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MASTER'S THESIS

The impact of grandchildren on retirement timing: evidence from SHARE data

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, May 4, 2021 Jan Srna

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This thesis uses data from the generated easySHARE data set see Gruber et al. (2014) for methodological details. The easySHARE release 7.1.0 is based on SHARE Waves 1, 2, 3, 4, 5, 6 and 7. (DOI: 10.6103/SHARE.easy.710)

Abstract

This thesis examines the role of grandchildren´s existence in the retirement timing decision-making process of grandparents. Previous literature has focused mostly on other aspects of retirement and potential causes that can affect its timing. Using the Two-Stage least squares estimation on the SHARE dataset, representing 17 European countries and Israel, we estimate the desired effect with respect to various data limitations (age groups, gender, child existence). Residential proximity is used as the instrument for estimation. Having at least one grandchild yields a statistically significant result that increases on average the likelihood of retirement by 19% when compared to a non-grandparent while holding other factors constant. As a secondary outcome, the estimated effect of an additional child on retirement likelihood is negative.

JEL Classification	C36, C51, J26
Keywords	grandchild, retirement, Instrumental variable, SHARE, IV, wide-ranging data, 2SLS
Title	The impact of grandchildren on retirement timing: evidence from SHARE data

Abstrakt

Tato práce pojednává o efektu, který může mít existence vnoučat na plánování odchodu do důchodu jeho prarodičů. Předchozí literatura tento dopad na načasování převážně ignorovala a soustředila se spíše na tradičně uznávané důvody. Tento efekt je odhadován pomocí regrese s dvoustupňovým odhadováním nejmenších čtverců (2SLS) na datech SHARE, ve kterých je reprezentováno 17 evropských států a Izrael. Jako instrument používáme rezidenční blízkost dětí k respondentům. Model je postupně užíván na různých setech dat, které jsou omezovány podle věku, pohlaví a existence dětí. Výsledek ukazuje, že člověk s alespoň jedním vnoučetem bude průměrně o 19 % pravděpodobněji v penzi než člověk bez vnoučat (když držíme ostatní faktory stabilní). Dále můžeme z výsledku vyčíst, že každé přidané dítě znamená pro respondenta oddálení odchodu do důchodu.

Klasifikace	C36, C51, J26
Klíčová slova	vnouče, důchod, instrumentální proměnná, SHARE, IV, vícerozměrná data, 2SLS
Název práce	Závislost načasování odchodu do důchodu na existenci vnoučat: evidence s využitím dat SHARE

Contents

List of Tables

List of Figures

Acronyms

EU	European Union
SHARE	Survey of Health, Ageing and Retirement in Europe
NA	Not available
N/A	Not available
NAs	Not availables
OLS	Ordinary least squares
IV	Instrumental variable
2SLS	Two-Stage least squares
VIF	Variance inflation factor

Master's Thesis Proposal

Author:	Bc. Jan Srna
Supervisor:	Mgr. Barbara Pertold-Gebicka, M.A., Ph.D.
Defense Planned:	June 2021

Proposed Topic:
The impact of grandchildren on retirement timing: evidence from SHARE data

Motivation:
The “right” age for retirement has been an issue for policy-makers for a very long time. With better and safer working conditions as well as extended life expectancy people can work longer and often surpass the legal required age for retirement set in their field of work. This means many people tend to leave the decision entirely as their own personal choice. Many aspects become relevant in this decision-making process. One of which is the grandparenthood. In other words, some people see grandchildren as one of the reasons to retire and have time to help with care. On the other hand, the relationship can have an opposite sign for people who would decide to keep their jobs in order to earn money to support their grandchildren. This relation is vital to examine to properly comprehend the choice of people to retire at different ages. It does not explain the whole picture, but it is another important piece in the puzzle for lawmakers to design policies accordingly.

Hypotheses:
1. Is there a positive relationship between arrival of the first grandchild and the willingness to retire in case of people around retirement age?
2. Is there evidence in the data that a single grandparent is more active in case of care-aid than a grandparent with a partner?
3. Is there a connection between family wealth and willingness of grandparents to provide care for grandchildren?

Methodology:
I will use data provided by the project SHARE. It provides datasets with detailed information about people of age over 50 from 27 different European countries and Israel. My plan is to use as much of the available information as possible to set up a formula that will be estimated. Since it is certain that retirement timing is not only affected by grandchildren, there are many variables included in the dataset that should be present in the formula. From the more expected ones such as number of grandchildren, age, nationality, education, occupation etc. trough the more “advanced” characteristics such as financial situation, health conditions, living arrangements (elderly house or not) to extremely detailed information such as willingness to answer and/or clarify, memory status, physical activity or years of daily smoking.
The main variable of interest is a dummy which describes whether the respondent is retired or not. On the explanatory side I will use as many characteristics mentioned in the previous paragraph as possible. One of them is going to be a dummy for having a grandchild to be able to examine the relationship. The interesting aspect of this additional variable is not only its statistical significance

itself (to show the importance of grandchildren in the retirement decision-making) but also the sign of the link (as explained in the Motivation part).
There is simply a wide spread of various characteristics about people that answered those questionnaires. When carefully estimated even simple OLS method should yield interesting results. However, OLS provides information on the correlation between the two examined variables but does not help to uncover potential causality. Three main forms of the relationship can arise. Firstly, there could be no actual link between retirement and a birth of a grandchild. In other words, children are born during the same time that their grandparents retire with no direct mutual effect between these two. That would be an example of a spurious correlation. Second option would be reversed causality which in this situation is a following scenario: future parents (the second generation) wait with their own children (the third generation) until their parents or at least mothers (the first generation) retire. The third option of the relationship is causality which is the expected relationship in my hypotheses. In this case a birth of a grandchild motivates its grandparents to retire.
There are a few ways how to examine the relationship more deeply to avoid potential confusing results described in the previous paragraph. It is possible to gather the data with a panel structure to follow people across several years to see if retirement came earlier than grandchildren or vice versa. Furthermore, estimation can be performed separately for men and women because women are believed to have children earlier than men. Another option is to use an instrumental variable to account for the birth of a child. Since women tend to have children earlier than men, people of age above 50 would more likely be grandparents sooner if their first child was a woman than if it was a man. Estimating this instrument would mean searching for a positive correlation between earlier retirements of the grandparents (the first generation) and having a girl as the first-born child (the second generation).
I plan to get additional inspiration about possible estimation techniques useful in this situation from the literature review.

Expected Contribution:
Relationship between retirement and grandchildren is very complicated to describe. Many papers have provided insides on the matter (usual only for a specific country) but using the advancement of technology nowadays more information can be gathered and then used in the estimation part to get more precise results relevant for larger areas. The purpose of the thesis should thus be to provide information for policy-makers to enable a development of a retirement system that reflects the outcomes of the paper.
My contribution to the field should be the examination of the relationships that can affect the decision-making for retirement using widely detailed data. This work is going to be relevant for European countries since the data origin from there and Israel. However, results can also be applicable as a “guide” for different countries (to some extend of course) that are on similar socio-economic levels such as countries in the EU.
In some cases, I can imagine, this work could benefit those who are not certain about their decision and need “justification” from the community. In other words, find comfort in the knowledge that there are others that deal with the same situation similarly.
Last but not least, results will be relevant even for the Czech Republic because it should reflect the general situation across the European countries. However, later in the process estimation of the restricted dataset with data only from the Czech

Republic can be performed to possible indicate deviations of Czech people from the European average behavior in this matter.

