1987) wrote that multiple imputation procedure replaces each missing value with a set of plausible values that represent the uncertainty about the right value to impute. These multiply imputed data sets are then analysed by using standard procedures for complete data and combining the results from these analyses. No matter which complete-data analysis is used, the process of combining results from different imputed data sets is essentially the same. This results in valid statistical inferences that properly reflect the uncertainty due to missing values.

We created five datasets by using the multiple imputations method. The correct procedure would be now to conduct the analyses on each dataset individually and then to combine all analyses into the overall estimate by averaging. Taking into consideration the purpose of our study and the higher number of estimated models, we have decided to create for simplicity one dataset, where for each observation the values are calculated as arithmetic averages of the respective observations from five datasets created by multiple imputation. The research will be performed with this newly created dataset instead of employing analysis for each original dataset individually. We are aware that using this method may cause a slight distortion of our results.

3.3 Description of variables

In this section, we will describe all the relevant variables important for our analysis. To begin with, we will introduce the variables, which are used as the dependent variables in our models. Afterwards we will introduce the independent variables. We employ the variables commonly used in asset poverty researches. For each variable, we describe how it was adjusted and which macroeconomic indicators were used to obtain data from 2019. The development between 2014 and 2019 of all macroeconomic indicators employed in our study together with the data sources is in table 3.2. Descriptive statistics are disclosed in table 3.1 or discussed in the following sections. Variables and applied macroeconomic indicators were selected by the author's intuition and supervisor's proposals and confirmations in accordance with the usual conventions and literature.

We collected aggregated macroeconomic indicators according to which we simulate recent economic development. The purpose is that the modelled data correspond to the indicators in the mean value. The data are simulated for each household individually with using a standard normal distribution. As a result, if someone would replicate the method to obtain the data, moderately different results might be received.

3.3.1 Dependent variables

In the thesis, our attention will be primarily put on different types of household assets. Based on the literature review, we are using variables proposed by authors dealing with asset poverty described in detail in sections 2.3.1 and 2.3.2.

Net_wealth

This variable can be characterized by the formula:

$$Net_wealth = Real_assets + Fin_assets - Fin_liabilities. \quad (3.1)$$

In other words, total household assets are composed of total real and financial assets from which the value of total outstanding household liabilities is deducted. The value of net wealth does not include public and employee pension wealth. Since this variable is composed of three other variables, we will describe the procedure for modelling data for 2019 separately for each of these

three variables. The distribution of the variable is right-skewed; more than 70% of households do not reach the mean value.

Real_assets

Total real assets include the value of main household housing, other real estate, assets from business and self-employment, vehicles, and valuables. Similarly to *Net_wealth*, distribution is skewed to the right, and almost 70% of households own the real assets in less than the mean value. To model the 2019 data, we divided the data into main housing and other real estate and consumer durables. According to OECD (2013), consumer durables comprise motor vehicles, electrical appliances, furniture, clothing, and other goods that are expected to be used for more than a year. Instead of consuming durables immediately, the household is viewed as a producing entity that invests in those items as capital expenditure.

We mentioned in section 2.6 that house prices rose between 2014 and 2019; therefore, we use the property price development indicator to model 2019 data for the value of main household housing and other real estates. In the literature, we can read that there is a significant positive relationship between house prices and household (durable) consumption. Zhang (2019) stated in his paper that an increase in home values leads to an increase in household consumption for homeowners. Fornero *et al.* (2009) or Arrondel *et al.* (2015) reached similar conclusions in their studies. Using property price development increases the values of real estates. Therefore, household consumption and consequently, the value of consumer durables should be increased as well. Based on this assumption, we employ the household consumption indicator to model 2019 data for consumer durables.

Fin_assets

Total financial assets comprise deposits, mutual funds, bonds, shares, saving accounts, private loans, assets (dividends) from a business where the household is a silent partner or investors, voluntary pension plans and life insurance. Interestingly, for this variable is the value of the 3rd quartile almost the same as the mean value. Nearly 78% of households do not reach this value. The median value is two times lower than the mean value, to which values above €100,000 significantly contribute. To model 2019 data, we use quarterly financial accounts (QFAs) statistics for the household sector, specifically financial

assets. NBS (2009) description of the QFAs primary role is straightforward. The goal is to give a comprehensive picture of the financial flows within the national economy as well as in relation to foreign countries.

Fin_liabilities

Financial liabilities consist of the total outstanding balance of mortgages, non-mortgage loans, credit cards, unsecured loans, private loans, and other non-private and non-mortgage loans. Only 30% of all households have any financial obligations. As in the case of *Fin_assets*, we used QFAs for data simulation.

NW_HE

The variable was calculated as follows:

$$NW_HE = Net_wealth - home \quad (3.2)$$

where *home* is value of main housing. The procedure for modifying the *home* variable in order to obtain data from 2019 is explained in the description of the *Real_assets* variable. We can read from the table that the values for the 25th percentile are negative. For about a quarter of households thus applies that if the main housing value is taken away, the debts outweigh the value of remaining assets.

Period

A variable indicating the number of months in which the household would receive income from the monetisation of its entire assets into money. The creation of this variable was inspired by the studies described in section 2.3.2. The variable is formed by a formula:

$$Period = \frac{Real_assets + Fin_assets}{no_members * pov_line} \quad (3.3)$$

where *no_members* is the number of household members and *pov_line* indicates the income poverty line in Slovakia. If an individual's income falls below this amount, the individual is considered to be income poor. The poverty line in Slovakia was €341 in 2014 and €373 in 2019 (SO SR 2019).

3.3.2 Independent variables

no_members

The number of household members. This number is recalculated according to the OECD modified equivalence scale, which is commonly used in asset poverty researches. This scale was firstly proposed by Hagenaars *et al.* (1994) and assigns a value of 1 to the household head, of 0.5 to each additional adult member and 0.3 to each child. A child is defined as a person younger than 14 years old (Želinský 2014). As the rate of natural increase of population for Slovakia was on average 0.62 persons per thousand population per year between 2014 and 2019, we decided to keep the values for 2019 the same as for 2014. Given the size of our dataset and the total number of household members, the resulting difference would be less than four people which we consider insignificant.

no_empmembers

The number of employed household members. Because we know from section 2.6 that unemployment in Slovakia has fallen sharply in the last five years, we wanted to reflect this fact in our analysis. We utilise the declining unemployment rate to simulate data for 2019.

mortgage

The dummy variable which indicates whether the household has a mortgage or not. A mortgage is a sum of mortgages that households owe for all owned properties. Only 12.5% of households take out a mortgage. Despite the growing indebtedness of Slovak households, we decided to leave this variable unchanged for 2019 in order to assess better the situation of households with a mortgage in 2014 and 2019. Taking into account the average annual increase in newly concluded mortgages, we would add mortgage drawdown only to 2% of households in the whole dataset, which is a tiny share. Therefore, we assume that our observations will not be significantly affected.

loan

Drawing of a non-mortgage loan by households in the form of a dummy variable. Non-mortgage loans include outstanding balances on overdrafts, credit cards, overdrafts on credit cards for which the holder must pay interest, and

outstanding amounts on all other loans (leases on cars, consumer loans, private loans from relatives, employers, etc.). The number of households that take out a non-mortgage loan is about 8% higher than in the case of mortgages. Just 73 households draw on a mortgage and a non-mortgage loan simultaneously. Regarding the simulation of data for 2019, we proceed in the same way as for *mortgage*.

income

It is defined as the sum of the employment income of all household members in one year. Employment income is recorded for all household members from 16 years of age. The average wage increase in Slovakia was simulated by using nominal average wage indicator adjusted for inflation in 2019 data.

gender

Dummy variable that indicates the gender of the reference member. It holds values of 1 if the interviewed person is man, and 0 if the interviewed person is female. For 2019, the values do not change. Of the 2,135 households, 1,416 households have a male reference person.

age

Dummy variable representing the age of the reference person. Age is categorised according to Rothwell & Haveman (2013) and their study about asset poverty in Canada. However, due to the small number of reference persons under 25, we have decided to join this group into the *juniors* category.

- *juniors* – (<35), base variable
- *adults* – (35–49)
- *seniors* – (50–66)
- *retiree* – (>66)

In 2019, we attributed 5 years to each reference person, thus ensuring a movement in time. There are significant shifts between categories. Of the 144 members, only 59 remain in *juniors*. The category *adults* lowered by 101 members. The number of *seniors* decreased by 124 from 876 in 2014 to 752 in 2019. As the number of members in the first three categories declined, there must

be an growth in the last category. The number of reference persons in *retiree* increased by 310 to 919 members.

education

The highest completed education of the reference person. It is a dummy variable classified as:

- *primary* – primary education, our base variable
- *highschool* – lower secondary or second stage of basic education, upper and post-secondary education
- *university* – all stages of university education

Given that only 16 reference persons are under the age of 26, which is 0.7% of all households, we do not expect the distribution of education to change significantly. Based on this assumption, we keep the data for 2019 fixed. In total, 79% of reference persons in our dataset have a secondary education, and only about 20% of reference persons have a tertiary education. While the Slovak Republic's share of tertiary graduates has been steadily increasing over the past decade, the share remains lower than the OECD average. Only 37% of young adults (aged 25-34) have completed tertiary education, compared to 47% on average across OECD countries. A majority of those who pursue tertiary education receive master's degrees (OECD 2019a).

type

Household type which is categorized into following dummy variables:

- *single* – one adult, base variable (576 households)
- *noChildren* – two or more adults (862 households)
- *singleParent* – single parent with dependent children (78 households)
- *parents* – two adults with one or two dependent children (361 households)
- *moreChildren* – two adults with three or more dependent children (76 households)
- *generation* – three or more adults with dependent children (182 households)

Considering not that high importance of these variables in our research and difficulty to define an appropriate algorithm for shifting data to 2019, we will leave the data the same as in 2014.

Table 3.1: Descriptive statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Original data from 2014						
Net_wealth	77,143	232,946	−42,800	25,530	84,641	8,796,127
Fin_assets	6,980	13,436	−300	1,000	6,979	183,209
NW_HE	17,674	224,546	−102,269	−18	12,570	8,746,127
Period	145	429	0	53	163	17,197
age	57	14	21	47	67	99
income	13,809	8,118	350	10,680	17,241	168,000
no_members	2	1	1	1	2	5
no_empmem	1	1	0	0	2	5
Simulated data from 2019						
Net_wealth	87,202	263,718	−30,875	27,179	92,498	9,742,958
Fin_assets	10,727	20,773	−448	1,535	11,108	278,330
NW_HE	10,650	254,358	−260,401	−25,238	10,912	9,678,884
Period	195	485	0	85	221	19,080
age	62	14	26	52	72	104
income	17,553	10,426	425	13,512	22,576	211,924
no_members	2	1	1	1	2	5
no_empmem	1	1	0	0	2	5

Table 3.2: Development of macroeconomic indicators in %

Statistic	2015	2016	2017	2018	2019	Source
GDP	4.2	3.1	3.2	4.1	2.4	NBS
Inflation rate	−0.3	−0.5	1.3	2.5	2.7	NBS
Unemployment	1.7	1.9	1.5	1.6	0.7	NBS
Nominal average wages	2.9	3.3	4.6	6.2	7.8	NBS
Household consumption	2.8	3.9	4.4	3.9	2.7	SO SR
Property price development	1.7	4.9	6.7	5.5	7.5	NBS
Financial assets	9.0	9.5	11.1	8.6	6.7	NBS
Financial liabilities	6.5	8.4	5.9	6.0	5.6	NBS

Looking at table 3.1, we can see that the values of all changed variables increased in 2019. It corresponds to the fact that Slovakia had very positive economic development in the last five years, which is evident also from table 3.2. The data for 2019 were modelled using the “rnorm” function in R Studio. The values for the standard deviation were calculated from the development of individual macroeconomic indicators over the last 15 years.

Chapter 4

Detailed description of the research

4.1 Empirical research background

4.1.1 Cross-sectional data formulation

Model selection should always consider the data format, the purpose of the study, and the nature of the experiment. Our data was collected at a particular point of time and represents only a one-time period, which means we work with cross-sectional data. The most commonly used method for this type of data is the Ordinary Least Square (OLS). If we assume linear dependencies between a dependent variable and independent variables, we can write the typically used general model as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + u, i = 1, 2, \dots, n. \quad (4.1)$$

where

y is dependent variable,

β_0 represents the so-called absolute element or level constant,

β_i is the i -th regression coefficient or parameter,

$i = 1, 2, \dots, k$ represents the number of independent variables in the model,

x_i stands for independent variables and

u is the disturbance or error term.

We do not know the coefficients of the regression equation or the parameters

of the error term, so we must be satisfied with their estimates obtained from the sample data. The model for i -th observation is written as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + u_i, i = 1, 2, \dots, n. \quad (4.2)$$

Regression using the OLS is an efficient method but cannot be done without verifying its assumptions. According to Wooldridge (2013), the results of the cross-sectional model are valid only if the Gauss-Markov (MLR) assumptions, such as linearity, constant variance, etc., for a classical linear model are met. We can rely on our results without any further consideration only when these conditions are verified. More details on MLR assumptions and their verification are attached in Appendix B.

4.1.2 Quantile regression

Our dependent variables contain outliers, so the least squares method is not the most appropriate estimation method. We have decided to keep outliers in the data because removing them could skew our results and we would lose information about the wealthiest households. OLS regression method measure differences in outcome variables between populations at the mean, after adjustment for other explanatory variables of interest. These are often done assuming that the regression coefficients are constant across the population. In other words, the relationships between the outcomes of interest and the explanatory variables remain the same across different values of the variables (Cook & Manning 2013). In OLS regression, the goal is to minimise the distances between the values predicted by the regression line and the observed values. In contrast, quantile regression (QR) differentially weights the distances between the values predicted by the regression line and the observed values, then tries to minimise the weighted distances (Koenker & Bassett 1978).

The main advantage of QR methodology is that the method allows for understanding relationships between variables outside of the mean of the data, making it useful in understanding outcomes that are non-normally distributed. It includes distant values, and we can estimate any quantile of a dependent variable, which will allow us to get greater robustness of our estimate. Also, QR makes no assumptions about the distribution of the residuals. An analysis of the properties between dependent and independent variables can be richer and more understandable as we are not only focused on the conditional averages. According to Huang *et al.* (2017), QR models could not only be used to detect

heterogeneous effects of covariates at different quantiles of the outcome but also offer more robust and complete estimates compared to the mean regression, when the normality assumption is violated or outliers, and long tails exist.

QR applied to broad application areas such as investment, finance, economics, medicine, and engineering. Many opportunities for using quantile regression exist in the literature. For example, Girma & Görg (2005) used QR modelling to explore the relationship between foreign direct investment and economic growth. Chernozhukov & Hansen (2004) examined wage structure and wealth distribution using QR. Melly (2005) conducted research to explore the gap in wage and wealth distribution. Martins & Pereira (2004) dealt in his paper with the impact of education on wage.

Although mean regression-based methods still dominate the statistical modelling field, QR can be viewed as a critical extension and complement when assumptions are violated. Therefore, we have decided to employ QR in our study, and we will carry out QR using the “quantreg” package in R Studio (Koenker 2013).

4.1.3 Robust standard errors

In order to present the reliable results of our empirical research, we need to ensure that estimators of coefficients and estimators of the variances are unbiased and consistent. We employed several tests to help us decide which methods are the most appropriate and what we need to control for when running regressions. A detailed description and test results are attached in Appendix C.

The tests revealed the heteroscedasticity and non-normality. Although heteroscedasticity does not produce biased OLS estimates, it leads to a bias in the variance-covariance matrix. The calculation of robust standard errors can help to mitigate this problem. The standard errors determine how accurate is our estimation. The asymptotic variance of an estimate of the classical linear regression model is defined as:

$$Var[\hat{\beta}|X] = (X'X)^{-1}X'(\sigma^2\Omega)X(X'X)^{-1} \quad (4.3)$$

Under homoscedasticity, $\Omega = I$, and in such case the $Var[\hat{\beta}|X] = \sigma^2(X'X)^{-1}$. However, under heteroscedasticity, $\Omega = I$ does not hold, and a different definition of standard errors is necessary. Several heteroscedasticity-robust standard errors were proposed in the literature due to the properties of our data sample,

the most commonly employed White heteroscedasticity-consistent standard errors (White 1980) may be useful.