Outline:

My plan is to start with comprehension of the papers mentioned bellow in the Core Bibliography section. One of these is a paper that describes that process of data extraction and explains all variables included in the datasets provided by the SHARE program. Before studying other related papers, understanding the structure and capacity of the data is crucial for me. Then I can choose such papers that can inspire me throughout my work while dealing inside the boundaries of the provided datasets. My writing section will follow a similar path. I want to start with a brief summary of the important papers in the field and then move straight to the methodology and estimation section. That should be sufficient to exclude those papers that would later turn out to be irrelevant because of the limits of my estimation techniques or the lack of available data.

Core Bibliography:

1. Lumsdaine, R. L.; Vermeer, S. J., Retirement timing of women and the role of care responsibilities for grandchildren. Demography 2015, 52 (2), 433-454.
2. Kridahl, L., Retirement timing and grandparenthood in Sweden: Evidence from population-based register data. Demographic Research 2017, 37, 957-994.
3. Feng, J.; Zhang, X., Retirement and grandchild care in urban China. Feminist Economics 2018, 24 (2), 240-264.
4. Bergmann, M., Scherpenzeel, A., & Börsch-Supan, A. (2019). SHARE Wave 7 Methodology: Panel innovations and life histories. Munich: MEA, Max Planck Institute for Social Law and Social Policy.
5. Börsch-Supan, A.; Axt, K.; Beck, P.; Bergmann, M.; Coscia, V.; Korbmacher, J.; Malter, F.; Oepen, A.; Scherpenzeel, A.; Schmidutz, D., SHARE-ERIC. 2017.
6. Coile, C.; Gruber, J., Future social security entitlements and the retirement decision. The review of Economics and Statistics 2007, 89 (2), 234-246.

1 Introduction

The retirement timing decision-making process had long been mostly ignored by researchers. The lack of importance for political strategies combined with non-existing large sets of data had caused experts to focus elsewhere. Throughout the several recent decades, the ageing population, voluntary early retirements, increasing costs of pension programs, and higher focus on gender inequality have uncovered the importance of the matter. The retirement timing became a major socio-economic issue for political debates all around the World towards the end of the second half of the 20th century, especially in the case of the European Union. Naturally, a few options designed to deal with the issue appeared: statutory retirement age postponing, motivation to join/stay longer in the workforce and recalibration of pension social programs. Ageing population relates to increasing life-length expectancy that combined with better working health conditions implies a larger possibility of a person remaining professionally active for a longer period of time. Therefore, postponing the statutory retirement age is a logical response (but not very popular for the ordinary public). Another side of the coin is the motivation to join the workforce in the first place. There have been major changes in terms of the gender inequality related to workforce participation. Historically, women had not been largely encouraged to seek employment attributed to the expectations of them being homemakers who take care of the home and children. Recently, the number of active women in the workforce has been significantly increasing. The effect of such actions is not necessarily immediate and not even sufficient alone. An increasing number of people eligible for pension programs requires more finances. Restructualization of the distribution, sources of financial funds, and those social programs, in general, should be imminent.

The objective of this thesis is to provide additional information on the decision-making process preferably focusing on a specific part that has not yet been widely examined. The impact that an existence of a grandchild can have on the retirement timing/likelihood does not have a large presence in the existing literature. It is generally assumed that there should be a statistical significance of the effect but mostly there is a lack of specification about the sign and size of the relationship. Using the

Instrumental variables regression (2SLS method) applied on data from the Survey of Health, Ageing and Retirement in Europe (SHARE) it is possible to test the statistical significance as well as specify the potential impact a grandchildren existence can have on retirement likelihood of grandparents.

The SHARE project has been gathering data since 2004 from (nowadays) 28 European countries and Israel. Altogether there are 7 different waves of data included in the whole dataset. The initial number of countries was limited but with each additional detailed questionnaire for a new wave, more countries have been joining the program. Larger amounts of observations and countries represented in the dataset create opportunities for better explanatory powers of models attributed to a larger probability of additional variations being included in the data. Two waves from the dataset are used in this thesis (waves 5 and 6) because they offer the most observations available in the grandchildren variable. These two waves provide a certain level of variability to the datasets with respect to countries because compared to wave 6, wave 5 contains one additional country – Netherlands while *vice versa* the additions are: Greece, Poland, Portugal, and Croatia. The empirical part of this thesis contains multiple regressions applied on miscellaneously restricted datasets to account for gender, age, the existence of a child, or even a particular wave. Such a strategy enables us to compare the results to ensure the consistency and validity of the estimated grandchild impact. Naturally, using more explanatory variables we can distinguish the other important factors as well. In combination with various models used on differently restricted datasets, we can specify the main variable impact for particular groups while accounting for the variable based on which the dataset is restricted. Statistically significant estimates (reported from these models) that converge around a certain value ensure the validity of the size of such impact.

The initial model used for estimation is an OLS regression even though evidence in the literature suggests existence of endogeneity in the variable grandchildren. Even when including variable children into the model, the potential risk of omitted variable bias is too great. The Instrumental variables regression is the chosen option to treat the endogeneity problem. “Residential proximity” is chosen as the instrument to describe variation within the grandchild variable. Residential proximity is a dummy variable that distinguishes respondents based on distance from the nearest child. Either a parent lives within a one-kilometer radius (often even the same household) from a child or further. Such a variable does not affect retirement timing alone but is related to the existence of a grandchild since one of the reasons to move out from parents is to start a new family. Hausman test confirms a better fit of the IV model on our dataset and therefore rejects the null hypothesis (no endogeneity present in the model).

The rest of this thesis is divided in the following parts: Chapter 2 – “Literature review” initially specifies the issue at hand and supports some ideas by ciations from existing literature. Chapter 3 – “Data” focuses on the structure of the SHARE dataset as well as necessary changes and restrictions performed. Chapter 4 – “Methodology” explains the process used to find a proper model for estimation. Chapter 5 – “Results and discussion” presents results from relevant estimations and interprets the estimated effects. Chapter 6 – “Conclusion” summarizes our findings and suggests the main potentials for a further research.

2 Literature review

When we think about the reasons behind the retirement timing many ideas appear leading with the most obvious one – “legal” retirement or so-called official pension ages established by individual governments. Various countries propose different required ages for retirement that allow one to gain full social benefits available. Of course, specific jobs, number of children, and other aspects can change the age number for each individual. Nevertheless, we often witness people retiring at distinct ages due to bad health conditions, decreasing will to continue with a person´s working carrier, sufficient financial situation, children, or even grandchildren. As was mentioned in the Introduction chapter, the main focus of this thesis will be to find evidence within the SHARE dataset indicating that, indeed, various aspects affect the decision-making process about retirement, especially the possession of grandchildren. The Literature review connects this task to existing publications that offer opinions from various perspectives. Unfortunately, only a limited number of authors have been examining the various reasons behind the decision-making process of retirement planning. Even fewer have tackled the issue of the direct impact a grandchild can have on a grandparent´s retirement timing. Therefore, the Literature review consists only of several papers that are directly connected to the topic of this thesis occasionally summarized in more detail due to some important messages they present and/or due to no other source of such thoughts available.

The gathered information from available literature is cited in several subparts. We begin with a wide overview of the political background in the EU including the historical evolution of the matter. With an established general setup next subsection narrows down the topic to an individual level. It covers the various incentives of a person in retirement timing planning with the main focus on the effect of grandchildren. The third subchapter remains with such a detailed scope and contributes with the impact of children and its connection to possession of grandchildren.

2.1 General political view of retirement planning in EU

2.1.1 Evolution of EU retirement policy strategy

Before we examine the matter in more detail concerning individual preferences we need to start more generally and consider the overall situation in the European Union. Decisions that involve plans about the right timing for retirement had long been ignored by researchers as well as politicians until the recent past. Various incentives and reasons for different behaviors among individuals were only examined on the surface at most. Throughout the last few decades of the 20th century, this issue gradually became more and more debated and since the early 2000s it has been one of the major topics of the European Union due to increasing levels of unemployment. The core factors in the matter were believed to be increasing ageing population, early retirements, generous social programs for retirement, etc. (Van Bavel and De Winter 2013, De Preter et al., 2013, Jappens and Van Bavel 2012). Such pattern eventuated in an increase of the average retirement age (cutting the raising costs of retirement programs due to reduced number of retired people), higher motivation to actively join the workforce for both men and women (especially), and recalibration of social pension programs.

First result – extended average retirement

With ageing population and the continuous extension of life expectancy governments naturally postpone the retirement age line – for most countries in Europe it is 65 (Van Bavel and De Winter 2013). People tend to work in better conditions which enables them to work longer. Contradicting this argument is Coile and Gruber (2007) that indicate the existence of a major development in retirement behavior among men in the second half of the 20th century. Among men of age 62, there had been a major 30% drop in employment before the end of the century. Multiple papers have examined this phenomenon with various reasons behind it. Social security program appears to be one of the major causes of this drop with the first spike of retirements in the age of 62 and the second one in 65 dues to part and full qualifications for the treatment respectively. Another significant but less impactful correlation seems to be between the retirement timing and the amplitude of the social treatment within the program. To be precise, there appears to be a more influential motivator than a simple “benefit for one more year” thought. The decision is driven concerning the whole wealth that is expected or can be expected in the future with respect to the work that is required to achieve it. There exists a maximization problem where the total utility of near and distant future is combined in order to form a retirement decision today.

Second result – increase of women in workforce

The simultaneous response was a desire to increase the number of employed people directly. According to Van Bavel and De Winter (2013), the targeted levels of employment of both men and women (established in Lisbon 2000) were 70% and 60% respectively with the higher burden on encouragement of women due to a larger percentage gap. Historically, men were considered the main income earners in households. Therefore, the workforce participation and employment levels were lower for women. Naturally, to achieve those percentage goals more women had to be encouraged to join the labor force[1]. More women (especially younger) in the labor force automatically increase the number of childcare services required since many of them are parents with young children. Of course, not every mom can afford traditional paid childcare service (either due to financial situation or reached capacity). According to Jappens and Van Bavel (2012), grandparents are involved in childcare almost 50% of the time in the case of men and nearly 60% in the case of women if they possess a grandchild no older than 15 years. But how often do they participate? Van Bavel and De Winter (2013) use the SHARE data from 2004 to estimate separately the involvement (at least once a week) of women and men in grandchild care which ranges from 20 to 40% and from 15 to 37% respectively. Jappens and Van Bavel (2012) support those results by their estimation of 30% (men and women combined). Authors continue with other results: average person over 50 is involved in grandchild care at least 0,5 hour a day[2] (Jappens and Van Bavel 2012, Van Bavel and De Winter 2013), additional 10% in traditional childcare services results in a drop of 23% among earlier retirements (Van Bavel and De Winter 2013). Most importantly (for the purposes of this thesis), Van Bavel and De Winter (2013) estimate that a 55-year-old grandparent

[1] Historically, women were expected to be the main source of house and childcare and even though a lot had changed throughout the decades before this century there were still significantly fewer women in the workforce.

[2] Average person is taken with no regard to possession of a grandchild.

is 88% more likely to retire than a non-grandparent with 55 years of age. That in no way determines a potential causal effect but still, it is a significant strong result.

Third result – social programs

Social initiatives built to support retired people were often designed for different sizes of populations among countries. Which means there are not enough resources to support everyone. That leads to even large differences among income groups within the nations. Some are qualified for substantial financial support sooner due to important job positions, some can finance themselves after retirement and others are left within increasingly less sufficient amounts. As De Preter et al. (2013) state that various social initiatives have lately been aimed to narrow down the income gaps and enable decent financial support even for the poorer people. As the population is ageing, higher demands are placed on the working class that provides contributions for the pension plans until the situation stabilizes (which is predicted to happen). Not surprisingly, people often say that working people generate sufficient amounts for the elderly but there won´t be anything left when they retire. Therefore, the ideal impact of current policies should be to enable and motivate older workers to remain or rejoin the working force if they can. Policies and regulations aimed at prolonging working life are usually not "public´s favorite actions" (Radl 2013). No matter the actual positive impacts it can have, rising the standard retirement age as well as cutting the number of people eligible for early retirement pensions are of course broadly rejected by the general population. In reality, there is no clear proof of earlier retirement being strictly more beneficial or worse than later retirement. Remaining at work can increase a person´s income, social status or for example create new experiences. It is by all means not only a negative circumstance in one's life. Similarly, the government cannot view a person retiring as an entirely negative action that only creates costs. Such a person can use time to help with childcare, educate others in his field of expertise, and otherwise generate positive externalities caused by his departure from the workforce.

2.1.2 Extend the evidence by theoretical ideologies

Rational choice theory vs Life course theory

According to De Preter et al. (2013), as rational choice theory assumes people act to achieve maximal utility possible. Under this ideology, even retirement timing is an optimization problem where many various inputs must be considered. The most important of common people is the financial aspect. Thus, earlier retirements are usually accompanied by such pension that sufficiently “matches”[3] an individual´s income in a scenario where would remain at work. Meanwhile, this theory entirely ignores some other aspects that can heavily influence the plan. People often act irrationally driven mostly by emotions and their decisions are, therefore, impossible to predict based on “pros and cons” alone. Also, optimizing based on imperfect information or even preferences leads to a different outcome. In terms of mandatory retirement, rational choice theory can only account for those features affecting the decision that are known ahead. Suddenly appearing circumstances such as unexpected layoffs or carrier-ending injuries cannot be part of the process. Therefore, as De Preter et al. (2013) claim: “Retirement may be less a matter of individual choice and more externally constructed.” On the other side stands the Life-course theory where the connection between work and life is examined. An individual is no longer retiring solely to reach the maximal potential utility but is also affected by the relationships in the family. Both theories describe a partial image of the retirement timing decision-making. For some people, one is more important than the other but on average people face decisions (relating to their retirement) in terms of maximizing utility as well as taking care of the family and spending time with its members.

Push and Pull

Another way to look at the incentives that lead to retirement planning is mentioned by Van Bavel and De Winter (2013). They divide reasons for retirement into two groups: Push and Pull. Push describes a situation when a person is literally driven out of the workforce. Usually, it applies to those whose work has been affected by high age and creates obstacles in terms of work continuation. On the other hand, Pull happens when a person desires the benefits of retirement and chooses to follow them. The main focus of this thesis is going to be a Pull situation because we search for a connection between

[3] In this case, “matches” means that it is a sufficient subsidy for the job revenue. That being said it does not necessarily mean these amounts are exactly the same. A rational person understands that job requires active involvement and pension rent does not. Which in conclusion means that a “sufficient” amount for pension is, of course, usually smaller than the actual work payment.

grandchildren and retirement when the expected relationship suggests that a person chooses to retire in order to go help with grandchildren. Radl (2013) reminds us that Push and Pull effects impact individuals differently possibly based on their socio-economic status. Besides, throughout the research of a few decades, it has not been determined which one is more significant for retirement planning. Another obstacle of the theory rests in the beliefs of various specialists that examine them based on their respective fields of expertise. Economists view work as a necessity to earn money vital for living therefore when enough money has been generated there is no longer a need to work. On the other hand, gerontologists argue that early retired people would often prefer to continue working but no longer can´t or shouldn´t for various reasons. Therefore, the Push and Pull theory alone does not seem to be a sufficient "explainer" of the incentives that guide the retirement timing. One should be aware to apply the theory carefully for different financial and social backgrounds of individuals. A simple example: a wealthy person does not have to fear potential lay-off (Push effect) due to his inability to perform as in the past because of his financial stability. On the other hand, involvement in childcare for grandchildren does not have to be a significant reason to retire early (Pull effect) when there is a bad financial situation in the family. According to Van Bavel and De Winter (2013), there appears to be a common pattern among countries: the larger is the standard retirement age the large is the average actual retirement age. 33% of the difference of actual retirement ages between countries can be explained by individual standard retirement ages (among men) and 31% for women. Multiple studies indicate that another "Pull" is created by the social programs in the country, the more generous they are the lower is the average actual retirement age. Lastly, since there is usually a lower standard retirement age for women even the average actual one is lower. When the effect of different standard retirement age is excluded women appear to be more likely active in the workforce until the standard age than men. Here the most probable cause seems to be health conditions.