4.2 Empirical models

In this section, we focus on the introduction of our models which will help us to investigate whether the macroeconomic development in Slovakia over the past five years had any effect on asset poverty, which variables affects asset poverty the most and whether the households which had a mortgage five years ago are in a better or worse position now. As mentioned earlier in this chapter, we will employ the ordinary least squares method (4.1.1) and quantile regression (4.1.2) to estimate our models.

We will deploy several different models to get the best picture of the household asset poverty situation in the difference of five years. We have decided to test four various models, each in four variations. All models will be estimated twice, once with the survey data from 2014 and the second time with the data modelled according to the development of macroeconomic indicators from 2014 to 2019.

In the first three models, the dependent variables are created according to the definitions from the measurement of asset poverty (2.3.1). In Model 1 we examine the effects and relationships of all independent variables on household net wealth (the total value of household assets minus the total value of outstanding household liabilities). In Model 2, liquid assets defined in the measurement of asset poverty are represented by household financial assets. The dependent variable from Model 3 represents household net wealth excluding the value of main household housing. In Model 4 we aim to analyse relationships and connections between the independent variables and the total value of household assets as described in section 2.3.2.

In the models mentioned above, we try to utilise the knowledge gained in the theoretical part of this study. The difference is between the formula used in section 2.3.2 and the formula based on which we created our dependent variable in Model 4. The formula in section 2.3.2 should be used in a way that the asset can be expressed as a discounted lifetime income. In other words, when a household sells all its real and financial assets, it earns money from it. This money will be deposited in a bank or another institution and will be paid monthly to the household in equal amounts. Money paid should be adjusted for expected inflation every year, which we did not deal with because

of the focus and scope of this thesis. Our goal is to identify developments in household asset poverty; we are not interested in the exact amount which the individual households would receive; therefore, it is not necessary to have inflation-adjusted amounts.

An overview of our models is presented in table 4.1. An overview of models in the text form is attached in Appendix D.

Table 4.1: Overview of our models

	Model 1				Model 2				Model 3				Model 4			
<i>Dependent variable</i>	<i>Net_wealth</i>				<i>Fin_assets</i>				<i>NW_HE</i>				<i>Period</i>			
<i>Variation</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>
adults	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓
seniors	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓
retiree	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓
income	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓
no_empmembers	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓
no_members	✓				✓				✓				✓			
gender	✓				✓				✓				✓			
mortgage	✓		✓	✓	✓		✓	✓	✓		✓	✓	✓		✓	✓
loan	✓			✓	✓			✓	✓			✓	✓			✓
highschool	✓				✓				✓				✓			
university	✓				✓				✓				✓			
no_children	✓				✓				✓				✓			
singleparent	✓				✓				✓				✓			
parents	✓				✓				✓				✓			
morechildren	✓				✓				✓				✓			
generation	✓				✓				✓				✓			

When it comes to variations, firstly, we start with the variation in which all independent variables are included. Then we incorporate only those variables whose values have been changed by modelling using macroeconomic indicators. In the third variation, we perform regression in which the independent variables are represented only by drawing a mortgage. Finally, our last variation is the combination of the second variation and household mortgage and non-mortgage loans.

Given models differ by dependent variables. Variations remain the same for all four models. Independent variables are mainly represented by demographic data (age, gender, education, income, etc.), which are commonly used when measuring asset poverty. Possible improvement of the models could be made by incorporating other independent variables, such as place of residence or job position. Unfortunately, we are not able to get this information from our dataset.

The coefficients in the models are interpreted as the amount by which the dependent variable increases or decreases when the independent variable is

increased by one unit. This interpretation does not apply to dummy variables. Their coefficient tells us how much the dependent variable increases or decreases compared to the variable we used as the base variable.

We are aware that the use of log-transformed variables in our regression models would be more suitable for comparing the impact of our independent variables on our dependent variables between 2014 and 2019. In addition, a log transformation could reduce the influence of outliers. However, the log transformation is only applicable when all the observations in the dataset are positive, which is not our case. Our observations contain negative values, so we use the linear model with no transformations.

Chapter 5

Evaluation of the results

In this chapter, we present and discuss the results of OLS and quantile regression estimates for all models specified in section 4.2. Unless stated otherwise, we usually use a 10% level of statistical significance to interpret the results. Mathematical software R for statistical computing and graphics is used to estimate models.

5.1 Results obtained by the OLS method

We start with Modella (see table 4.1 and section 4.2 for detailed description), the results can be found in the table 5.1. Looking at the age category coefficients, we can see that all of them increased in 2019 compared to 2014 and are statistically significant. It is evident that with the increasing age of the reference person, the net wealth of a household increases. It is not surprising, because with increasing age people tend to accumulate assets, and their liabilities decrease. For example, retired people usually paid off their mortgages already. The *income* became statistically significant at a 10% level in 2019. The sign of the coefficient is as expected because net wealth usually grows with higher income. However, its effect on net slightly diminished, which is remarkable when taking into account that the average wage has increased. The coefficients representing the number of household members and the number of employed household members rose but stayed statistically insignificant. Being a man as a reference person increases the net wealth of a household by €3,500 more in 2019 than in 2014. In our original data sample, men have on average higher net wealth than women, therefore improving economic situation has a greater effect on them which could explain our result.

Table 5.1: Estimation results of Model1a & Model1b

	<i>Dependent variable:</i>			
	Net_wealth		Net_wealth_19	
	Model1a	Model1b	Model1a	Model1b
adults	22,539.150** (9,352.447)	19,796.580*** (7,335.234)	29,407.360** (13,842.740)	24,096.740** (11,367.000)
seniors	45,651.420*** (9,440.989)	43,620.610*** (8,542.059)	58,057.520*** (14,353.770)	51,466.050*** (12,781.900)
retiree	54,489.900** (21,952.670)	44,868.680** (17,456.280)	69,906.930*** (17,700.830)	57,401.060*** (15,051.730)
income	3.744 (2.475)	4.573** (2.317)	3.611* (2.160)	4.297** (2.052)
no_empmembers	12,027.880 (9,734.690)	15,942.480** (7,734.787)	13,563.220 (12,047.930)	18,927.580** (9,084.621)
no_members	1,363.853 (10,062.670)		2,495.498 (11,851.930)	
gender	14,081.740* (8,258.191)		17,584.440** (7,567.610)	
mortgage	-8,222.717 (8,088.875)		-8,725.757 (9,859.356)	
loan	-13,023.840** (6,071.223)		2,235.255 (7,473.869)	
highschool	18,688.160** (8,306.552)		14,567.650 (9,987.863)	
university	91,748.910*** (29,770.230)		96,989.430*** (29,636.470)	
nochildren	32,138.710** (14,631.910)		26,824.860 (16,660.660)	
singleparent	37,345.790** (15,308.210)		37,575.080** (17,868.330)	
parents	13,684.080 (16,137.240)		10,816.620 (19,744.950)	
morechildren	27,499.950 (25,243.650)		23,570.760 (30,541.830)	
generation	11,939.090 (28,474.720)		2,868.642 (33,703.710)	
Constant	-85,726.960*** (28,528.180)	-36,913.590* (22,039.140)	-106,034.400*** (31,104.290)	-52,707.480** (24,610.910)
Observations	2,135	2,135	2,135	2,135
R ²	0.059	0.037	0.060	0.040
Adjusted R ²	0.052	0.035	0.053	0.038
Residual Std. Error	226,807.500 (df = 2118)	228,826.700 (df = 2129)	256,667.200 (df = 2118)	258,644.400 (df = 2129)
F Statistic	8.317*** (df = 16; 2118)	16.505*** (df = 5; 2129)	8.428*** (df = 16; 2118)	17.909*** (df = 5; 2129)

Notes: The table reports the results of the OLS estimation with the response variable *Net_wealth*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

The negative and statistically insignificant coefficient of *mortgage* almost has not changed in this model, so having a mortgage did not affect net wealth in any of two periods. The biggest change between 2014 and 2019 is for non-mortgage loans borrowers. The coefficient changed its sign and became small and insignificant. A possible explanation could be that as the economic situation improves, household assets and incomes increase, which may outweigh and reduce the importance of non-mortgage loans. In terms of education, the situation became better for the reference persons with a university degree by €5,240 in 2019 compared to persons with primary education. This does not hold for the reference persons with high school education as the coefficient decreased by more than €4,000 and is insignificant now. Of the different types of households, the situation has improved only for households where a single parent lives with a child. Unfortunately, we do not have any economic explanation for this result so we will take a look at these variables in more detail in other models.

It is visible from the table 5.1 that all variables are statistically significant at least at 5% level in Model1b. Age categories follow the same trend as in Model1a. The coefficient for income slightly declined as in the previous model. If we take a deeper look at table 3.2 showing the development of macroeconomic indicators over the last five years, we can see that financial assets grew far more considerably than average wages ¹ and household consumption grew at similar or mildly lower level. This could lead to a reduction in the impact of income on net wealth. However, this issue might be more complex.

We continue our analysis with Model1c and Model1d (5.2). In Model1c we use *mortgage* as the only independent variable. Even though the coefficient increased between 2014 and 2019, it is statistically insignificant (negative adjusted R^2 means insignificance of explanatory variables as well). Unlike Model1a and Model1b, the coefficient is positive, which would mean that having a mortgage increases net wealth. From a purely economic point of view, this would be improbable because we know that any liabilities reduce the value of net wealth. We consider this model poor.

In Model1d, the coefficient for *mortgage* has expected sign, i.e. negative. Nevertheless, it has remained statistically insignificant. So the mortgage drawing affected neither the value of net wealth in 2014 nor the value in 2019. *Loan* coefficient follows the same pattern as in Model1a - it became insignificant. In 2014, the drawing of a non-mortgage loan reduced the value of net wealth

¹applies to years 2015-2018

by €20,621, which is not the case for 2019. For age variables apply again that economic development favours older people. The difference between *retiree* and *juniors* is by €16,588 larger in 2019 than it was in 2014. If one more member in a household is employed, the household net wealth increases by €2,250 more in 2019 than in 2014. The reason for growth might be more complex as we do not know if it is the effect of an increase in the nominal wage or the fact that unemployment declined from 13.2% in 2014 to 5.8% in 2019.

Table 5.2: Estimation results of Model1c & Model1d

	<i>Dependent variable:</i>			
	Net_wealth		Net_wealth_19	
	Model1c	Model1d	Model1c	Model1d
mortgage	7,574.126 (7,969.330)	-5,229.466 (8,476.530)	11,278.260 (9,204.136)	-3,824.011 (10,304.920)
loan		-20,621.320*** (6,436.057)		-5,267.215 (8,359.185)
adults		19,507.440** (7,628.690)		24,525.720** (11,225.230)
seniors		40,849.360*** (8,297.637)		50,666.540*** (12,722.410)
retiree		39,391.470** (17,396.420)		55,978.790*** (14,807.580)
income		4.544* (2.324)		4.294** (2.059)
no_empmembers		17,236.270** (7,842.419)		19,488.010** (9,329.113)
Constant	76,202.650*** (5,699.823)	-30,152.420 (21,167.400)	85,801.880*** (6,447.211)	-50,787.010** (24,250.540)
Observations	2,135	2,135	2,135	2,135
R ²	0.0001	0.039	0.0002	0.040
Adjusted R ²	-0.0004	0.035	-0.0003	0.037
Residual Std. Error	232,987.300 (df = 2133)	228,790.300 (df = 2127)	263,753.600 (df = 2133)	258,755.500 (df = 2127)
F Statistic	0.245 (df = 1; 2133)	12.176*** (df = 7; 2127)	0.424 (df = 1; 2133)	12.806*** (df = 7; 2127)

Notes: The table reports the results of the OLS estimation with the response variable *Net_wealth*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

In Model 2, we study the effect of independent variables on household financial assets. The results for Model2a and Model2b are enclosed in the table 5.3. In Model2a, out of all independent variables, only age dummy variables, *income*, *loan* and *university* are statistically significant. Interestingly, household type, gender, mortgage, or the number of members do not influence the value of household financial assets. Income is highly statistically significant in this model, however, the coefficient size is not much greater than zero. We find it surprising, as it might seem that income would have a major impact on financial assets, which proved to be untrue.

Table 5.3: Estimation results of Model2a & Model2b

	<i>Dependent variable:</i>			
	<i>Fin_assets</i>		<i>Fin_assets_19</i>	
	Model2a	Model2b	Model2a	Model2b
adults	1,783.977* (920.284)	1,593.686* (893.595)	2,978.445* (1,535.003)	2,106.078 (1,414.860)
seniors	2,198.911* (1,127.773)	1,638.499** (780.852)	5,403.517*** (1,541.940)	4,142.668*** (1,345.579)
retiree	2,176.929* (1,237.764)	1,203.625 (853.736)	5,691.207*** (1,714.273)	3,793.604*** (1,420.594)
income	0.335*** (0.104)	0.413*** (0.100)	0.397*** (0.125)	0.488*** (0.122)
no_empmembers	417.880 (373.255)	761.126** (336.131)	825.052 (705.019)	1,473.926** (626.970)
no_members	629.308 (858.151)		938.768 (1,368.645)	
gender	770.938 (644.806)		1,270.822 (973.798)	
mortgage	-1,767.158 (1,234.405)		-2,632.992 (1,906.340)	
loan	-1,198.184 (765.161)		-1,910.944* (1,124.978)	
highschool	-1,257.284 (824.671)		-1,738.985 (1,188.589)	
university	5,653.305*** (1,230.649)		9,062.716*** (1,842.534)	
nochildren	1,118.668 (710.910)		1,724.049 (1,128.096)	
singleparent	-349.964 (1,168.387)		216.159 (1,741.133)	
parents	1,683.715 (1,403.326)		3,199.205 (2,081.859)	
morechildren	1,835.568 (3,259.787)		3,089.882 (4,671.328)	
generation	-27.960 (1,929.871)		-135.104 (3,050.881)	
Constant	-2,065.428 (1,903.225)	-864.230 (1,231.090)	-5,439.221* (2,824.823)	-2,657.884 (1,886.978)
Observations	2,135	2,135	2,135	2,135
R ²	0.125	0.076	0.126	0.075
Adjusted R ²	0.118	0.073	0.120	0.073
Residual Std. Error	12,618.500 (df = 2118)	12,933.810 (df = 2129)	19,489.100 (df = 2118)	19,999.330 (df = 2129)
F Statistic	18.850*** (df = 16; 2118)	34.814*** (df = 5; 2129)	19.151*** (df = 16; 2118)	34.658*** (df = 5; 2129)

Notes: The table reports the results of the OLS estimation with the response variable *Fin_assets*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

Another interesting fact is that both senior and retiree positions improved by more than €3,000 in 2019 compared to juniors. The same applies to the reference persons with a university degree. This could mean that the current economic situation has brought many more resources to secure financial assets to people over 50 with a university degree. Having a loan worsens the value of financial assets by €700 more in 2019 than in 2014.

The result of Model2b estimation, where we included only age categories, income, and the number of employed members, shows that the influence of another employed household member on financial assets doubled. We got the same results in Model2a as well, but it was not statistically significant. In this model, the situation of senior people is better for the first time than that of retirees. However, the difference is not so great.

The variable *mortgage* proved again to be statistically insignificant in Model2c. The negative adjusted R^2 indicates that *mortgage* does not affect the dependent variable on its own and more independent variables should be included in the regression.

The results presented in table 5.4 for Model2d are similar to those in Model2a. It is worth mentioning variable *loan* because this time it is significant at a 5% level. Having a loan in 2019 worsens the value of financial assets by €898 more than in 2014. This is an important difference and the intuition behind it is that while the economic situation of most people is improving and they gain more resources which can be invested into financial assets, people with loans have to repay their debt instead of expanding their assets. So the difference between these people is widening, and the impact of the loans becomes more serious.