2.2 Grandchildren vs retirement (core of the thesis)

2.2.1 Age as a relevant factor

Historically, retirement planning has been a great puzzle, and research examining the potential effect of grandchildren on retirement basically nonexistent. Initially, socio-economic studies directed to the retirement process and care were usually examining the possibility of an impact by care for elderly parents. The focus has been increasing during the last three decades acknowledging the fact that grandchildren can directly affect the decision, especially among women (which appears to be a larger case in elderly care as well). Furthermore, among those grandmothers that do not share residence with their children but live close by at least 50% are involved in grandchild care of children under 13 years old. In the case of employed women, the percentage is even higher (Lumsdaine and Vermeer 2015). There is an obvious phenomenon here that should not be forgotten. This result suggests that those women who have less time available seem to be more likely to be involved in childcare. Logically, that could be due to health conditions because those who can no longer work might have a physical problem with childcare as well. But there is no doubt that working women should be of a younger age. Therefore, this may not be a case of a relationship between employment and likelihood of grandchild care but more likely an impact of age on the involvement in childcare. During the first decade of the 21st century, an increase in grandchild care has been recorded related to the Great Recession of 07-08 in the United States. Many people sought to help their children. One of the options was involvement in grandchild care which served as an indirect financial help as well. Another possible reason for an increase in care due to the crisis could have been layoffs and newly acquired free time as a result. Even before the depression, studies found evidence among people that involvement in grandchild care appears to be often financially motivated (Lumsdaine and Vermeer 2015).

2.2.2 Distance from children and grandchildren

Although there seems to be a generally accepted conception in this matter that grandparents are on average involved in the grandchild care it does not (at all) ensure a significant impact between them. Some families have no ties across generations, others have too many grandchildren creating an impossible task to be involved with them or there can be severe health problems disabling any involvement. Grandchild care is a universal activity that happens all around the globe. According to Feng and Zhang (2018), there are different average ratios of involvement between the USA and Europe and China. Whilst Europe and the USA have around 25% of grandparents involved, in China, it is around 50%. There appear to be a few reasons behind the likelihood of safekeeping. First of all, the distance between the grandparents and the child is important, especially when they share a residence. Further, it is a number of grandchildren that directly causes parents to seek help from the grandparents. Personal characteristics of a child and a grandparent are also significant. Evidence also supports the traditional claim that women are more likely to be involved in grandchild care as the social norms in China dictate. With a rising number of women that enter the labor market and become eligible for the social benefits of retirement, there appears to be an increase in free time after retirement for activities such as childcare.

2.2.3 Health vs grandchild care – reverse causality?

Relating to health conditions, Kridahl (2017) informs about scientific evidence from the literature indicating that grandparents have on average worse health conditions than non-grandparents when heavily involved in grandchild care. That shows a possibility of reverse causality among important aspects. In such a case, bad health is actually caused by heavy involvement in grandchild care and large amounts of energy spent on activities connected to it (unlike the general assumption that bad health is a reason not to be involved). This creates a potential discussion about the core relationship of this thesis itself – grandchildren and retirement. Does reverse causality apply also in such a relationship? Feng and Zhang (2018) use China´s compulsory age for retirement law to quantify the impact retirement has on grandchild care. The study identifies a positive statistically significant effect equal to 29% for women and 21% for men. That means that retired women are 29% likely to be involved in grandchild care. Furthermore, results suggest that for men safekeeping of grandchildren generally happens when it is necessary. For women, it is the desired activity. Meanwhile, women with lower education seem to be more likely to extend their working life past the mandatory age but are also more likely to be involved in grandchild safekeeping after retirement. Postponing retirement is not necessarily connected only to women with lower education. Kridahl (2017) shows evidence of grandparents likely to postpone retirement to provide financial support to children and grandchildren which is more often the case of men. Even today, there seems to be a higher likelihood of men being the main income-earners of the family and women retiring sooner to be involved in grandchild care.

2.2.4 The effect of grandchildren on retirement timing

Considering the potential effect of grandchildren on retirement Kridahl (2017) performs an estimation for Sweden. No matter the age or additional regressors people with grandchildren are more likely to be retired than those who have none. Lumsdaine and Vermeer (2015) quantify this impact to be 8% in the probability of retirement-related to a birth of a new grandchild for women even though there seems to be no statistically significant (contradicting Kridahl 2017) impact of grandchild care on retirement and *vice versa*. As a result, family attributes seem to be relevant for both likelihoods to care as well as retirement timing. For example, evidence by Kridahl (2017) shows that the more sub-families (families of a child of the respondent) the less likely a person is involved in the care of all the grandchildren in the family but a likelihood to be involved in the care of at least one increases.

2.3 Potential endogeneity problem

2.3.1 Correlation of children and grandchildren

Retirement is usually accompanied by a long and detailed planning process during which a person weighs all the pros and cons of the action. Jeong and Kim (2020) investigate the connection between retirement and quantity/quality (education) of a person´s children. There might not be a direct relation to the topic of this thesis since it covers the impact of grandchildren (literally one generation further) but in reality, decisions made in this matter can severely affect the impacts that grandchildren can have. As Jeong and Kim (2020) state there appears to be a link between retirement timing and the number of children as well as their education. The notion is simple: more children can provide more care for their parents when they can no longer work. The same applies to better-educated children because they can provide financial support. For example, in the US in 1999 researchers estimated that a little more than 25% percent of retired people were financially supported by their children with yearly funds exceeding 600 thousand dollars. A similar percentage result happened in Korea where almost 25% of households with main income-earner retired were financially supported by a member of the family. Even with the modern possibilities of social programs providing pensions for the elderly, the family appears to be one of the key factors in terms of money and care. Therefore, retirement planning in Korea is significantly impacted by the funds that can the children provide. To be precise, one additional child is accompanied by an almost 10% higher likelihood of retirement. Furthermore, for one additional year of education for each child likelihood of retirement increases by over 20%. Since these results were generated using data from Korea, we cannot take them as given for European countries. But since it is a country nowadays widely considered as developed it can serve as an approximate sign of a potential relationship. For the purposes of this thesis, it would be interesting to quantify the impact (if there is one) of a larger number of grandchildren on retirement timing. It seems to be beneficial for elders to have more children that can provide for them to speed up retirement. Larger number of children increases the probability of a larger number of grandchildren. And since our hypothesis is that an existence of a grandchild increases the likelihood of retirement and a large number of grandchildren (therefore likely large number of children) should also increase the likelihood, then large numbers of grandchildren could be a significant factor in the decision-making process.

3 Data

3.1 Theoretical background – expectations

3.1.1 Important variables

Initial thought about the importance of grandchildren suggests that the impact will on average be a decrease in the age of retirement. In other words, people with grandchildren are on average more likely to be retired than people of the same age without grandchildren. For many individuals, that does not have to be the case. Some elderly might exchange the time to help with the care of a grandchild for additional years of work to provide financial support. Furthermore, it is important to distinguish whether the positive or negative effect depends on having any grandchildren in general or a specific number. The common expectation here indicates that the highest absolute effect corresponds to the first grandchild. Additional ones should not have such a major effect on retirement (at least according to our expectation). Another general presumption expects women to retire at an earlier age mainly due to higher involvement in grandchild care or no pressure to earn wages when there exists a partner that is the main income-earner. Our society has been changing and breaking such "stereotypes" lately so it would be interesting to see if there is any significant distinction between men and women. The next example can be education. Multiple papers show that a number of years of education often has effect on the number of children and on earnings that can provide a safer environment for the grandchildren. With that in mind, it is difficult to blindly guess the effect such a variable can have on retirement decisions. On the one hand, low education usually means a more physically demanding job that can force a person to an early retirement due to bad health conditions. On the other hand, education has also been shown to affect earnings. Low-educated people usually earn less and consequently have lower retirement and fewer savings. This means they could be motivated to work for longer to generate enough earnings. Age is a major influencer of retirement timing for obvious reasons. The last of the factors that are discussed here in this paragraph to be (potentially) influencing retirement planning is the location of a household. To be precise, there will be two aspects inspected here. Number one: where do the respondents live (large city, suburbs, small city, villages). An expected effect of household location is the following: the larger the city/village is the more likely later retirement is. Generally, this is assumed due to easier access to better services (including health care, education, etc.) and greater costs of living (necessary to keep generating income for a longer time). Number two: how far do families of their children live. In this case, we separate people into two groups – those who live within a one-kilometer distance from their children and those who live further. The logic behind this is simple – grandparents living in the same village, street or even house (as families of their children) are more likely to be involved in grandchild care but do not need to retire altogether because of the short distance.

3.1.2 Causality and omitted variable bias

A little side-note on these relationships. Since the impacts are often hidden and not generally known there is a high possibility of interconnection between these aspects that we try to explain retirement timing with. For example, the basic concept of connection between low education to higher numbers of children as well as earlier birth of children is well-known and supported by multiple papers. Some papers also suggest that people with low education must participate in a job that is more physically demanding and directly shortens the time of a person being able to work (as mentioned in the previous paragraph). When these two generally accepted thoughts intersect, we get an idea that early retirement can occur with earlier appearance of grandchildren (or a higher number of grandchildren) but without any causal effect. In other words, both retirement decision and having grandchildren at a specific point in time might be given by the education level of the analyzed individual and not affect one another. This means one must be careful during the estimation as well as interpretation period. It may also be the case that the impact is spread among other factors that are used in our analysis and thus there won´t be any interesting result in this matter.

Another way to comprehend the possible connection is that the likelihood of possession of at least one grandchild increases with the number of children. Therefore, earlier retirement might not be partly caused by existence of a grandchild but by the larger number of children and *vice versa*. Especially when using the basic OLS (Ordinary least squares) estimation one has to be cautious not to leave out a significant variable this is correlated to one of the regressors. The effect might be biased, or the interpretation can be wrong. In this particular example having more children might be the main cause for early retirement with no real connection to the existence of grandchildren. But since there is likely a strong correlation between a number of children and a number of grandchildren the effect would thus be caught by the grandchildren regressor (when a variable with children is not included in the model) creating an endogeneity problem.

3.2 Dataset construction

3.2.1 SHARE – general information

For the purposes of this work a great data set is provided by the Survey of Health, Ageing, and Retirement in Europe (SHARE) program which, as stated by SHARE (2020), relies on deep questionnaires performed in waves for 27 nations (in case of the last wave number 7). Countries included in the SHARE program: Portugal, Spain, France, Belgium, Netherlands, Luxembourg, Germany, Poland, Czech Republic, Austria, Switzerland, Italy, Sweden, Finland, Denmark, Slovakia, Slovenia, Hungary, Croatia, Malta, Greece, Romania, Bulgaria, Latvia, Lithuania, Estonia, Cyprus, and Israel. Starting in 2004 with the first wave over 380,000 observations (interviews) have been gathered in 8 waves of questionnaires. Over 140,000 people older than 50 have been questioned. Data even contains some people with age below 50 (questionnaires are designed to gather information also about the partner of the respondent). These statistics make this program one of the most complex microeconomic data surveys in Europe generating a sufficient amount for a panel dataset (Börsch-Supan 2020). The default structure of the SHARE dataset combines close to 25 files for each of the waves with various characteristics and answers from targets of the questionnaires as well as their partners/spouses. Together it creates a complicated structure.

3.2.2 easySHARE

To help navigate through the data a simplified dataset called easySHARE was generated for easier research analysis. This dataset still consists of more than 100 variables and the number of observations remains the same. Such simplification, therefore, means only one file that the information is gathered into creating a much simpler way to navigate through and estimate models. In some cases, the full dataset even includes individual hand-written answers with additional information about a person. The resulting dataset is then easier to compare with the Health and Retirement Study performed in the USA. The dataset includes various types of factors and characteristics. We begin with basic personal information such as gender, age, country of citizenship, education, and others with similar information about a partner that is not a respondent alone. Size of a household, living with a partner and/or children with their own families, and other variables give hints about the relationships within the family. Some of the variables related to the social life of a respondent include distance of household from children, number of children and/or grandchildren, living siblings and/or parents, involvement in social activities, etc. Family-related information covers, for example, the main abilities of a respondent at a given age such as reading, writing, and mathematical skills at age 10, health conditions especially at younger age as well as vaccination status. Considering the health conditions dataset also includes details about the respondent such as chronic and mental diseases, depression level, usage of drugs including alcohol and cigarettes, general satisfaction with the quality of life, and so on. In terms of subjective view on personal motor skills and body limitations SHARE gather data on mobility, muscle strength, motor skills, daily activities performed, and even brain functions. In the last category, we can observe answers about money, current work status, and satisfaction, work history, retirement plans, etc. Dataset is designed in a long format to keep track of returning respondents and generate a useful panel data structure. Each observation is identified by a specific unique ID number and naturally, answers from a returning respondent are situated below each other starting with the earliest of waves. This means for ordering purposes the first factor is a name and then (for multiple outcomes of one person) a number of a respective wave. After the previous arrangement, each observation gets a unique ID. Additional classification variable is a combination of name and wave number created after the ordering process (Gruber, S., C. Hunkler and S. Stuck 2014, Börsch-Supan and Gruber 2020).