Table 5.4: Estimation results of Model2c & Model2d

	<i>Dependent variable:</i>			
	Fin_assets		Fin_assets_19	
	Model2c	Model2d	Model2c	Model2d
mortgage	640.901 (1,141.890)	-1,263.317 (1,296.925)	739.813 (1,644.676)	-1,608.587 (1,983.093)
loan		-1,830.362** (811.414)		-2,728.156** (1,178.839)
adults		1,523.506* (899.539)		2,290.291 (1,473.344)
seniors		1,199.840 (918.578)		3,779.359*** (1,456.737)
retiree		522.335 (1,003.795)		3,119.913** (1,527.484)
income		0.412*** (0.100)		0.486*** (0.122)
no_empmembers		927.726*** (324.358)		1,739.400*** (624.001)
Constant	6,900.189*** (292.714)	-92.945 (1,274.229)	10,635.270*** (461.801)	-1,715.636 (1,914.447)
Observations	2,135	2,135	2,135	2,135
R ²	0.0002	0.079	0.0001	0.078
Adjusted R ²	-0.0002	0.076	-0.0003	0.075
Residual Std. Error	13,437.880 (df = 2133)	12,915.730 (df = 2127)	20,776.400 (df = 2133)	19,975.060 (df = 2127)
F Statistic	0.528 (df = 1; 2133)	26.074*** (df = 7; 2127)	0.294 (df = 1; 2133)	25.842*** (df = 7; 2127)

Notes: The table reports the results of the OLS estimation with the response variable *Fin_assets*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HCO scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

As has been already mentioned in Chapter 4, in Model 3, we test the effect of independent variables on the value of net wealth without the value of the main housing. As we can see from the table 5.5, the results of Model3a are quite different from the results of Model1a and Model2a. Our attention was caught by *mortgage* variable. It is statistically significant for the first time in our analysis, even on a 1% significance level. This result is meaningful. In most households, the main housing represents a large part of their assets. Therefore, families with limited budgets invest mainly in this real estate, and they do not have many resources left to accumulate other assets. So we can see that if we subtract the value of the main housing from net wealth, this wealth becomes weakened by the payment of a mortgage. And in the current economic situation, this wealth becomes weakened by the mortgage even more, as the drawing of the mortgage reduces the value of the net wealth by almost €5,000 more in 2019 than it reduced in 2014. It is also surprising that, compared to other models, the position of retirees improved only slightly (less than €2000) between years, and the advantage of people with a university degree even dropped by €4,000.

Table 5.5: Estimation results of Model3a & Model3b

	<i>Dependent variable:</i>			
	NW_HE		NW_HE_19	
	Model3a	Model3b	Model3a	Model3b
adults	18,197.260** (8,361.555)	17,562.680*** (6,560.094)	18,265.110 (13,435.350)	12,540.150 (10,948.100)
seniors	38,831.820*** (8,515.321)	44,068.070*** (7,864.540)	44,599.730*** (13,874.250)	47,213.190*** (12,229.220)
retiree	44,656.690** (21,172.180)	45,293.920*** (16,799.950)	46,254.420*** (17,240.740)	48,077.900*** (14,513.480)
income	3.153 (2.265)	3.773* (2.136)	3.137 (1.966)	3.619* (1.884)
no_empmembers	7,125.679 (9,115.123)	9,787.957 (7,165.731)	4,260.235 (11,431.860)	8,738.638 (8,478.094)
no_members	4,625.613 (9,123.527)		10,989.640 (10,926.500)	
gender	10,300.500 (8,007.016)		10,566.280 (7,298.380)	
mortgage	−19,664.080*** (7,090.841)		−24,637.730*** (8,955.187)	
loan	−14,706.640*** (5,465.138)		149.893 (6,997.976)	
highschool	−769.653 (7,222.182)		−8,645.341 (8,594.222)	
university	56,005.570* (29,197.210)		52,827.100* (28,871.080)	
nochildren	25,534.350* (14,158.410)		17,813.260 (16,135.590)	
singleparent	27,592.230** (14,053.910)		18,595.690 (16,129.150)	
parents	3,906.428 (14,970.190)		−7,786.903 (18,449.360)	
morechildren	13,216.940 (22,083.120)		−5,793.713 (26,705.330)	
generation	6,747.140 (26,632.060)		−7,204.776 (31,684.480)	
Constant	−98,771.810*** (26,352.320)	−79,105.420*** (20,304.170)	−119,747.100*** (28,761.290)	−100,469.000*** (22,841.510)
Observations	2,135	2,135	2,135	2,135
R ²	0.042	0.026	0.041	0.028
Adjusted R ²	0.034	0.024	0.033	0.026
Residual Std. Error	220,637.600 (df = 2118)	221,824.700 (df = 2129)	250,075.800 (df = 2118)	251,005.700 (df = 2129)
F Statistic	5.767*** (df = 16; 2118)	11.537*** (df = 5; 2129)	5.606*** (df = 16; 2118)	12.475*** (df = 5; 2129)

Notes: The table reports the results of the OLS estimation with the response variable *NW_HE*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

Variables representing different household types lost their significance in 2019, so recent developments have eradicated the differences in the contribution of the different types of households to the value of net wealth. Last but not least, the *loan* variable became statistically insignificant, although it had a major impact on the depreciation of net wealth in 2014. It seems that with increasing incomes and household consumption, drawing on a non-mortgage loan has become non-influencing the accumulation of the household net wealth (without the value of the main housing).

In Model3b, we would like to mention the fact that the coefficient of the dummy variable *adults* was highly statistically significant in 2014 and is insignificant now. Being a reference person in adult age increased household net wealth by €18,197 more than being in junior age in 2014. In 2019, the position of junior and adult reference persons in terms of the net wealth value is the same.

When it goes to Model3c, we can see that *mortgage*, as the only independent variable in our model, is statistically significant at a 10% significance level. Similarly to Model1a, drawing a mortgage reduces household net wealth by €3,520 more in 2019 than in reduced in 2014. Creating variation *c* in the models was therefore not entirely unnecessary.

From table 5.6 is obvious that the results from Model3d are coincident with the results from Model3a. The effects of all the variables involved in this model on household net wealth remained similar. The only minor difference is that people in senior age are slightly in a better position concerning net wealth than retired people. However, the difference between these two groups has considerably diminished over the past five years.

Table 5.6: Estimation results of Model3c & Model3d

	<i>Dependent variable:</i>			
	NW HE		NW HE_19	
	Model3c	Model3d	Model3c	Model3d
mortgage	−11,746.890* (6,861.468)	−18,099.790** (7,331.300)	−15,267.980* (8,152.038)	−22,298.940** (9,213.847)
loan		−20,462.190*** (5,757.212)		−5,114.170 (7,780.296)
adults		16,536.430** (6,829.113)		14,853.790 (10,877.510)
seniors		38,103.990*** (7,553.733)		43,899.420*** (12,170.570)
retiree		36,579.210** (16,665.810)		43,551.130*** (14,242.350)
income		3.769* (2.137)		3.642* (1.885)
no_empmembers		11,900.880 (7,264.314)		10,521.810 (8,703.235)
Constant	19,132.190*** (5,515.982)	−69,501.450*** (19,416.370)	12,545.580** (6,238.074)	−95,983.730*** (22,453.520)
Observations	2,135	2,135	2,135	2,135
R ²	0.0003	0.028	0.0004	0.029
Adjusted R ²	−0.0002	0.025	−0.0001	0.026
Residual Std. Error	224,565.400 (df = 2133)	221,724.800 (df = 2127)	254,367.400 (df = 2133)	251,028.000 (df = 2127)
F Statistic	0.635 (df = 1; 2133)	8.808*** (df = 7; 2127)	0.836 (df = 1; 2133)	9.141*** (df = 7; 2127)

Notes: The table reports the results of the OLS estimation with the response variable *NW_HE*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

When observing the results of the first three models, we can notice that for some variations, the intercept in 2019 decreased considerably. Even though some coefficients increased in 2019 compared to 2014, the decline of the intercept could outweigh this effect. In order to verify the real impact of economic development on a given household asset, we created sample household types, for which we calculated the actual effect. As one typical household, we chose a household in which two adults live; a reference person is a man aged 57 (in 2014) with a secondary education who receives an average income. The other person also receives an average income, and the household draws a non-mortgage loan. This household is compiled based on average and most frequently repeated values in our dataset. Recent economic development might reduce the threat of asset poverty for this household according to the measurement definitions used in Model1 and Model2.

Unlike the first three models, our dependent variable does not represent any form of asset in Model4 but the period for which the household would receive the income from monetising its entire assets. From the results (table 5.7) we can see that the income payout period grows with the increasing age of the reference person. If the household reference person is someone aged 35-50, the period increases by 58 months in 2019, which is almost twice as much as in 2014. For seniors, it is 89 months more and for retirees even 110 months more. We are talking about a comparison with a situation where a reference person is a person under the age of 35. In 2014, these figures were substantially smaller, 68 months for seniors, and 87 months for retirees. In this model, we assume that income would be paid out until fully depleted. As the differences between years were similar for all age categories, we can suspect that economic development between 2014 and 2019 did not favour any age category. Although income became significant at 10% level, the value of the coefficient has not changed and stayed close to zero. We consider this result to be correct because the payout period is based purely on household assets, and income should not affect it. The same applies to the number of employed household members. On the other hand, each additional household member reduces this period by 59 months in 2019, which is 10 months more than in 2014. The increase is likely to be due to the growth in the monthly payment per household member, driven mainly by an increase in the income poverty threshold each year. It is interesting that *gender* coefficient got statistically significant and increased by 4 months. Unfortunately, it is not easy to figure out the economic reasoning for why the income payout period for households with a man as a reference person has been extended. While having a loan did not affect the income period in any of the examined years, a mortgage significantly increased this period in 2014. In 2019, this variable was no longer statistically significant. From dummy variables representing the various type of education is observable that people who graduated from the university could enjoy receiving income for more than 12 years longer than people with primary education. In 2014, this period was 10 months longer, which indicates that even though people with a university degree are strongly favoured, economic development has slightly reduced their advantage. Households without children or households with only one parent had a longer income period compared to households where an only single person lives, but this effect has been minimised over the years since we have all household type coefficients insignificant in 2019.

Table 5.7: Estimation results of Model4a & Model4b

	<i>Dependent variable:</i>			
	Period		Period_19	
	Model4a	Model4b	Model4a	Model4b
adults	32.030** (15.510)	2.266 (13.111)	58.697*** (20.645)	19.825 (17.711)
seniors	68.321*** (16.249)	48.098*** (15.105)	89.325*** (21.367)	58.564*** (19.672)
retiree	87.091** (40.010)	53.738* (31.622)	110.541*** (28.186)	74.187*** (24.116)
income	0.005 (0.004)	0.007** (0.003)	0.005* (0.003)	0.006** (0.003)
no_empmembers	15.470 (15.026)	5.205 (11.203)	15.807 (17.537)	-4.690 (12.424)
no_members	-49.964*** (14.069)		-59.177*** (15.403)	
gender	23.605 (15.329)		27.743** (12.758)	
mortgage	34.680*** (12.491)		22.072 (14.002)	
loan	-11.108 (10.102)		-8.507 (11.529)	
highschool	32.933* (17.119)		17.339 (17.645)	
university	165.739*** (56.889)		155.037*** (51.130)	
nochildren	46.590* (26.961)		17.245 (27.999)	
singleparent	44.891* (26.922)		17.499 (27.459)	
parents	5.396 (24.594)		-23.329 (26.995)	
morechildren	29.603 (34.887)		-1.496 (38.336)	
generation	15.929 (41.922)		-14.909 (45.201)	
Constant	-20.053 (46.199)	5.500 (32.295)	22.388 (44.567)	14.661 (33.202)
Observations	2,135	2,135	2,135	2,135
R ²	0.044	0.022	0.047	0.024
Adjusted R ²	0.037	0.019	0.040	0.022
Residual Std. Error	421.479 (df = 2118)	425.312 (df = 2129)	434.379 (df = 2118)	438.538 (df = 2129)
F Statistic	6.098*** (df = 16; 2118)	9.363*** (df = 5; 2129)	6.596*** (df = 16; 2118)	10.511*** (df = 5; 2129)

Notes: The table reports the results of the OLS estimation with the response variable *Period*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

The results of Model4b show statistical insignificance of variable *adults*. Thus, according to this model, households whose reference person is more than 50 years old have a longer income period of at least 4 years compared to households with younger reference persons. Economic development has increased this difference by almost a year for seniors and 2 years for retirees.

In Model4c we can see the same phenomenon as in Model4a. A mortgage extended the income period by more than 2 years in 2014 and did not affect it in 2019. Even the size of the *mortgage* coefficients is similar as in Model4a. In Model4d, the *mortgage* coefficient is significant for both years but declined in 2019. It follows that having a mortgage has a positive effect on the period, but this effect is reduced due to recent economic development. On the contrary to mortgages, loans shorten the payout period by 31 months in both years. Age categories follow the same trend as in Model4b. The coefficient for *income* is again statistically significant, but its value is zero as in the previous models (4a & 4b). The complete results for Model4c and Model4d can be found in table 5.8.

Table 5.8: Estimation results of Model4c & Model4d

	<i>Dependent variable:</i>			
	Period		Period_19	
	Model4c	Model4d	Model4c	Model4d
mortgage	32.644** (13.804)	39.708*** (13.019)	16.634 (14.793)	29.057** (14.607)
loan		-31.490*** (10.710)		-31.040** (13.072)
adults		4.572 (12.957)		17.087 (17.488)
seniors		55.808*** (14.101)		60.896*** (19.566)
retiree		57.550* (31.128)		74.538*** (23.839)
income		0.007** (0.003)		0.006** (0.003)
no_empmembers		4.202 (11.392)		-4.827 (12.689)
Constant	141.242*** (10.530)	5.083 (31.078)	175.908*** (10.860)	18.704 (33.133)
Observations	2,135	2,135	2,135	2,135
R ²	0.001	0.023	0.0002	0.025
Adjusted R ²	0.0002	0.020	-0.0003	0.022
Residual Std. Error	429.425 (df = 2133)	425.155 (df = 2127)	443.468 (df = 2133)	438.482 (df = 2127)
F Statistic	1.341 (df = 1; 2133)	7.203*** (df = 7; 2127)	0.327 (df = 1; 2133)	7.873*** (df = 7; 2127)

Notes: The table reports the results of the OLS estimation with the response variable *Period*. The first two columns are results for 2014 data, the third and fourth columns for 2019 data. The robust standard errors with HC0 scheme suitable for large samples are used and shown in parentheses.

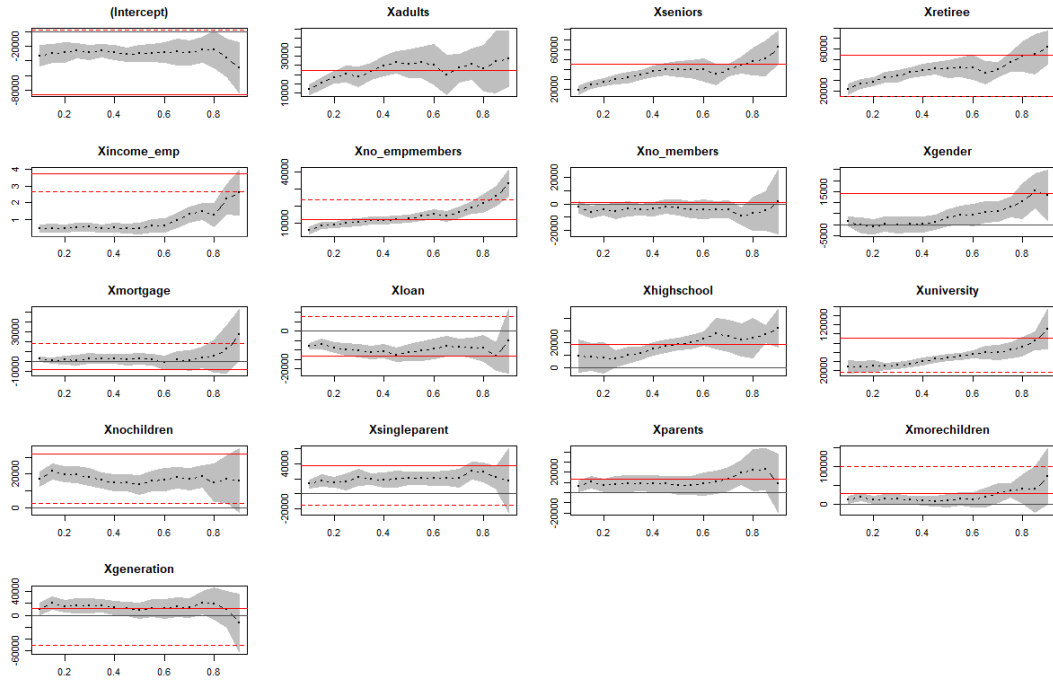
*, **, *** indicates significance at 10 percent ($p < 0.10$), 5 percent ($p < 0.05$) and 1 percent ($p < 0.01$), respectively.

5.2 Results obtained by quantile regression

In this section, we will focus on the results obtained by the quantile regression method. With regard to the objective of our study, we have decided that in this section it is not necessary to estimate models in all variations, so we will only estimate the model in variation *a*, in which all our independent variables are included. Models are performed at the 10th, 25th, 50th, 75th, and 90th percentiles. The results of the quantile regression are provided in the tables A.1-A.8 (in Appendix). Figures 5.1-5.7 illustrate the quantile regression graphically, which helps with the interpretation of the results.

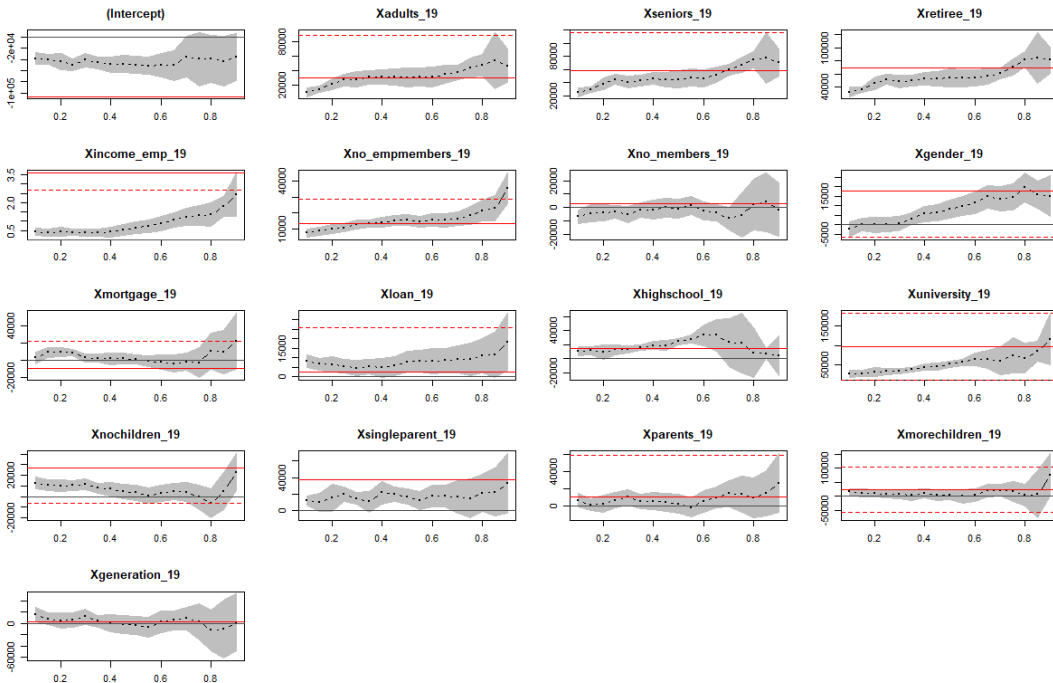
We start by analysing the difference between the years 2014 and 2019 for Model 1. All dummy variables representing different age categories are highly statistically significant for all quantiles. The coefficient values vary across chosen quantiles. The higher the quantile, the greater the effect on *Net_wealth*. As quantiles increase, the difference between years increases. The greatest differences in age coefficients are for 75th quantiles. For instance, for 10% of households that own the least amount of net wealth, the reference person in retiree age increases net wealth at maximum by €21,567 in 2014 compared to *juniors*. Whereas for 75% of households which own the least amount of net wealth, the reference person in retiree age increases net wealth at maximum by €47,449. In 2019, these amounts are €32,953 for 10th quantile and €71,076 for 75th quantile. It means that the difference between years increased from 11,383 for 10th quantile to 23,623 for the 75th quantile. It is worth noting that the coefficients for *seniors* and *retirees* were similar in 2014, but in 2019 we can see a significant difference. Therefore as with OLS, we could conclude that economic development helps older people the most. The coefficients for income have not changed a lot between years. They are significant and, except for the 50th quantile, are lower in 2019. As all coefficients for *no_empmembers* are highly statistically significant and positive, we know that each additional employed member increases the value of household net wealth. The coefficients increased slightly in 2019 compared to 2014 (except for the 75th quantile), but interesting is the difference between quantiles.

Figure 5.1: Quantile regression plots - Model 1 (2014)



Notes: The figure shows the results of quantile regression for Model1a in 2014 where the response variable is *Net_wealth*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

Figure 5.2: Quantile regression plots - Model 1 (2019)

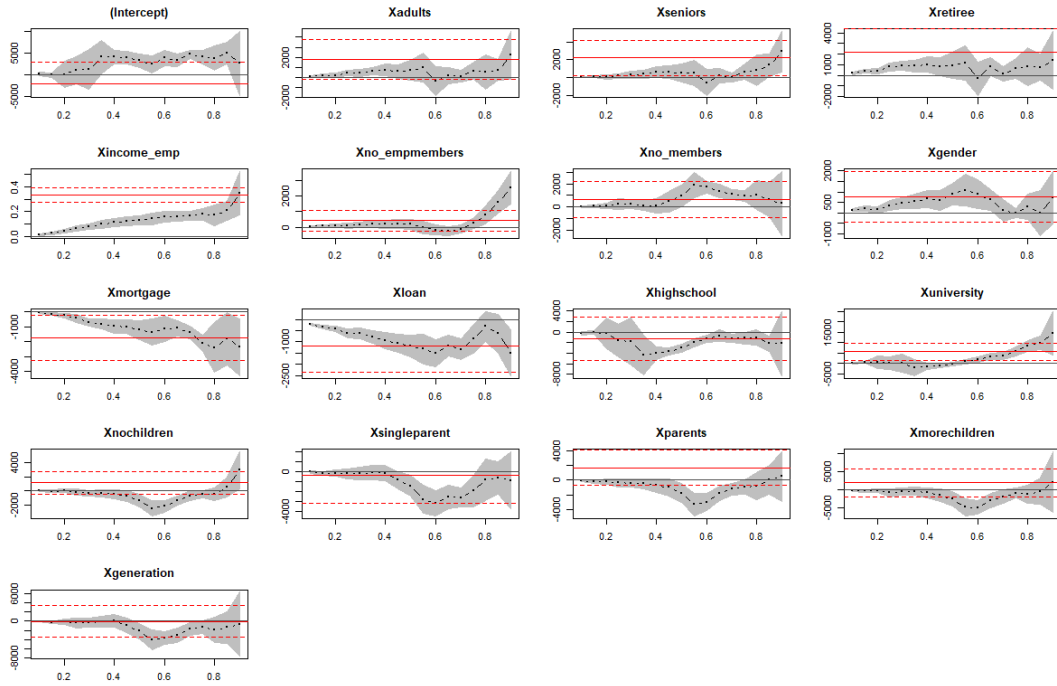


Notes: The figure shows the results of quantile regression for Model1a in 2019 where the response variable is *Net_wealth*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

We can say that for the first 10% people with the lowest net wealth, one additional employed member leads to an increase in the household net wealth of €7,805 at most in 2019. In the case of the 90th quantile, net wealth increases with one additional employed member maximally by €35,359. On the other hand, the coefficients representing the number of household members are not statistically significant and therefore do not affect the value of net wealth. Whether the household reference person was male or female was important only for 25% households with the highest value of net wealth in 2014 and for 50% with the highest value in 2019. When considering the 0.75 quantiles, a male reference person increases household net wealth by €6,618 more in 2019 than in 2014 compared to a female reference person. The results we got for mortgages were a bit chaotic. The coefficients were positive and statistically significant for different quantiles in each year, so it is not easy to find an economic explanation. The coefficients on the *loan* dummy variable changed from negative to positive across the years. If we consider the 0.25 quantile in 2014, for households in the bottom quartile having a loan decreases the value of net wealth €9,639 at most. Looking at the 0.25 quantile in 2019, having a loan, on the other hand, should increase the value of net wealth by €9,088 at most, which is quite a big difference. It could seem that drawing a loan has become an advantage. When it comes to education, we can see the same results for reference persons with a university degree as in OLS. Economic development has considerably improved the position of households whose reference person has a university degree (except the 10th quantile). Lastly, when we look at the results of different types of households, we can see that the effect on net wealth is ambiguous.

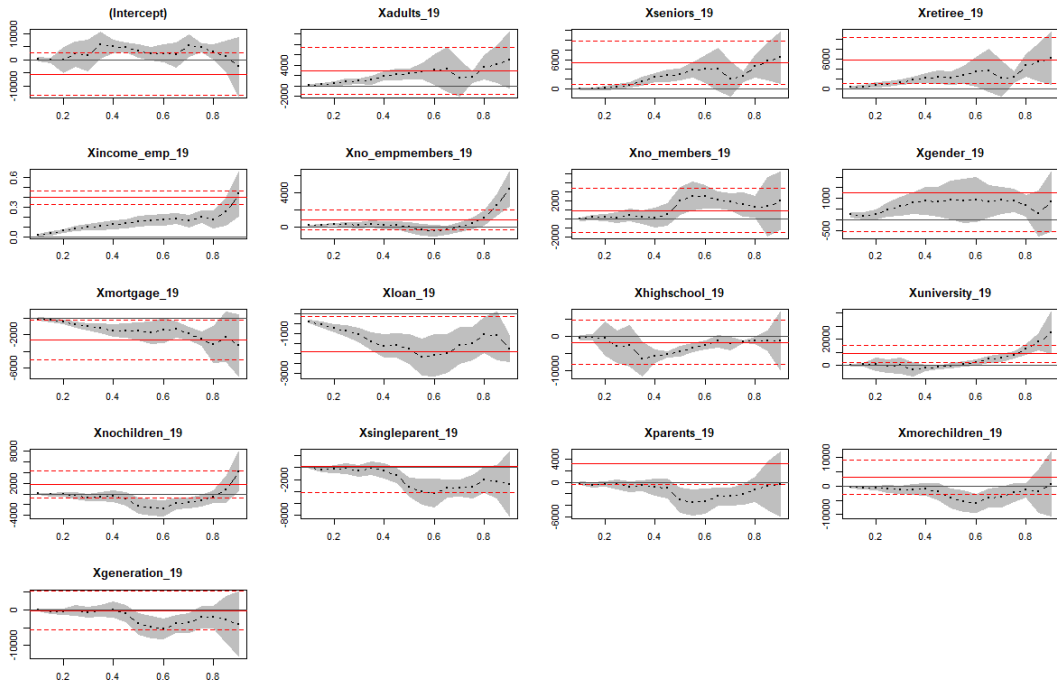
We continue our analysis with Model 2. The results indicate that the age of the reference person did not have much effect on the household financial assets in 2014. That changed in 2019 when most of the coefficients became significant. Unlike the previous model, the position of seniors and retirees does not differ much since the 50th percentile. Income has a similar effect on financial assets as it had on net wealth. The number of employed members is relevant in both years only to 10% of households with the lowest and with the highest value of financial assets. In the former case, one additionally employed member add maximally by €82 more to the value of financial assets in 2019. In the latter case, financial assets are increased by €1,860 more at most in 2019 compared to 2014. For households in the bottom half having a male reference person raised the value of financial assets in 2019 slightly more than in 2014.

Figure 5.3: Quantile regression plots - Model 2 (2014)



Notes: The figure shows the results of quantile regression for Model2a in 2014 where the response variable is *Fin_assets*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

Figure 5.4: Quantile regression plots - Model 2 (2019)

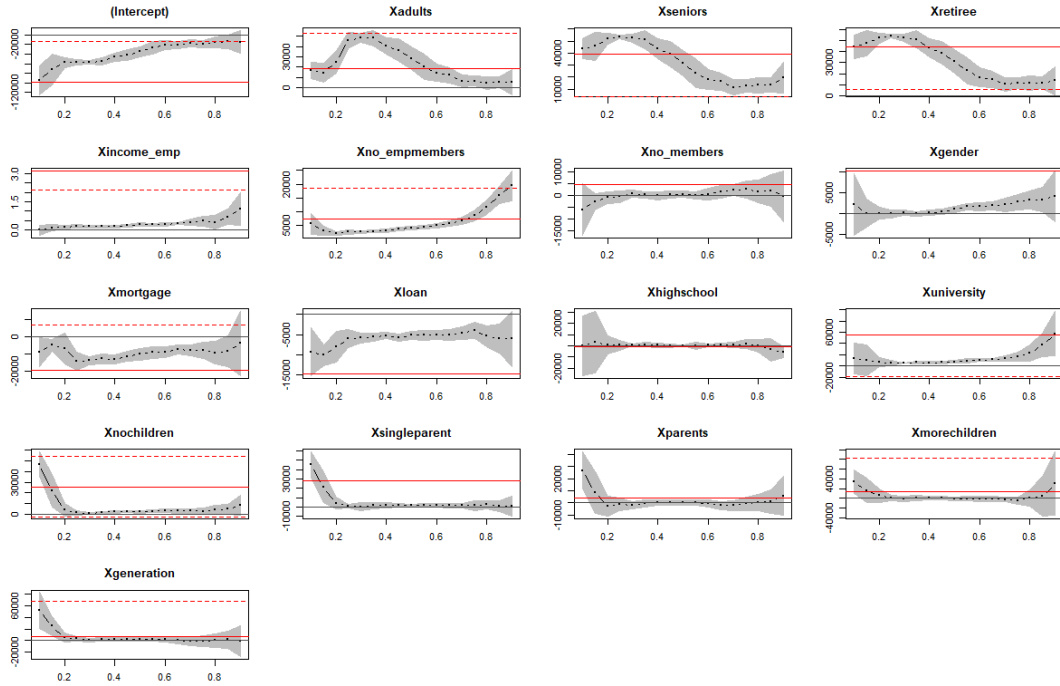


Notes: The figure shows the results of quantile regression for Model2a in 2019 where the response variable is *Fin_assets*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

The coefficients for *mortgage* and *loan* show the same pattern of affecting amount of financial assets. For both variables, the coefficients are negative, significant and their effect on financial assets intensified in 2019. The lower quartile of households with the lowest financial assets is least affected, as financial assets grow, the effect gains strength. For 50% of households with the lowest financial assets, there is no difference whether a reference person has only primary education or university degree. Whereas for 90% of households with the highest financial assets, having a reference person with a university degree means an increase in financial assets at maximum by €24,797 in 2019 (approx. €10,000 more than in 2014). We should also mention the statistical significance of variables representing various household types across quantiles. As visible in the tables A.3 and A.4 in the Appendix, the variables are statistically insignificant across all quantiles of financial assets except the 0.50 quantile.