3.2.3 Wave choice – main variables´ statistics

Wave 6 – main analysis

Since wave 8 was not part of the easySHARE dataset (it came out later) and it also includes special information about the pandemic, the original choice was to use wave 7. Wave 7 was performed the most recently (out of those included in the easySHARE

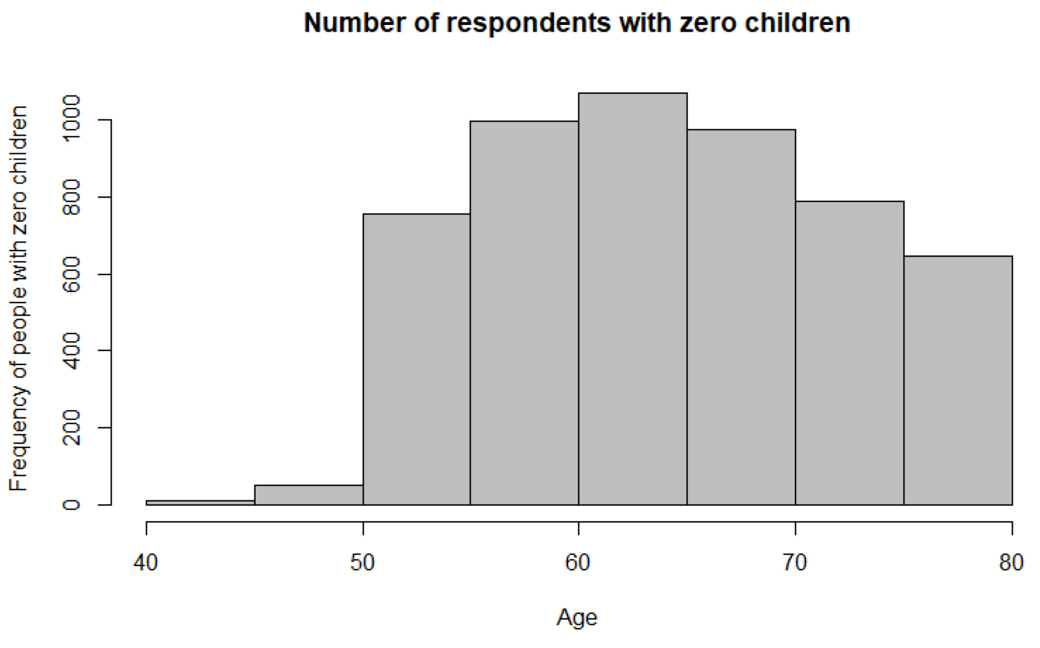

Figure 3. 1 – Histogram report of zero values among children

Note: Zero children in the examined datasets means NA values for grandchild variable

dataset) and should therefore serve as the best representation of the present communities. Additionally, all 27 nations are represented. Employment status seems to have the values distributed somewhat evenly among the countries. Information about grandchildren is missing for almost 82% of all observations (over 70 thousand) to be not available. Although several thousands of observations can for some models still perform very well but, in this situation, it is a severe problem especially because the majority of these missing values represent all of the values from multiple countries. Therefore, estimation with such a dataset would yield results valid only for specific countries that remain represented in the dataset not mentioning the number of observations would be significantly limited.

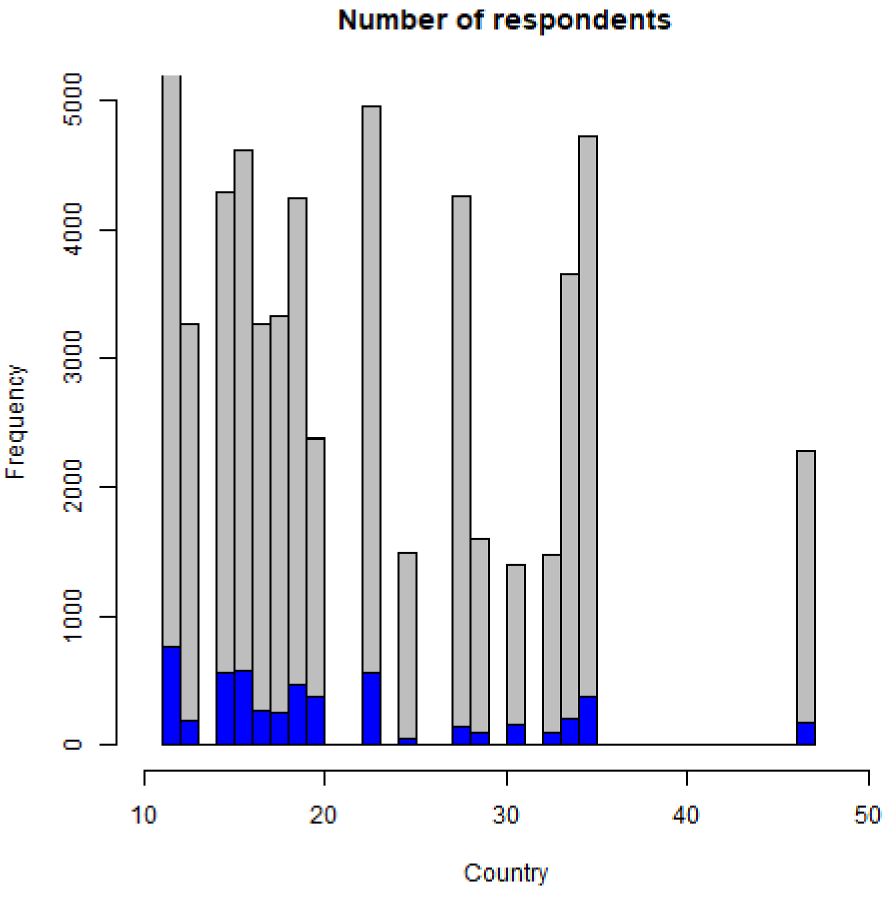

Figure 3. 2 – Histogram report of zero values among children for each country
Note: Countries in the dataset all have a specific code number ranging from 11 to 47 in our case. Gray columns represent the overall amount of observations generated by each country. The blue areas represent zeros for the case of variable children (NA for grandchild).

The authors of the whole SHARE program explained this defect rather simply. Wave 7 is special, mainly designed for current respondents to fill values for previous waves (in case that they had missed them). Therefore, some factors were only available to those who participated in wave 3. That constitutes only about 18% of observations and also it means that most of the countries are excluded because wave 3 was performed in only about 10 countries. Automatically, wave 6 appeared to be the next best choice being the most recent, covering the most countries and overall having the most observations (out of the remaining waves in the dataset). Inspection of wave 6 did not encounter any problematic missing values or distributions of them. For estimation purposes, the NAs can be withdrawn from the dataset without losing the assumption of randomness within the data. Even including only people with at least one child (as described in the previous subchapter) in the dataset does not heavily affect the statistics of the core variables. Lastly, it is worth mentioning that compared to wave 7 the following countries are not represented in wave 6: Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania, Slovakia, and Hungary. Figures 3.3 and 3.4 offer a graphic representation of the "even" spread of NA values in grandchild (which equal zero for variable children) with respect to age (see Figure 3.3) and country (see Figure 3.4). In both cases, the amounts of NAs stay on average evenly proportional to the overall amount of observations for each represented factor (across all factors).

Wave 5 - comparison

Even less countries were involved in wave 5 but the overall number of observations is only slightly smaller than in wave 6. In addition to missing countries in wave 6 the following nations are not included in wave 5: Greece, Poland, Portugal and Croatia. Contrastingly, Netherlands is missing from wave 6 but included in wave 5. Nevertheless, estimation on two separate datasets can yield interesting comparisons and ideally more reliable results. Similar results from both estimations on different datasets support the consistency of the results. Since both datasets consist of similar developed countries whose tradition in societies are often alike, on average we do not expect large differences. Either way, examination of the proper behavior of data among core variables in number 5 is necessary as well. The inspection yields satisfactory results with no visible issue in terms of missing values. Exclusion of NAs does not violate the random spread of data among countries. There is even only a small negligible change when we restrict the data only for those respondents that have at least one child. Even mean (average) values of the two main dummy variables – grandchild and retired are practically the same with and without data for respondents without any children because the NAs are impossible to be included in the calculation of the average value. For illustration of the process, Figures 1 to 4 in Appendix A are available. Behavior is closely similar to wave 6, therefore is not included into the main part because it brings no new information.