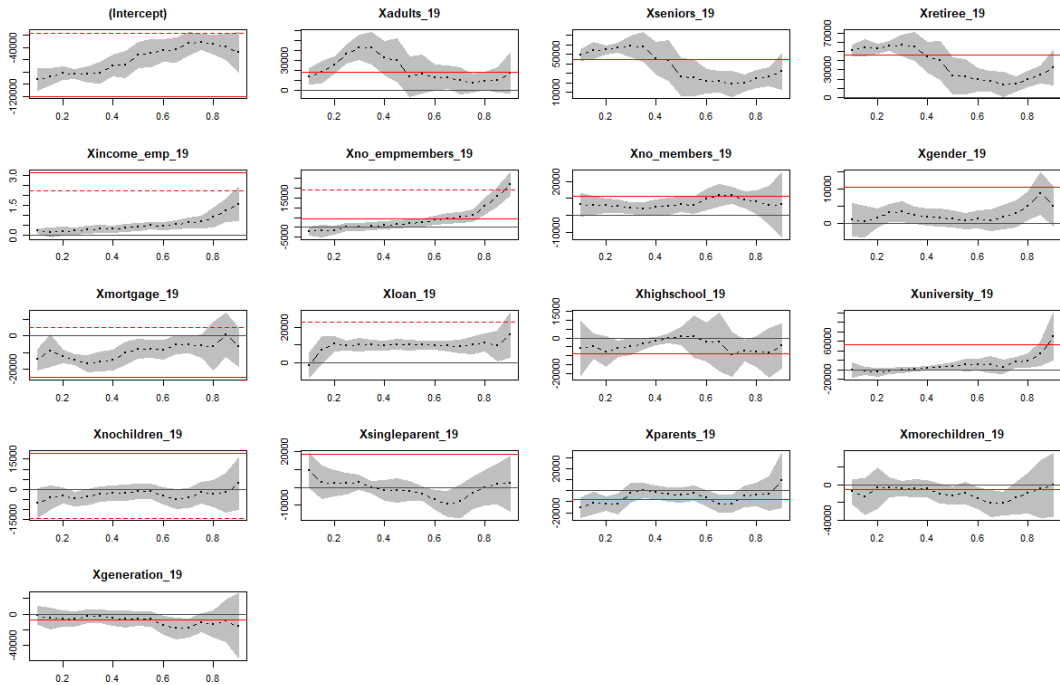
In the next model, we look at the value of household net wealth less value of main housing. In figures 5.5 and 5.6, we can notice that the graphs representing the age categories look differently from the ones in Model 1 or Model 2. The greatest effect on a dependent variable has an increasing age for 10th and 25th quantiles, then the effect fades. Comparing 2014 and 2019, the position for adults deteriorated, while for seniors and retirees it improved (except the 50th quantile). For 75% of households with the lowest net wealth, another employed member added much more value to net wealth in 2014 than in 2019. On the contrary, with each additional household member, the value of net wealth increased in 2019 more than in 2014. When it comes to drawing a mortgage and its effect on the net wealth without the value of main housing, for households in the bottom tenth reduced drawing a mortgage the value of net wealth by €4,892 at most more in 2019 than in 2014. For other quantiles has the situation slightly improved in 2019 and the reduction effect was not as strong as in 2014. In 2019, the direction of the *loan* coefficients changed from negative to positive for all significant coefficients. Drawing a loan has, therefore, become an advantage in terms of net wealth value due to economic development. In this model, we do not see any major differences between years in the *university* coefficients. When we move to different types of households, most coefficients are statistically insignificant, as was the case with previous models. We mention only the *parents* dummy variable when the situation changed completely for 10% of the households with the lowest net wealth value. Instead of increasing the value by €26,712 as in 2014, the value decreased by €15,559 in 2019.

Figure 5.5: Quantile regression plots - Model 3 (2014)



Notes: The figure shows the results of quantile regression for Model3a in 2014 where the response variable is *NW_HE*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

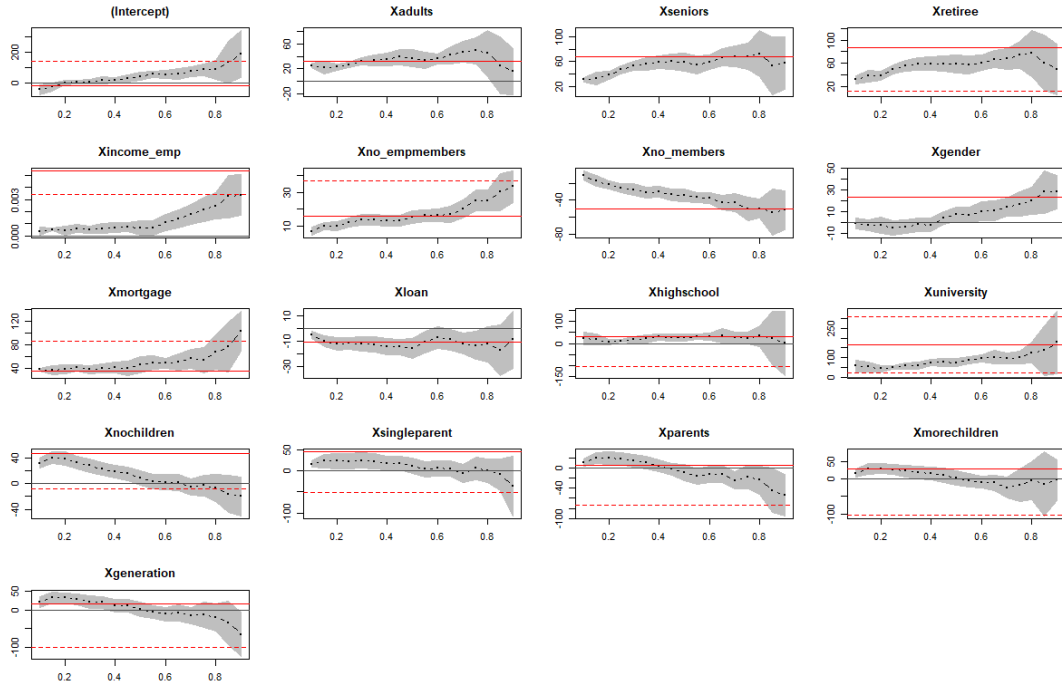
Figure 5.6: Quantile regression plots - Model 3 (2019)



Notes: The figure shows the results of quantile regression for Model3a in 2019 where the response variable is *NW_HE*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

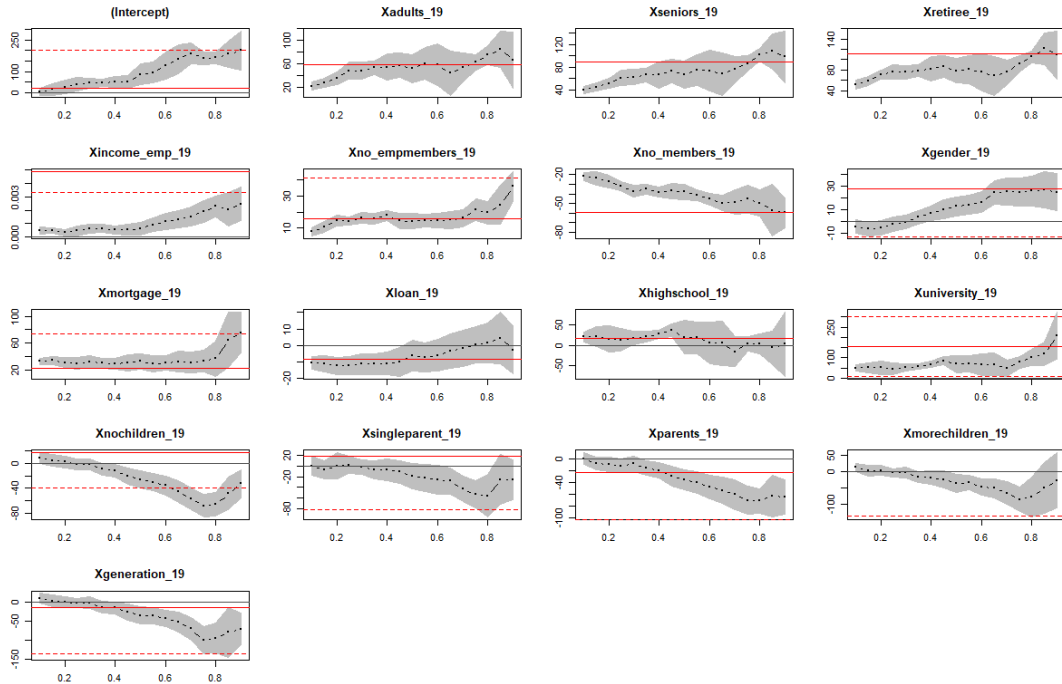
When estimating the effect of independent variables on the dependent variable *Period*, we have found that the results of age dummy variables are similar to those from Model 1. Thus, the older the household reference person is, the longer the income period. Economic development has increased the differences between age categories. As we have already seen in the OLS models, even though the *income* coefficients are significant, they equal zero, and thus the income does not affect the income period. The variables *no_empmembers* and *no_members* do not show surprising results. While another member of the household shortens the income period, another employed member extends the income period. The higher the quantile, the greater the effect on *Period*. Unfortunately, we cannot say whether the effect increased or decreased between 2014 and 2019 because it varies across quantiles. The dummy variable *mortgage* is significant and positive for all coefficients both in 2014 and 2019. It means that having a mortgage extends the income period. However, economic development weakened the effect approx. of about one year for lower quantiles and about two years for higher quantiles. On the contrary to the mortgages, loans shorten the income period. In 2014, the effect of loans is slightly lower, but the coefficients are statistically significant for all quantiles except for the last one. On the other hand, in 2019 is the effect stronger but applies only to 10th and 25th quantile. Although households with a university-educated reference person have a longer income period, the difference compared to households with an uneducated reference person has narrowed due to economic development. As the last thing in this chapter, we look at the coefficients of different household types. Their significance and sign are different across quantiles in both years. When considering the 75th quantile in 2019, which is for all variables highly statistically significant, the income period shortened for all household types compared to households where only a single person lives. This effect was not observable in 2014.

Figure 5.7: Quantile regression plots - Model 4 (2014)



Notes: The figure shows the results of quantile regression for Model4a in 2014 where the response variable is *Period*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

Figure 5.8: Quantile regression plots - Model 4 (2019)



Notes: The figure shows the results of quantile regression for Model4a in 2019 where the response variable is *Period*. The shaded area provides quantile regression parameters and confidence intervals. The red line represents the OLS coefficient estimates and 95% confidence interval (two red dashed lines).

Chapter 6

Conclusion

Poverty is currently considered one of the most pressing problems in a globalised world. In this study, we focused on asset poverty. A household or an individual is considered to be asset-poor if their wealth is not sufficient to secure a basic standard of living for a certain period of time (Brandolini *et al.* 2009).

The primary aim of our thesis was to find out whether recent economic development has reduced the risk of asset poverty for households. Another goal was to determine how a mortgage drawdown affects asset poverty and how this effect has changed due to economic development. Lastly, we wanted to find out if the gap between rich and poor households is widening. To our knowledge, research on this specific topic has not been carried out yet. As a consequence, we decided to contribute to this niche literature concerning asset poverty and economic development using real empirical data from 2014 and simulated data after five years. We estimated four models based on different methods of measuring asset poverty. We used two estimation methods - the OLS and quantile regression. Due to detected heteroscedasticity, we employed White standard errors to obtain robust statistical inference when estimating with OLS.

We analysed the data for 2,135 households in Slovakia. We found that economic development might reduce asset poverty, but this does not apply to all households. It turned out that people older than 50 years are in better asset position than younger people. The result is consistent with the results of studies conducted on asset poverty by Rothwell & Haveman (2013) or Wolff & Haveman (2001). Years of stable earnings serve for accumulating of net wealth and net financial assets. Wealth increases with age, peaking between the ages of 55 and 65, and decreases faintly in retirement age, but still maintains higher values

than in the period around the age of 50 (Oliver & Shapiro 1990). According to our results, the situation of older people improved even more during the last five years compared to younger people. It could be thus concluded that recent economic development has contributed the most to the increase in households' assets where the reference person is older than 50 years.

The results showed that households with male reference persons are in a better situation. That is true primarily for households with a higher value of their assets. This might stem from an unbalanced salary situation between men and women. Despite legislation measures in Slovakia, there are still considerable differences in the female and male remuneration. The gender pay gap in Slovakia is one of the highest in the European Union (Rizman 2017). Unfortunately, economic development has exacerbated the gender disparity in asset poverty.

Similarly to the research carried out by Azpitarte (2008), we found out that households whose reference person graduated from a university own assets of higher value and are therefore less endangered by asset poverty. From the results, we could observe that the impact of university degree on household assets was stronger in 2019. This applies to all models except Model 4 where the independent variable is a period for which the household receives income from the monetisation of its assets. When estimating with QR, we noticed substantial differences between quantiles. As the value of the assets increases, the impact of the university degree intensifies.

The results revealed that the mortgage does not always play an essential role in determining the value of household assets. Nevertheless, in most cases where the coefficient was significant, it turned out that drawdown of the mortgage reduced household net assets slightly more in 2019 than in 2014.

It seems that economic development moderately reduces the impact of income on asset poverty. In the models in which we examine the influence of independent variables on various forms of assets, it was shown that in both inspected years the number of household members does not affect the value of household assets. On the contrary, each additional employed member increases the value of household assets. Economic development has amplified this effect which intensifies with the growing amount of household assets. It also turned out that the type of household does not matter when estimating asset poverty. The results for these independent variables were ambiguous, and the significance varied across quantiles and years.

To sum up, we personally consider the most interesting conclusion of this

thesis that economic development in Slovakia between 2014 and 2019 most likely helped to reduce the threat of asset poverty regardless of the measurement method. However, this does not apply to all households. The results of the quantile regression indicate that the gap between poor and rich households might widen due to economic development. Mortgages worsen the household situation in terms of asset poverty only according to certain definitions of asset poverty. Economic development strengthens the effect of mortgages on household assets only fractionally.

Finally, as estimation results provide us with rather theoretical implications, it would be beneficial to perform the analysis on real data. We recommend to re-estimate the relationships once the data from the third HFCS wave are available. Moreover, the research could be extended further by employing different methods or independent variables.

Bibliography

- ABDELKRIM, A. & J.-Y. DUCLOS (2006): “Dad: A software for poverty and distributive analysis.” *PEP-PMMA, Cahiers de recherche PMMA* **34**.
- ARRONDEL, L., P. LAMARCHE, & F. SAVIGNAC (2015): “Wealth effects on consumption across the wealth distribution: Empirical evidence.” *SSRN Electronic Journal* .
- AZPITARTE, F. (2008): “Measurement and identification of asset-poor households: A cross-national comparison of Spain and the United Kingdom.” *The Journal of Economic Inequality* **9**.
- BRANDOLINI, A., S. MAGRI, & T. M. SMEEDING (2009): “Asset-related measures of poverty and economic stress.” *Institute for Research on Poverty* **1372(10)**.
- BRANDOLINI, A., S. MAGRI, & T. M. SMEEDING (2010): “Asset-based measurement of poverty.” *Journal of Policy Analysis and Management* **29(2)**: pp. 267–284.
- CHAKRAVARTY, S. & J. SILBER (2008): *Measuring Multidimensional Poverty: The Axiomatic Approach*, pp. 192–209. Palgrave Macmillan UK.
- CHERNOZHUKOV, V. & C. HANSEN (2004): “The effects of 401(k) participation on the wealth distribution: An instrumental quantile regression analysis.” *The Review of Economics and Statistics* **86**: pp. 735–751.
- CITRO, C. F. & R. T. MICHAEL (1995): *Measuring Poverty: A New Approach*. Washington, DC: The National Academies Press.
- COOK, B. & W. MANNING (2013): “Thinking beyond the mean: a practical guide for using quantile regression methods for health services research.” *Shanghai archives of psychiatry* **25**: pp. 55–9.

- CUPÁK, A. & A. STRACHOTOVÁ (2015): *Výsledky druhej vlny HFCS*. Národná banka Slovenska. ISSN 1337-5830.
- DOHOO, I., C. DUCROT, C. FOURICHON, A. DONALD, & D. HURNIK (1997): “An overview of techniques for dealing with large numbers of independent variables in epidemiologic studies.” *Preventive Veterinary Medicine* **29(3)**: pp. 221–239.
- DUDIC, B. a. Z., E. BEŇOVÁ, & V. MIRKOVIC (2019): “Economic development in the Slovak Republic: Achieved results and prospects for future development.” *Ekonomija: teorija i praksa* **12**: pp. 18–32.
- DURLAUF, S. & L. BLUME (2008): *The New Palgrave: A Dictionary of Economics*, volume 2. Palgrave Macmillan UK. ISBN 978-0-333-78676-5.
- EUROSTAT (2013): “The measurement of poverty and social inclusion in the EU: achievements and further improvements.” *Luxembourg: Publications Office of the European Union*.
- EUROSTAT (2019): “Europe 2020 indicators – poverty and social exclusion.” *Luxembourg: Publications Office of the European Union*.
- FORNERO, E., R. CALCAGNO, & M. ROSSI (2009): “The effect of house prices on household consumption in Italy.” *The Journal of Real Estate Finance and Economics* **39**: pp. 284–300.
- GIRMA, S. & H. GÖRG (2005): “Foreign direct investment, spillovers and absorptive capacity: Evidence from quantile regressions.” *Discussion paper series 1: Economic studies*, Deutsche Bundesbank.
- GORNICK, J., E. SIERMINSKA, & T. SMEEDING (2009): “The income and wealth packages of older women in cross-national perspective.” *The journals of gerontology. Series B, Psychological sciences and social sciences* **64**: pp. 402–414.
- HAGENAARS, A., K. DE VOS, & M. ZAIDI (1994): *Poverty Statistics in the Late 1980s: Research Based on Micro-data*. Office for Official Publications of the European Communities.
- HELÍSEK, M. (2002): *Makroekonomie: Základní kurs*. Melandrium. ISBN 80-86175-25-1.

- HLAVAC, M. (2018): *stargazer: Well-Formatted Regression and Summary Statistics Tables*. Central European Labour Studies Institute (CELSI), Bratislava, Slovakia. R package version 5.2.2.
- HUANG, Q., H. ZHANG, J. CHEN, & M. HE (2017): “Quantile regression models and their applications: A review.” *Journal of Biometrics & Biostatistics* **08**.
- JÄNTTI, M. (1993): *Essays on income distribution and poverty*. Ph.D. thesis, Finland.
- JOLLIFFE, D., M. NEGRE, & M. SCHMIDT (2018): *Poverty and Shared Prosperity 2018 : Piecing Together the Poverty Puzzle*. Washington, DC: World Bank.
- JUREČKA, V. & A. JÁNOŠÍKOVÁ (2004): *Makroekonomie: Základní kurs*. VŠB: Technická univerzita Ostrava. ISBN 80-248-0530-8.
- KADERÁBKOVÁ, A. & KOLEKTIV (2005): *Metodologické hodnocení národní konkurenceschopnosti*. Centrum ekonomických studií vysoké školy ekonomie a managementu. ISBN 1801-2728.
- KAMAL, J. B. (2014): “Asset based poverty and wealth accumulation in low income households in Bangladesh.” *The Bangladesh Development Studies* **37(4)**: pp. 35–51.
- KOENKER, R. (2013): *quantreg: Quantile Regression*. R package version 5.05. R Foundation for Statistical Computing, Vienna, Austria.
- KOENKER, R. & G. BASSETT (1978): “Regression quantiles.” *Econometrica* **46(1)**: pp. 33–50.
- MARTINS, P. S. & P. T. PEREIRA (2004): “Does education reduce wage inequality? Quantile regression evidence from 16 countries.” *Labour Economics* **11(3)**: pp. 355–371.
- MELLY, B. (2005): “Decomposition of differences in distribution using quantile regression.” *Labour Economics* **12**: pp. 577–590.
- NAM, Y., J. HUANG, & M. SHERRADEN (2008): “Assets, poverty, and public policy: Challenges in definition and measurement.” *Center for Social Development Washington University in Saint Louis* p. 33.

- NBS (2009): “Quarterly financial accounts in the Slovak Republic.” *Národná banka Slovenska, November 2009* .
- NBS (2019): “Financial stability report.” *Národná banka Slovenska, November 2019* .
- NISBET, R. A., J. ELDER, & G. D. MINER (2009): *Handbook of Statistical Analysis and Data Mining Applications*. Elsevier Academic Press. ISBN ISBN 9780123747655.
- NOVOTNÝ, J. & V. NOSEK (2009): “Nomothetic geography revisited: Statistical distributions, their underlying principles, and inequality measures.” *Geografie* **114**: pp. 282–297.
- OECD (2013): *OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*. OECD Publishing, Paris.
- OECD (2019a): *Education at a Glance 2019: Slovak Republic*. OECD Publishing, Paris.
- OECD (2019b): *OECD Economic Surveys: Slovak Republic 2019*. OECD Publishing, Paris.
- OLIVER, M. L. & T. M. SHAPIRO (1990): “Wealth of a Nation.” *American Journal of Economics and Sociology* **49(2)**: pp. 129–151.
- OZTUNA, D., A. ELHAN, & E. TUCCAR (2006): “Investigation of four different normality tests in terms of type 1 error rate and power under different distributions.” *Turkish Journal of Medical Sciences* **36**: pp. 171–176.
- PEDACE, R. (2013): *Econometrics For Dummies*. For dummies. Wiley.
- PEJČOCH, D. (2011): *Metody řešení problematiky neúplných dat*. Data Quality Tutorial.
- PROJECTOR, D. & G. WEISS (1969): “Income - net worth measures of economic welfare.” *Social Security Bulletin* **Vol. 32**: pp. 14–17.
- R DEVELOPMENT CORE TEAM (2006): *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0.

- REVENDA, Z., M. MANDEL, J. KODERA, P. MUSÍLEK, & P. DVOŘÁK (2017): *Peněžní ekonomie a bankovníctví*. Management Press. ISBN 9788072613021.
- RIZMAN, J. (2017): "Rovnaký plat za rovnakú robotu?" *Institute of Financial Policy, Ministry of Finance of the Slovak Republic, Policy brief, No 05* .
- ROTHWELL, D. W. & R. HAVEMAN (2013): "Definition and measurement of asset poverty in Canada." *Social Science Research Network* .
- RUBIN, D. B. (1987): *Multiple Imputation for Nonresponse in Surveys*. Wiley.
- SHORT, K. & P. RUGGLES (2005): "Experimental Measures of Poverty and Net Worth: 1996." *Journal of Income Distribution* **13(3-4)**: pp. 1–1.
- SO SR (2019): "Chudoba alebo sociálne vylúčenie ohrozuje každého šiesteho obyvateľa Slovenska." *Statistical Office of the Slovak Republic, June 2019* .
- WEISBROD, B. & W. HANSEN (1968): "An income-net worth approach to measuring economic welfare." *American Economic Review* .
- WHITE, H. (1980): "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity." *Econometrica: Journal of the Econometric Society* pp. 817–838.
- WOLFF, E. & A. CANER (2004): "Asset poverty in the United States, 1984–1999: Evidence from the panel study of income dynamics." *Review of Income and Wealth* pp. 493–518.
- WOLFF, E. & R. HAVEMAN (2001): *Who are the asset poor?: Levels, trends and composition, 1983-1998*, pp. 61–86. United States: Oxford University Press.
- WOLFF, E. & R. HAVEMAN (2005): "The concept and measurement of asset poverty: Levels, trends and composition for the U.S., 1983–2001." *Journal of Economic Inequality* **2**: pp. 145–169.
- WOLFF, E. N. (1990): "Wealth holdings and poverty status in the U.S." *Review of Income and Wealth* **36(2)**: pp. 143–165.
- WOOLDRIDGE, J. (2013): *Introductory Econometrics: A modern approach*. Mason, OH: South-Western Cengage Learning. ISBN 1-111-53104-1.
- ŽÁK, M. (2002): *Velká ekonomická encyklopedie*. Linde. ISBN 9788072013814.

ŽELINSKÝ, T. (2014): *Chudoba a deprivácia na Slovensku: Metodologické aspekty a empiria*. Košice: Equilibria. ISBN 978-80-8143-133-3.

ZHANG, L. (2019): “Do house prices matter for household consumption?” *Cpb discussion paper*, CPB Netherlands Bureau for Economic Policy Analysis.

Appendix A

Estimation results of quantile regression

Table A.1: Estimation results of quantile regression - Model 1 (2014)

	<i>Dependent variable: Net_wealth</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults	11,803.770*** (1,542.561)	20,313.150*** (2,688.624)	25,834.270*** (4,590.314)	25,856.620*** (5,000.612)	28,675.450*** (9,292.269)
Xseniors	19,422.930*** (2,539.131)	30,326.920*** (2,687.345)	40,236.030*** (4,663.946)	44,248.330*** (4,995.319)	61,983.560*** (10,259.450)
Xretiree	21,569.930*** (2,963.948)	33,004.920*** (2,982.906)	41,184.230*** (4,951.642)	47,448.330*** (5,409.217)	61,669.600*** (9,668.882)
Xincome	0.467*** (0.135)	0.559*** (0.141)	0.494** (0.193)	1.493*** (0.278)	2.619*** (0.807)
Xno_empmembers	5,723.715*** (1,238.272)	10,057.260*** (1,215.975)	12,538.730*** (1,420.105)	19,163.780*** (2,002.678)	33,363.290*** (4,763.560)
Xno_members	-2,431.685 (2,642.272)	-5,443.844 (3,412.233)	-2,692.552 (3,400.637)	-9,166.069** (3,815.576)	1,513.302 (14,486.400)
Xgender	1,541.876 (1,212.974)	125.400 (1,975.248)	3,176.887 (2,272.391)	7,933.869*** (2,719.609)	13,428.610* (6,887.841)
Xmortgage	2,825.761** (1,374.842)	1,453.905 (3,023.016)	3,248.960 (3,421.988)	4,162.375 (6,395.957)	27,203.250* (15,732.540)
Xloan	-7,926.283*** (948.360)	-9,638.566*** (1,877.580)	-11,206.400*** (2,678.645)	-8,824.277*** (3,115.385)	-5,311.756 (10,276.660)
Xhighschool	9,625.718 (7,954.395)	7,293.400* (4,021.345)	19,176.600*** (2,800.492)	22,450.000*** (8,003.092)	31,897.790*** (9,095.615)
Xuniversity	27,160.840*** (8,252.457)	29,029.810*** (4,344.702)	47,698.390*** (4,247.223)	64,463.030*** (10,372.810)	110,444.600*** (26,783.700)
Xnochildren	16,918.840*** (2,678.760)	19,400.210*** (2,897.776)	13,735.500*** (3,395.053)	18,340.000*** (3,898.620)	16,059.340 (11,484.550)
Xsingleparent	12,957.970*** (3,364.840)	15,742.510** (6,459.702)	20,886.550*** (4,887.575)	30,326.510*** (6,893.272)	17,415.450 (25,658.210)
Xparents	6,373.699** (3,059.129)	8,351.975* (4,662.467)	7,336.058 (5,226.149)	19,828.050*** (7,117.012)	9,051.749 (17,374.100)
Xmorechildren	12,013.620** (5,899.407)	12,770.600* (7,760.088)	8,584.683 (9,748.444)	35,991.040*** (11,091.400)	72,934.870 (44,978.580)
Xgeneration	10,291.400* (6,130.353)	16,121.810** (7,534.838)	7,916.866 (8,059.516)	20,838.900* (11,515.490)	-12,914.500 (29,812.190)
Constant	-33,065.350*** (8,498.186)	-26,087.430*** (5,844.002)	-29,493.530*** (6,901.162)	-25,254.690** (10,431.260)	-49,355.350** (20,865.920)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.2: Estimation results of quantile regression - Model 1 (2019)

	<i>Dependent variable: Net_wealth_19</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults_19	10,322.110*** (3,792.951)	27,003.980*** (5,070.117)	30,489.480*** (8,190.665)	44,482.670*** (7,825.634)	46,934.570*** (13,976.160)
Xseniors_19	25,395.370*** (3,826.707)	44,996.100*** (4,416.156)	44,967.460*** (8,157.980)	67,066.660*** (7,248.597)	70,081.930*** (12,506.800)
Xretiree_19	32,952.840*** (4,242.713)	52,140.910*** (4,575.091)	54,480.200*** (8,392.179)	71,075.560*** (7,591.137)	81,353.690*** (12,011.740)
Xincome_19	0.440*** (0.121)	0.413*** (0.116)	0.653*** (0.185)	1.307*** (0.332)	2.435*** (0.708)
Xno_empmembers_19	7,805.316*** (1,522.479)	10,983.040*** (1,414.556)	15,881.380*** (2,010.754)	18,437.880*** (3,343.223)	35,358.680*** (5,795.266)
Xno_members_19	-6,927.455** (3,218.732)	-3,271.870 (2,957.762)	-889.157 (4,334.159)	-5,643.053 (9,929.658)	-1,695.012 (12,137.480)
Xgender_19	-2,410.266 (2,418.661)	109.375 (2,262.081)	8,253.222*** (2,912.641)	14,551.640*** (4,171.400)	15,076.410** (6,536.392)
Xmortgage_19	3,075.410 (4,041.778)	8,995.954*** (2,146.585)	1,293.756 (3,378.948)	-2,495.269 (10,409.820)	22,223.370 (19,645.040)
Xloan_19	8,183.806*** (1,950.867)	5,526.041*** (2,079.944)	7,832.278** (3,235.368)	9,087.589* (5,215.876)	18,340.110** (9,115.253)
Xhighschool_19	10,563.420*** (3,940.910)	12,597.710*** (4,155.311)	24,342.670*** (2,863.017)	22,132.300 (26,114.800)	4,074.967 (17,093.300)
Xuniversity_19	26,650.830*** (5,304.522)	33,119.120*** (4,785.330)	52,255.190*** (4,606.904)	73,905.830*** (27,608.830)	116,606.800*** (40,557.310)
Xnochildren_19	12,678.340*** (3,310.105)	10,257.860*** (3,084.922)	3,535.427 (4,317.263)	-804.015 (7,223.167)	22,847.910** (10,627.700)
Xsingleparent_19	12,201.940*** (3,491.764)	19,929.440*** (5,153.916)	16,639.910*** (5,629.547)	14,800.080 (14,409.310)	33,001.670 (21,796.480)
Xparents_19	6,874.436 (5,004.819)	6,716.412 (5,507.335)	2,681.372 (6,494.951)	13,730.310 (12,744.980)	26,784.020 (20,764.780)
Xmorechildren_19	15,018.820** (6,976.026)	6,910.917 (7,176.764)	4,011.402 (10,548.420)	17,165.180 (21,273.670)	75,872.190* (45,918.270)
Xgeneration_19	15,560.240** (7,791.234)	5,906.229 (8,210.578)	-3,069.805 (9,655.065)	3,242.788 (19,415.570)	1,289.001 (30,550.000)
Constant	-38,202.620*** (6,014.734)	-49,391.270*** (6,668.845)	-49,505.200*** (9,296.218)	-39,009.670 (28,987.810)	-36,071.510 (25,386.040)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.3: Estimation results of quantile regression - Model 2 (2014)

	<i>Dependent variable: Fin_assets</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults	75.141* (42.084)	439.301** (183.396)	705.681 (621.636)	650.836 (510.620)	2,209.056 (1,464.367)
Xseniors	28.710 (43.147)	163.827 (170.023)	509.725 (643.511)	650.836 (527.961)	2,925.034** (1,411.194)
Xretiree	207.573*** (73.200)	783.009*** (249.919)	935.707 (742.784)	650.836 (552.460)	1,432.274 (1,673.729)
Xincome	0.015*** (0.004)	0.066*** (0.014)	0.132*** (0.023)	0.178*** (0.028)	0.349*** (0.107)
Xno_empmembers	57.565*** (15.946)	113.881 (98.077)	195.513 (190.078)	277.285 (212.260)	2,512.129*** (641.358)
Xno_members	13.800 (49.787)	239.898 (283.753)	973.333* (568.792)	956.250*** (302.796)	304.022 (1,699.344)
Xgender	132.432*** (32.819)	344.584** (145.357)	888.487*** (311.116)	−0.000 (130.956)	715.978 (764.261)
Xmortgage	−50.127* (27.267)	−451.993*** (151.276)	−1,234.764*** (394.290)	−2,108.635*** (344.018)	−2,383.419** (1,154.212)
Xloan	−220.316*** (25.969)	−607.483*** (124.229)	−1,181.732*** (290.218)	−867.015** (392.557)	−1,492.760** (622.609)
Xhighschool	−218.305 (238.172)	−1,592.829 (1,856.913)	−3,063.739*** (443.178)	−1,156.357* (656.395)	−2,220.261 (3,691.518)
Xuniversity	236.685 (238.784)	136.199 (1,889.378)	−270.020 (575.472)	5,752.859*** (1,326.770)	14,450.410** (6,308.439)
Xnochildren	20.212 (63.078)	−157.968 (244.691)	−1,351.153** (547.611)	−478.125* (284.661)	2,902.272* (1,565.420)
Xsingleparent	−31.241 (63.525)	−188.347 (298.590)	−1,427.066** (643.948)	−1,953.939** (993.875)	−867.989 (1,746.381)
Xparents	−112.774 (76.305)	−355.327 (340.935)	−1,796.404** (784.693)	−956.250 (615.019)	473.078 (2,039.994)
Xmorechildren	−238.564 (183.585)	−872.669 (687.922)	−2,659.371** (1,222.307)	−974.788 (867.280)	2,036.998 (5,125.054)
Xgeneration	−18.408 (111.437)	−379.629 (622.753)	−2,122.952** (997.429)	−1,287.446 (881.192)	−680.275 (4,208.669)
Constant	94.703 (251.185)	1,067.921 (1,888.965)	3,246.241*** (935.684)	4,070.254*** (948.669)	2,645.069 (4,476.208)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.4: Estimation results of quantile regression - Model 2 (2019)