3.2.4 Data inspection and modification

Modify N/As, categorical variables and dummies

There are a few steps that should be carried out even before the first approximation. Some variables have to be modified for R in order to be used properly without confusion. Firstly, negative variables have to be encountered carefully. All of them suggest a not-existing value but for various reasons. Some questions (variables) are only included in specific waves creating an uneven panel dataset. Other values are missing due to inability or reluctance to answer. For some variables, the origin of a missing value is not important, but it is useful to keep track in case a pattern among missing values appear. Different types of variables are included in the dataset. For categorical and dummy variables especially a modification of data is required. For example, a dummy variable that distinguishes whether a person lives within a kilometer from children and their families can equal 1 if true and 5 when false. This can confuse R software because dummies usually take values 0 and 1. Which means one should modify the variable accordingly. In the case of categorical variables such as area of living, it is possible to face various levels which are again coded equally to numbers that R can misplace for common numbers. Therefore, the estimation has to be performed treating it as factors and R will generate a unique effect for each of the categories. Such an approach is applied to variables: country and area of living. The country carries the fixed effects of every country in the model (specific rules, traditions, etc.) and area of living (large city, suburbs, small town, village) describes the magnitude of the surrounding community. Estimating as a categorical variable is a correct treatment to account for each level and its possible effect. R usually takes zero or the lowest available value of a categorical variable as a base level. Such value is not included in the results because it serves as the default stage for other levels to compare to. Leaving R to decide automatically does not damage the explanatory power of the model but complicates the interpretation period. A best practice is to manually set up the default factors to reflect our personal view of the variable. For the fixed effect of countries, the base country used in all estimations in the next section is the Czech Republic and in terms of variable informing about the area of living the default level is a large city. To use reasonable ages in a study about retirement planning the dataset is restricted only for ages 40 to 80 years. Generally, all questionnaires for each wave in the SHARE dataset are targeted at people over 50 years old, but their partners are included as well. In reality, the dataset includes also people between 40 and 50 years old because of the partner addition. To avoid disturbances caused by outliers we also restrict the data with respect to the number of grandchildren. After a proper check of the variable distribution only people with 16 grandchildren at most are included in the model. Larger values accounted for less than 1% each representing only a little fraction.

Treatment of N/As – retirement and grandchildren

The two main variables for the purposes of this thesis are “retired” and “grandchildren” which were not a part of the original dataset. Initially, the dataset contained a variable that indicates the work status (“ep005”) of each respondent having options not only working and retired but also unable to work, unemployed, homemaker. For this simplified estimation, a dependent variable “retired” is used. It simply equals 1 or “true” when retired and otherwise 0 or “false”. In Figure 3.1 we can observe the development of a number of retired people with respect to age. According to expectation the number steadily grows with age to about 67 years. Then it declines due to fewer respondents available in the dataset.

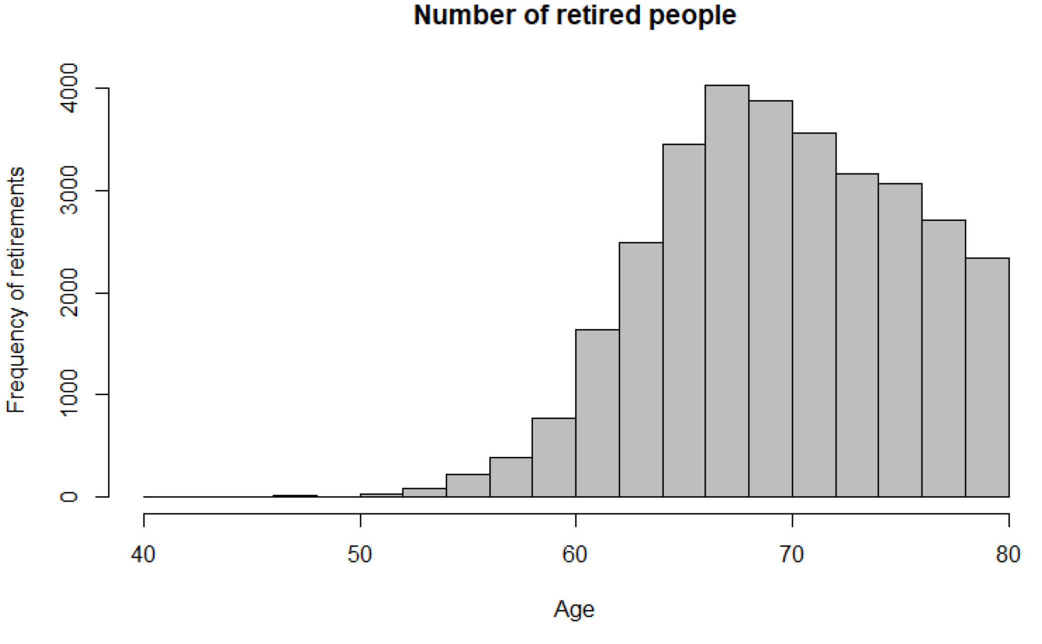

Figure 3. 3 – Histogram of retirements with respect to age

Note: In the general dataset there are available values for retirement numbers for people over 80 but for the purposes of the grandchild effect study they have no reason to be included.

The variable grandchild is a dummy simplification of variable called “ch021_mod”. The original variable described the exact number of grandchildren that a respondent has (including partner´s). As we are interested in the effect of a grandchild possession a simple dummy with values “0” for no grandchild and “1” for at least one grandchild is sufficient. In Figure 3.2 we observe also an expected growth of observation with at least one grandchild. Decreasing numbers of respondents after the peak age of 67 starts the declining trend in the graph.

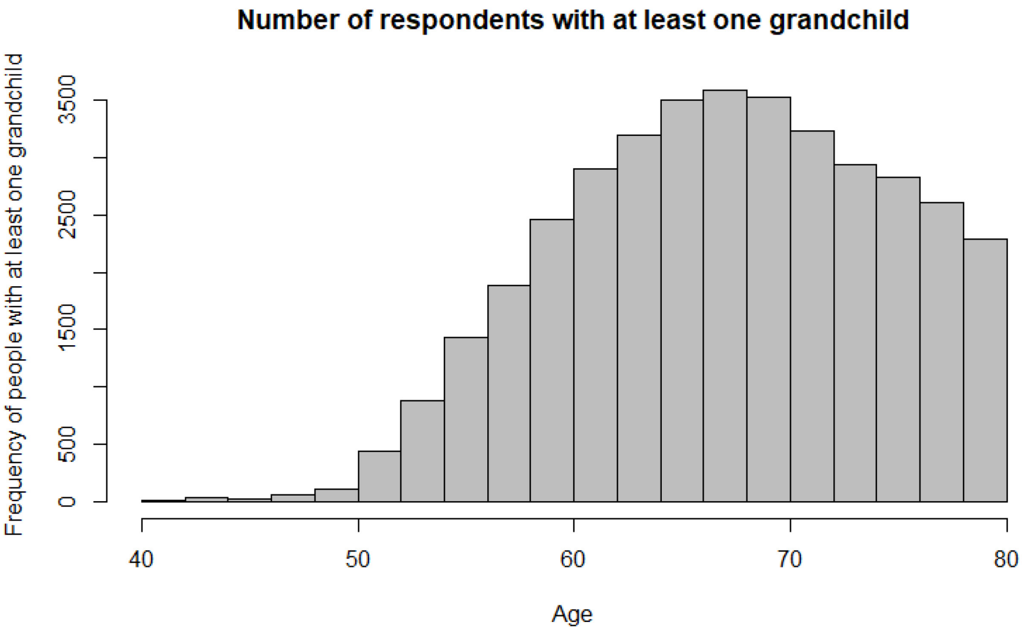

Figure 3. 4 – Histogram of respondents with at least one grandchild

The overall statistics of available values in these particular characteristics is necessary to examine the behavior and possibly uncover patterns of missing data. Randomly spread unavailable data among the dataset usually creates no serious problems for estimations. When we lose too many observations due to missingness or N/As concentrate in a specific part of the dataset assumptions for proper usage of models tend to be violated. All involved countries and even age groups should be sufficiently represented for the interpretation of results to be valid for "all". Ensuring that missing values are randomly distributed is especially important for OLS models because the dependent variable cannot have an NA value included for R to be able to estimate.