	<i>Dependent variable: Fin_assets_19</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults_19	179.880* (93.324)	799.768*** (305.184)	2,312.997*** (610.207)	1,726.462*** (645.812)	5,018.241 (3,333.549)
Xseniors_19	98.078 (95.079)	473.568* (274.838)	2,950.413*** (669.892)	2,522.257*** (624.791)	6,407.826** (3,197.933)
Xretiree_19	346.145*** (105.718)	923.003*** (308.931)	2,185.874*** (765.622)	2,327.681*** (626.358)	6,131.851* (3,253.715)
Xincome_19	0.019*** (0.005)	0.086*** (0.016)	0.159*** (0.028)	0.204*** (0.035)	0.433*** (0.136)
Xno_empmembers_19	139.188*** (38.411)	263.984* (154.562)	-63.665 (349.279)	377.585 (361.056)	4,372.579*** (1,226.405)
Xno_members_19	-24.683 (84.520)	146.576 (353.239)	1,955.882** (913.585)	1,590.492** (782.331)	2,003.213 (1,934.555)
Xgender_19	232.300*** (55.502)	477.124** (196.378)	929.270* (544.509)	895.914*** (326.079)	856.003 (844.690)
Xmortgage_19	-101.072 (87.059)	-784.386*** (213.174)	-1,608.092*** (622.110)	-2,525.178*** (494.664)	-3,296.551 (2,231.373)
Xloan_19	-377.250*** (42.722)	-860.337*** (168.711)	-1,752.220*** (436.871)	-1,467.607*** (493.314)	-1,748.009*** (398.182)
Xhighschool_19	-420.415 (431.946)	-2,965.938 (2,724.257)	-4,332.470*** (909.811)	-1,537.283*** (195.657)	-1,340.936 (5,112.829)
Xuniversity_19	297.891 (439.598)	-391.450 (2,765.334)	-130.183 (1,060.569)	8,143.010*** (1,557.261)	24,796.940** (9,642.997)
Xnochildren_19	24.830 (83.444)	-291.766 (335.930)	-2,226.885** (876.907)	-1,240.862** (604.234)	4,206.518* (2,182.584)
Xsingleparent_19	34.885 (86.659)	-158.883 (485.152)	-3,329.834*** (915.762)	-3,210.159*** (1,122.289)	-2,764.260 (3,258.097)
Xparents_19	-146.866 (111.243)	-350.732 (471.346)	-3,088.806** (1,253.899)	-2,017.843* (1,055.426)	-309.884 (3,386.434)
Xmorechildren_19	-369.299 (264.161)	-912.272 (798.497)	-4,205.958** (2,027.197)	-2,311.113 (1,961.262)	702.872 (6,831.015)
Xgeneration_19	6.243 (161.311)	-188.292 (822.771)	-3,830.388** (1,758.419)	-2,089.368 (1,846.709)	-4,023.281 (5,472.233)
Constant	137.867 (450.775)	2,130.234 (2,768.856)	3,266.279** (1,436.151)	4,535.053*** (1,039.497)	-2,525.430 (6,788.293)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.5: Estimation results of quantile regression - Model 3 (2014)

	<i>Dependent variable: NW_HE</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults	16,947.020*** (4,702.445)	45,959.080*** (4,735.179)	28,640.110*** (6,532.003)	6,443.613** (3,034.219)	5,410.651 (7,323.512)
Xseniors	43,747.330*** (4,935.048)	53,573.610*** (1,056.990)	31,593.510*** (6,531.079)	12,865.010*** (3,067.734)	19,615.690** (7,891.101)
Xretiree	44,273.530*** (6,368.492)	54,223.610*** (1,118.277)	30,887.310*** (6,532.750)	11,589.060*** (3,017.708)	13,610.650* (7,700.648)
Xincome	-0.014 (0.157)	0.189*** (0.051)	0.279*** (0.062)	0.467*** (0.155)	1.117** (0.515)
Xno_empmembers	5,471.548** (2,261.227)	2,460.612*** (424.318)	3,972.052*** (419.158)	8,456.895*** (1,201.629)	19,437.980*** (3,313.514)
Xno_members	-5,798.866 (6,602.035)	-333.868 (1,446.428)	718.066 (863.009)	2,702.926 (2,123.968)	-187.052 (6,577.429)
Xgender	2,320.000 (4,499.288)	0.000 (601.817)	1,115.215** (490.640)	2,819.649** (1,165.081)	4,289.754 (3,690.297)
Xmortgage	-9,152.873* (5,148.018)	-14,212.030*** (3,295.869)	-10,263.820*** (1,982.065)	-8,039.424*** (2,809.191)	-4,055.432 (11,331.080)
Xloan	-9,237.453** (3,610.393)	-6,016.132*** (1,328.529)	-5,156.200*** (629.679)	-4,001.751*** (1,204.857)	-6,086.356 (4,151.835)
Xhighschool	0.000 (16,299.380)	350.000 (2,811.562)	100.000 (218.409)	1,175.800 (2,431.702)	-5,889.632** (2,887.762)
Xuniversity	13,339.620 (16,813.160)	5,598.400** (2,831.125)	7,621.748*** (1,360.217)	16,719.000*** (4,507.158)	57,485.820** (24,074.150)
Xnochildren	47,028.440*** (6,967.551)	1,166.934 (1,102.780)	2,225.752*** (662.840)	2,803.088 (1,745.412)	8,079.882 (5,768.678)
Xsingleparent	45,361.030*** (8,095.799)	905.841 (1,346.023)	1,781.349** (740.359)	1,650.872 (3,185.002)	681.526 (6,495.759)
Xparents	26,711.620*** (9,281.515)	-1,445.671 (3,059.131)	-2.465 (1,273.728)	-694.155 (3,435.828)	5,619.408 (9,878.143)
Xmorechildren	34,080.590** (14,917.920)	984.188 (3,185.026)	-1,048.905 (2,063.463)	-4,434.115 (4,381.157)	30,271.210 (39,459.030)
Xgeneration	51,381.920*** (18,824.040)	3,087.509 (2,686.219)	2,137.252 (2,173.957)	-737.066 (5,869.271)	-951.124 (16,369.010)
Constant	-94,749.110*** (17,922.770)	-56,844.120*** (3,383.551)	-35,451.650*** (6,633.453)	-19,591.410*** (4,967.003)	-14,764.510 (14,771.940)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.6: Estimation results of quantile regression - Model 3 (2019)

	<i>Dependent variable: NW_HE_19</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults_19	13,845.880*** (4,684.991)	36,164.530*** (5,585.499)	14,022.270 (12,064.820)	7,618.672 (5,496.170)	17,214.550 (11,884.510)
Xseniors_19	49,232.530*** (3,282.275)	56,811.780*** (2,776.742)	26,122.930** (11,907.740)	19,836.260*** (5,212.915)	31,697.330*** (11,208.590)
Xretiree_19	51,400.070*** (3,650.554)	55,968.040*** (2,757.488)	23,350.850* (11,941.300)	14,282.390*** (4,863.587)	32,514.920*** (11,218.660)
Xincome_19	0.226*** (0.068)	0.221** (0.102)	0.427*** (0.108)	0.678*** (0.185)	1.567*** (0.500)
Xno_empmembers_19	-1,878.575 (1,281.714)	88.538 (1,087.201)	2,117.393* (1,083.486)	5,979.069*** (1,906.989)	21,940.900*** (3,576.153)
Xno_members_19	6,186.911 (4,103.014)	5,342.428** (2,153.400)	6,577.179*** (2,533.248)	9,021.040*** (2,895.696)	6,277.324 (11,505.990)
Xgender_19	1,159.456 (2,817.342)	3,148.190** (1,466.323)	1,412.907 (1,430.205)	2,868.029 (2,332.770)	5,075.809 (3,420.065)
Xmortgage_19	-14,045.530*** (3,877.194)	-14,135.710*** (1,696.152)	-7,714.831** (3,527.073)	-5,934.213 (4,146.331)	-6,452.041 (6,981.949)
Xloan_19	-1,343.160 (4,214.095)	9,550.421*** (1,617.653)	10,000.640*** (1,610.548)	10,083.780*** (2,887.769)	15,697.960** (7,616.631)
Xhighschool_19	-5,941.164 (9,171.764)	-5,978.763** (2,577.123)	942.513 (2,926.184)	-7,210.357** (3,621.118)	-4,496.789 (7,435.923)
Xuniversity_19	105.911 (9,351.225)	-1,859.493 (3,415.613)	8,215.157** (3,788.198)	16,499.090** (6,426.772)	69,646.130** (30,126.460)
Xnochildren_19	-7,023.435 (4,395.784)	-4,779.657** (2,075.725)	-1,024.044 (2,126.387)	-1,745.257 (3,072.410)	2,879.495 (7,871.533)
Xsingleparent_19	9,464.353 (5,824.424)	2,150.639 (3,473.451)	-1,967.033 (3,308.257)	-3,065.242 (5,350.159)	2,194.335 (9,467.800)
Xparents_19	-15,558.500*** (5,531.491)	-11,863.190** (5,449.457)	-3,956.331 (3,808.104)	-5,121.428 (5,666.272)	9,077.261 (14,975.450)
Xmorechildren_19	-7,740.883 (8,541.531)	-2,765.266 (6,554.442)	-11,960.880** (6,019.874)	-14,698.180 (10,770.630)	-322.516 (21,679.590)
Xgeneration_19	-1,706.149 (7,186.197)	-5,884.623 (5,705.017)	-5,832.998 (5,353.123)	-10,424.740 (7,035.361)	-15,188.760 (24,934.810)
Constant	-92,403.240*** (10,895.900)	-83,921.450*** (4,394.391)	-52,765.580*** (12,541.700)	-31,314.530*** (7,706.186)	-48,321.410** (19,928.480)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.7: Estimation results of quantile regression - Model 4 (2014)

	<i>Dependent variable: Period</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults	24.928*** (2.291)	26.118*** (2.986)	37.081*** (8.535)	49.460*** (12.839)	15.431 (22.359)
Xseniors	30.604*** (2.215)	46.571*** (3.703)	58.655*** (8.793)	68.020*** (12.963)	57.769** (26.044)
Xretiree	31.790*** (4.054)	49.399*** (4.893)	58.727*** (9.482)	74.496*** (13.997)	49.917* (26.436)
Xincome	0.0004** (0.0002)	0.001*** (0.0002)	0.001* (0.0003)	0.002*** (0.001)	0.003*** (0.001)
Xno_empmembers	6.771*** (1.395)	12.006*** (1.553)	15.246*** (2.354)	25.178*** (3.736)	33.487*** (5.737)
Xno_members	-10.474*** (3.303)	-25.526*** (3.249)	-34.318*** (4.595)	-50.184*** (8.675)	-51.709*** (14.115)
Xgender	-1.160 (2.918)	-5.190 (3.978)	7.384* (4.269)	16.915** (6.919)	28.035*** (9.437)
Xmortgage	37.381*** (1.640)	40.496*** (3.146)	45.454*** (8.117)	53.539*** (12.993)	102.284*** (20.678)
Xloan	-5.185*** (1.676)	-11.526*** (2.808)	-15.501*** (4.838)	-13.372** (6.657)	-8.854 (13.379)
Xhighschool	23.650 (18.074)	12.714*** (4.669)	27.211** (11.103)	24.365 (16.200)	0.386 (88.866)
Xuniversity	57.719*** (18.619)	50.316*** (5.864)	74.764*** (13.124)	99.068*** (19.919)	177.978* (96.379)
Xnochildren	31.630*** (4.431)	32.248*** (5.917)	8.878 (6.796)	-3.104 (9.775)	-19.947 (18.538)
Xsingleparent	15.959*** (4.362)	22.580** (11.164)	11.803 (10.663)	6.019 (16.467)	-36.021 (43.553)
Xparents	10.761** (4.225)	17.792** (7.104)	-9.202 (9.324)	-17.999 (14.032)	-54.446** (24.891)
Xmorechildren	17.496*** (6.624)	27.840*** (8.743)	2.555 (12.652)	-17.651 (28.456)	-2.826 (35.889)
Xgeneration	20.725** (8.292)	29.300*** (8.820)	2.114 (11.685)	-12.754 (20.246)	-65.814* (36.408)
Constant	-45.061** (18.680)	3.364 (7.486)	41.152** (16.480)	85.678*** (22.736)	190.377** (94.720)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.8: Estimation results of quantile regression - Model 4 (2019)

	<i>Dependent variable: Period_19</i>				
	(tau=0.10)	(tau=0.25)	(tau=0.50)	(tau=0.75)	(tau=0.90)
Xadults_19	21.357*** (4.183)	48.194*** (8.942)	51.577*** (14.326)	62.103*** (7.530)	66.062** (29.083)
Xseniors_19	39.742*** (4.171)	60.774*** (8.420)	66.886*** (14.222)	86.544*** (8.160)	97.908*** (27.869)
Xretiree_19	51.616*** (5.137)	75.958*** (8.291)	78.611*** (14.576)	92.242*** (9.437)	108.921*** (28.489)
Xincome_19	0.0005*** (0.0002)	0.0005** (0.0002)	0.001** (0.0003)	0.002*** (0.0005)	0.002*** (0.001)
Xno_empmembers_19	7.630*** (1.492)	14.266*** (1.576)	14.294*** (3.016)	21.254*** (4.053)	35.931*** (5.645)
Xno_members_19	-21.516*** (2.632)	-32.267*** (2.848)	-38.028*** (4.920)	-45.436*** (9.002)	-59.908*** (9.494)
Xgender_19	-4.555 (3.578)	-2.482 (3.607)	12.431*** (4.760)	24.540*** (7.130)	24.425** (9.565)
Xmortgage_19	32.495*** (3.132)	28.998*** (5.413)	32.451*** (6.942)	33.253*** (9.982)	75.732*** (18.409)
Xloan_19	-10.448*** (2.337)	-12.162*** (3.457)	-6.232 (5.637)	0.490 (6.758)	-2.811 (8.814)
Xhighschool_19	20.475*** (7.427)	13.091 (17.201)	19.925 (24.950)	3.184 (11.064)	2.232 (47.978)
Xuniversity_19	49.781*** (9.950)	45.734*** (17.507)	68.296*** (25.941)	77.145*** (17.678)	208.783*** (69.773)
Xnochildren_19	8.727* (5.201)	-0.813 (5.385)	-25.622*** (8.260)	-67.966*** (11.164)	-32.697** (13.514)
Xsingleparent_19	0.206 (10.549)	1.837 (9.874)	-18.716 (14.275)	-52.855*** (15.427)	-25.565 (22.226)
Xparents_19	0.607 (5.917)	-11.750 (7.239)	-35.844*** (10.512)	-70.660*** (14.402)	-64.700*** (17.823)
Xmorechildren_19	11.751 (7.172)	-4.264 (7.755)	-36.918** (16.872)	-85.745*** (22.862)	-27.534 (51.093)
Xgeneration_19	9.964 (7.342)	-2.941 (7.519)	-35.111*** (13.160)	-100.356*** (21.111)	-71.521*** (25.288)
Constant	4.126 (9.460)	39.739** (18.995)	86.736*** (29.770)	165.015*** (18.166)	200.348*** (57.120)
Observations	2,135	2,135	2,135	2,135	2,135

Note:

*p<0.1; **p<0.05; ***p<0.01

Appendix B

Gauss-Markov assumptions

To get the estimates of parameters efficient, consistent, and unbiased certain assumptions must be fulfilled.

1. *MLR.1. Linearity in parameters*

The model (4.2) should be linear in all parameters and also in the disturbance term. The equations of models used in this study are always linear in parameters, we assume that the relationship between the dependent variable and the independent variables is linear.

2. *MLR.2. Random sampling*

The data $\{(x_{i1}, \dots, x_{ik}, y_i), i = 1, \dots, n\}$ is a random sample drawn from the population, i.e., each data point follows the equation (4.2). Our sample contains households selected based on probability sampling, which consists of two parts - the planning of the sampling procedure and the estimation procedures. The selection plan includes the creation and selection of all subsequently used methods and mathematical models. Random number generators are most commonly used as a random selection mechanism, however, it may also be any other type of random draw. This type of selection fulfills this requirement.

3. *MLR.3. No Perfect Collinearity*

In the sample, none of the independent variables should be constant and there should not be exact relationships among the independent variables. Constant variables are also ruled out (collinear with intercept). We assume that there are no exact linear relationships between independent variables in our sample. None of our independent variables is constant. To avoid multicollinearity between independent dummy variables, one of

the dummy variables is always chosen as the base one. To investigate multicollinearity, we used the correlation matrix to determine the extent to which multicollinearity of independent variables affects the variance of an OLS estimate. The outcome is a table containing the correlation coefficients between each variable and the others. Our results can be checked in the table (B.1). According to Dohoo *et al.* (1997), multicollinearity is certain at the 0.9 level of a correlation coefficient or higher. The results do not show the threat of multicollinearity.

4. *MLR.4. Zero conditional mean*

The value of the explanatory variables must contain no information about the mean of the unobserved factors.

$$E[u_i|x_{i1}, \dots, x_{ik}] = 0 \quad (\text{B.1})$$

Explanatory variables that are correlated with the error term are called *endogenous*; endogeneity is a violation of assumption MLR.4. Explanatory variables that are uncorrelated with the error term are called *exogenous*; MLR.4 holds if all explanatory variables are exogenous. Exogeneity is the key assumption for a causal interpretation of the regression and the unbiasedness of the OLS estimators. We cannot test this assumption, but we tried to include as many independent variables as possible to ensure that the independent variables do not correlate with the error term.

5. *MLR.5. Homoskedasticity*

The value of the explanatory variables should not contain information about the variance of the unobserved factors.

$$\text{Var}[u_i|x_{i1}, \dots, x_{ik}] = \sigma^2 \quad (\text{B.2})$$

If this assumption is not met, we are talking about heteroscedasticity. Heteroscedasticity makes the OLS method ineffective. There are several tests to detect heteroscedasticity. We will discuss them later in this study.

Under these five assumptions mentioned above, the OLS estimators are the best linear unbiased estimators of the regression coefficients (Wooldridge 2013).

6. *MLR.6. Normality*

The error term should be independent of the explanatory variables

and should be normally distributed with zero mean and variance $\sigma^2 : u \sim \text{Normal}(0, \sigma^2)$. We can use the Anderson-Darling test and the Shapiro-Wilk test to verify this assumption. Both tests are described in Appendix C.

Since assumptions MLR.5. and MLR.6. are not required for quantile regression, we can rely on the estimates made by the method described in section 4.1.2 if these two assumptions are not met.

Table B.1: Correlation matrix

	Net_W	Fin_A	NW_HE	Per.	age	inc_e	no_m	no_e.m	gend.	mortg.	loan	educ.	type
Net_wealth	1	0.333	0.985	0.981	0.007	0.178	0.058	0.094	0.079	0.011	-0.029	0.166	-0.090
Fin_assets	0.333	1	0.307	0.298	-0.021	0.267	0.089	0.126	0.106	0.016	-0.037	0.255	-0.096
NW_HE	0.985	0.307	1	0.971	0.025	0.148	0.038	0.060	0.057	-0.017	-0.036	0.123	-0.067
Period	0.981	0.298	0.971	1	0.027	0.138	-0.034	0.030	0.038	0.025	-0.036	0.154	-0.026
age	0.007	-0.021	0.025	0.027	1	-0.030	-0.343	-0.480	-0.245	-0.360	-0.236	-0.219	0.276
income	0.178	0.267	0.148	0.138	-0.030	1	0.116	0.258	0.113	0.100	0.0004	0.222	-0.061
no_members	0.058	0.089	0.038	-0.034	-0.343	0.116	1	0.602	0.371	0.197	0.207	0.043	-0.586
no_empmembers	0.094	0.126	0.060	0.030	-0.480	0.258	0.602	1	0.283	0.295	0.205	0.208	-0.412
gender	0.079	0.106	0.057	0.038	-0.245	0.113	0.371	0.283	1	0.130	0.045	0.176	-0.493
mortgage	0.011	0.016	-0.017	0.025	-0.360	0.100	0.197	0.295	0.130	1	0.066	0.138	-0.121
loan	-0.029	-0.037	-0.036	-0.036	-0.236	0.0004	0.207	0.205	0.045	0.066	1	-0.036	-0.131
education	0.166	0.255	0.123	0.154	-0.219	0.222	0.043	0.208	0.176	0.138	-0.036	1	-0.139
type	-0.090	-0.096	-0.067	-0.026	0.276	-0.061	-0.586	-0.412	-0.493	-0.121	-0.131	-0.139	1

Appendix C

Tests

In order to make the data suitable for econometrics analysis several tests are to be applied.

Testing for homoskedasticity

1. Breuch-Pagan test

Homoskedasticity is the state in which the variance of the error u_i is always constant unconditionally on the explanatory variables, i.e. $Var(u_i|X'_i) = \sigma^2\mathbb{I}$. The Breusch-Pagan (BP) test is one of the most common tests to investigate the existence of heteroscedasticity. It is usually applied by assuming that heteroscedasticity may be a linear function of all the independent variables in the model. The BP test firstly constructs the model then obtains the residuals. Generally, the BP test is based on the estimation of

$$\hat{\epsilon}_i^2 = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + u_i, i = 1, 2, \dots, n, \quad (C.1)$$

where $\hat{\epsilon}_i^2$ are calculated from the residuals and used as proxies for ϵ_i^2 .

We tested for the presence of heteroscedasticity using the PB test and the results are in the table below:

The test results ¹ show that the null hypothesis is rejected only for the Model 2 (for variations a , b and d). For other models, the p-value is above the appropriate threshold ($p > 0.05$), thus the error variances are

¹The results are for models with data from 2014, the results for models with simulated data from 2019 are very similar, therefore we do not present them here.

Table C.1: Breusch-Pagan test against heteroscedasticity

	statistic	p-value	parameter
Model1a	11.704	0.764	16
Model2a	89.871	0.001	16
Model3a	11.162	0.780	16
Model4a	10.936	0.814	16
Model1b	3.109	0.683	5
Model2b	58.004	0.001	5
Model3b	2.856	0.722	5
Model4b	2.593	0.8762	5
Model1c	0.230	0.632	1
Model2c	3.007	0.083	1
Model3c	0.230	0.632	1
Model4c	0.201	0.654	1
Model1d	3.229	0.863	7
Model2d	57.169	0.001	7
Model3d	2.951	0.889	7
Model4d	2.660	0.915	7

equal. We need to adjust standard errors for heteroscedasticity in the Model 2 (discussed in section 4.1.3).

Pedace (2013) stated that a weakness of the BP test is the assumption of the heteroscedasticity being a linear function of the independent variables. Failing to find evidence of heteroscedasticity with the BP does not rule out a nonlinear relationship between the independent variable(s) and the error variance. Additionally, the BP test is not useful for determining how to correct or adjust the model for heteroscedasticity.

2. White's test

White's test is used to test for heteroscedastic errors in regression analysis. According to Pedace (2013), White's test allows the heteroscedasticity process to be a function of one or more of our independent variables. It is a special case of the (simpler) Breusch-Pagan test, but the White's test allows the independent variable to have a nonlinear and interactive effect on the error variance. In other words, it can be used when the errors are not normally distributed. The White's test is based on the

estimation of

$$\hat{\epsilon}_i^2 = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \beta_{k+1} x_{ik}^2 + \dots + \beta_{2k} x_{ik}^2 + \dots + \beta_{2k+1} (x_{i1} x_{i2}) + \dots + u_i, \quad (\text{C.2})$$

where $\hat{\epsilon}_i^2$ are calculated from the residuals and used as proxies for ϵ_i^2 .

One issue with White's test is that it can return a significant result even if the variances of the errors are equal. This happens because the model is a general one and adds a lot of terms to test for more types of heteroscedasticity (for example, adding the squares of regressors). The addition of all these terms may make the test less powerful in those situations when a simpler Breusch-Pagan test would be appropriate.

Testing for normality

1. Anderson-Darling test

The Anderson-Darling test for normality is one of three general normality tests. It is used to determine if a data set follows a specified distribution. The test involves calculating the Anderson-Darling statistic, which can be used to compare how well a data set fits different distributions. The test makes use of the cumulative distribution function. The Anderson-Darling statistic is given by the following formula:

$$AD = -n - \frac{1}{n} \sum_{i=1}^n (2i - 1) [\ln F(X_i) + \ln(1 - F(X_{n-i+1}))], \quad (\text{C.3})$$

where n is a sample size and $F(X)$ is the specified normal cumulative distribution function.

The test rejected the null hypothesis saying that the data are normally distributed. The results are enclosed in table (C.2).

The Anderson-Darling test is generally considered to be one of the most powerful tests for normality, however, it is severely affected by identical values (ties) in the data due to poor precision. When a significant number of ties exist, the Anderson-Darling will frequently reject the data as non-normal, regardless of how well the data fits the normal distribution.

2. Shapiro-Wilk test

The Shapiro-Wilk test is a test of normality that assesses whether a sam-

ple is likely to originate from a normal distribution. Despite the fact that the Shapiro-Wilk serves the exact same purpose as the Anderson-Darling test, we have decided to employ both tests, because the Shapiro-Wilks test is not as affected by ties as the Anderson-Darling test. The Shapiro-Wilk statistic is given by the following formula:

$$W = \frac{(\sum_{i=1}^n a_i x_i)^2}{(\sum_{i=1}^n x_i - \bar{x})^2}, \quad (\text{C.4})$$

where n is sample size, x_i are the ordered sample values and a_i are constants generated from the means, variances, and covariances of the order statistics.

As with the Anderson-Darling test, we rejected the null hypothesis of normality for all variables. Results can be seen in table (C.2). Robust standard errors which are discussed in section 4.1.3 may compensate for this problem.

The two above mentioned tests have limitations, most importantly that the test have a bias by sample size. For small sample sizes, normality tests have little power to reject the null hypothesis, and therefore small samples most often pass normality tests. For large sample sizes, significant results would be derived even in the case of a small deviation from normality, although this small deviation will not affect the results of a parametric test (Oztuna *et al.* 2006).

Table C.2: Normality testing

	<i>Anderson-Darling test</i>		<i>Shapiro-Wilk test</i>	
	statistic	p-value	statistic	p-value
Net_wealth	458.023	$2.2*10^{-16}$	0.156	$2.2*10^{-16}$
Fin_assets	317.604	$2.2*10^{-16}$	0.428	$2.2*10^{-16}$
Fin_liabilities	345.321	$2.2*10^{-16}$	0.518	$2.2*10^{-16}$
Real_assets	477.942	$2.2*10^{-16}$	0.144	$2.2*10^{-16}$
NW_HE	564.132	$2.2*10^{-16}$	0.104	$2.2*10^{-16}$
Period	454.636	$2.2*10^{-16}$	0.145	$2.2*10^{-16}$
juniors	748.262	$2.2*10^{-16}$	0.271	$2.2*10^{-16}$
seniors	399.891	$2.2*10^{-16}$	0.624	$2.2*10^{-16}$
retiree	478.454	$2.2*10^{-16}$	0.565	$2.2*10^{-16}$
income	168.977	$2.2*10^{-16}$	0.666	$2.2*10^{-16}$
no_members	78.217	$2.2*10^{-16}$	0.872	$2.2*10^{-16}$
no_empmembers	146.487	$2.2*10^{-16}$	0.822	$2.2*10^{-16}$
gender	438.219	$2.2*10^{-16}$	0.596	$2.2*10^{-16}$
mortgage	669.289	$2.2*10^{-16}$	0.385	$2.2*10^{-16}$
loan	562.363	$2.2*10^{-16}$	0.495	$2.2*10^{-16}$
highschool	551.274	$2.2*10^{-16}$	0.505	$2.2*10^{-16}$
university	565.750	$2.2*10^{-16}$	0.492	$2.2*10^{-16}$
single	820.902	$2.2*10^{-16}$	0.043	$2.2*10^{-16}$
nochildren	402.398	$2.2*10^{-16}$	0.623	$2.2*10^{-16}$
singleparent	787.763	$2.2*10^{-16}$	0.181	$2.2*10^{-16}$
parents	607.825	$2.2*10^{-16}$	0.452	$2.2*10^{-16}$
morechildren	788.881	$2.2*10^{-16}$	0.178	$2.2*10^{-16}$
generation	723.912	$2.2*10^{-16}$	0.311	$2.2*10^{-16}$
home	85.373	$2.2*10^{-16}$	0.778	$2.2*10^{-16}$

Appendix D

Overview of models

Model 1

Modell1a:

$$\begin{aligned} Net_wealth = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree + \beta_4 income \\ & + \beta_5 no_empmembers + \beta_6 no_members + \beta_7 gender + \beta_8 mortgage \\ & + \beta_9 loan + \beta_{10} highschool + \beta_{11} university + \beta_{12} nochildren \\ & + \beta_{13} singleparent + \beta_{14} parents + \beta_{15} morechildren + \beta_{16} generation + u \end{aligned} \quad (D.1)$$

Modell1b:

$$\begin{aligned} Net_wealth = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree \\ & + \beta_4 income + \beta_5 no_empmembers + u \end{aligned} \quad (D.2)$$

Modell1c:

$$Net_wealth = \beta_0 + \beta_1 mortgage + u \quad (D.3)$$

Modell1d:

$$\begin{aligned} Net_wealth = & \beta_0 + \beta_1 mortgage + \beta_2 loan + \beta_3 adults + \beta_4 seniors \\ & + \beta_5 retiree + \beta_6 income + \beta_7 no_empmembers + u \end{aligned} \quad (D.4)$$

Model 2

Model2a:

$$\begin{aligned}
Fin_assets = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree + \beta_4 income \\
& + \beta_5 no_empmembers + \beta_6 no_members + \beta_7 gender + \beta_8 mortgage \\
& + \beta_9 loan + \beta_{10} highschool + \beta_{11} university + \beta_{12} nochildren \\
& + \beta_{13} singleparent + \beta_{14} parents + \beta_{15} morechildren + \beta_{16} generation + u
\end{aligned} \tag{D.5}$$

Model2b:

$$\begin{aligned}
Fin_assets = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree \\
& + \beta_4 income + \beta_5 no_empmembers + u
\end{aligned} \tag{D.6}$$

Model2c:

$$Fin_assets = \beta_0 + \beta_1 mortgage + u \tag{D.7}$$

Model2d:

$$\begin{aligned}
Fin_assets = & \beta_0 + \beta_1 mortgage + \beta_2 loan + \beta_3 adults + \beta_4 seniors \\
& + \beta_5 retiree + \beta_6 income + \beta_7 no_empmembers + u
\end{aligned} \tag{D.8}$$

Model 3

Model3a:

$$\begin{aligned}
NW_HE = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree + \beta_4 income \\
& + \beta_5 no_empmembers + \beta_6 no_members + \beta_7 gender + \beta_8 mortgage \\
& + \beta_9 loan + \beta_{10} highschool + \beta_{11} university + \beta_{12} nochildren \\
& + \beta_{13} singleparent + \beta_{14} parents + \beta_{15} morechildren + \beta_{16} generation + u
\end{aligned} \tag{D.9}$$

Model3b:

$$\begin{aligned}
NW_HE = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree \\
& + \beta_4 income + \beta_5 no_empmembers + u
\end{aligned} \tag{D.10}$$

Model3c:

$$NW_HE = \beta_0 + \beta_1 mortgage + u \tag{D.11}$$

Model3d:

$$NW_HE = \beta_0 + \beta_1 mortgage + \beta_2 loan + \beta_3 adults + \beta_4 seniors + \beta_5 retiree + \beta_6 income + \beta_7 no_empmembers + u \quad (D.12)$$

Model 4

Model4a:

$$\begin{aligned} Period = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree + \beta_4 income \\ & + \beta_5 no_empmembers + \beta_6 no_members + \beta_7 gender + \beta_8 mortgage \\ & + \beta_9 loan + \beta_{10} highschool + \beta_{11} university + \beta_{12} nochildren \\ & + \beta_{13} singleparent + \beta_{14} parents + \beta_{15} morechildren + \beta_{16} generation + u \end{aligned} \quad (D.13)$$

Model4b:

$$\begin{aligned} Period = & \beta_0 + \beta_1 adults + \beta_2 seniors + \beta_3 retiree \\ & + \beta_4 income + \beta_5 no_empmembers + u \end{aligned} \quad (D.14)$$

Model4c:

$$Period = \beta_0 + \beta_1 mortgage + u \quad (D.15)$$

Model4d:

$$\begin{aligned} Period = & \beta_0 + \beta_1 mortgage + \beta_2 loan + \beta_3 adults + \beta_4 seniors \\ & + \beta_5 retiree + \beta_6 income + \beta_7 no_empmembers + u \end{aligned} \quad (D.16)$$