There is a serious issue present in the dataset. When a respondent does not have any children there is no option of having grandchildren as well. The value representing such circumstance among the grandchildren variable is non-available (NA). Dropping out all NAs from the grandchildren factor means restricting the dataset only for people with at least one child. Of course, several other observations have no information about grandchildren unrelated to children but a strong majority (about 6500 observations) is caused only by not having any children.

4 Methodology

As was mentioned before, the core effect that is about to be estimated is of the grandchild (possession of at least one) on retirement (likelihood of a respondent being retired). A positive correlation between these two variables suggests a possible relationship but no information about the causality. Both can be caused by the same effect (for example age) and therefore have no interconnection between them. Regression analysis is a step further to have a general idea about the significance of grandchildren in the retirement decision-making process, because it allows estimation of the relationship while controlling for other factors, such as age, education, etc... The following estimation procedure was developed to find the appropriate model for the dataset, test its validity and then use it to quantify potential effects under various scenarios. Since the main focus is the impact of the grandchild variable the dataset used in the upcoming estimations is restricted to only those respondents that have at least one child.

4.1 Step 1 – OLS

The first model to be estimated is OLS (Ordinary least squares) or linear regression. The dependent variable of the equation is retired which equals 0 when one is employed, self-employed, unemployed, permanently disabled, or a homemaker, and 1 in case that a respondent is retired. Among the regressors, we need a dummy grandchild which equals 0 when a person has no grandchildren and 1 otherwise. Other variables are believed to be relevant when explaining retirement and should be included in the model as well to increase its explanatory power, but more importantly, avoid problems with omitted variable bias when these variables are correlated with one of the regressors. Therefore, the following variables are included: age in years as a discrete variable, country fixed effect as a categorical variable, area of location also as a categorical variable, gender as a dummy variable, and number of years of education as a discrete variable. All of those are likely to be relevant when we seek as high comprehension of the retirement decision-making process as possible. The following equation (1) demonstrates the model structure:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \dots + \beta_k X_{ki} + u_i \qquad (1)$$

where Y_i is a dependent variable (retired in our case) for i-th observation, β_0 is the intercept, β_k corresponds to the coefficient for the k-th regressor, X_{ki} represents the value from k-th regressor and i-th observation and u_i is the error term for the i-th observation. A number of observations is a positive integer and dependes on a specific length of the dataset. A number of regressors is also a positive integer and in this case, will vary around 30 (including the fixed effects of countries and area of living). For the OLS model to be valid four main assumptions have to hold:

a) Variables $X_{1i}, \dots, X_{ki}, Y_i$ have to be independent identically distributed
b) $E(u_i | X_{1i}, \dots, X_{ki}) = 0$ => no endogeneity within the model
c) Unlikely outliers
d) No perfect multicollinearity

An initially doubted regressor is the number of children. Since we are fairly certain that the potential endogeneity problem is caused (at least partly) by omitted

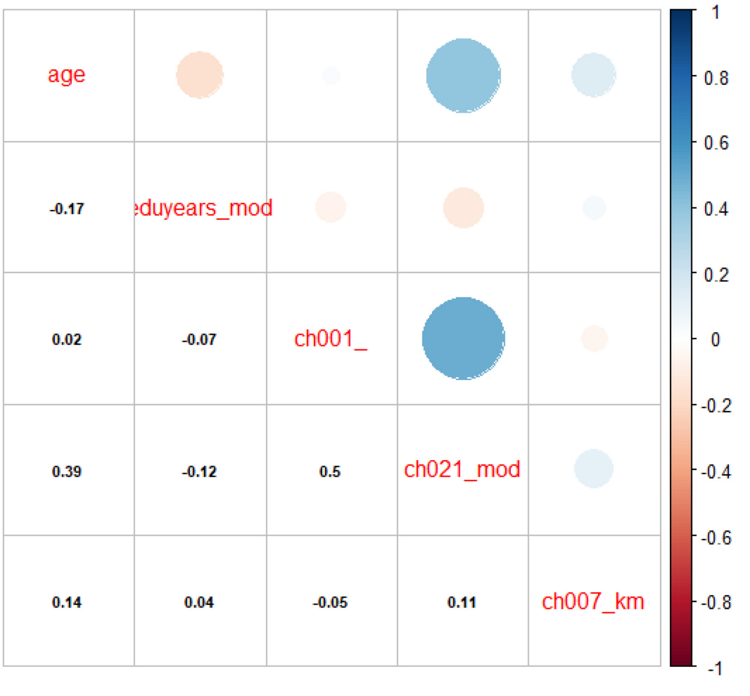

Figure 4. 1 – Correlation between important variables

Notes: The highest positive absolute value of correlation is represented by the circle with the largest diameter. Variable ch001_ is number of children, ch021_mod – number of grandchildren, ch007_km represents residential proximity.

variable bias due to exclusion of the number of children from the model in some cases adding the variable into the model can treat the problem. Originally, the number of children was not of interest of this thesis because various papers have shown significant impacts that it can have on retirement timing. Having this factor in the model would potentially create a multicollinearity problem because the number of children is expected to be correlated to the number of grandchildren. In Figure 4.1, we test correlations of age, years of education, number of children, number of grandchildren, and residential proximity. No perfect correlations are present but the number of grandchildren (ch001_) and the number of grandchildren (ch021_mod) are positively correlated. The "advantage" of the model is that it uses only simplified versions of the number of grandchildren and residential proximity. Generally, the largest change in the likelihood of having grandchildren occurs when a respondent has one child compared to zero. Additional children do not strongly impact the probability of at least one grandchild being born. No matter the results that we can take from a measurement of the correlation between regressors when an omitted variable problem is possible next step should be an IV regression to use the Hausman test to determine the existence of an endogeneity.

4.2 Step 2 – IV model

Instrumental variables (IV) might help when the OLS model is in danger of the endogeneity problem. 2SLS estimation uses an instrument – variable expected to explain at least a portion of the variance of the endogenous variable. The process follows two steps. Firstly, linear regression is estimated with the possibly endogenous regressor from the original OLS model stands as a dependent variable, and remaining exogenous explanatory variables from the original model accompany the instrument as regressors. The resulting fitted values are saved and used in the second step instead of the endogenous variable in the original model. This method is called Two-Stage least squares and for one endogenous variable and multiple other exogenous regressors can be demonstrated by the following equations. We start with the general equation where one variable is instrumented:

$$\text{IV: } Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_{k-1} X_{k-1i} + \delta_1 W_i + u_i \qquad (2)$$

where characters represent the same aspects as in equation (1) but this time the endogenous variable is denoted by W_{1i} with δ_1 as its coefficient. This variable represents the instrumented originally endogenous variable. The 2SLS procedure describes the general IV model in a two-equation setup:

$$\text{1. stage: } Z_i = \alpha_0 + \alpha_1 X_{1i} + \cdots + \alpha_{k-1} X_{k-1i} + \gamma_1 I_i + \varepsilon_i \tag{3}$$

$$\text{2. stage: } Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_{k-1} X_{k-1i} + \delta_1 \hat{Z}_i + u_i \tag{4}$$

where Z_i is the endogenous variable from OLS model, $\hat{Z}_i$ its fitted value after equation (3) is estimated (therefore equal to W_i from equation 2) and I_i is the instrument used to partly explain variation within the endogenous variable. For an instrument to be valid two main conditions have to be fulfilled (using notations from equations 3 and 4):

1) $E(Z|I) \neq 0$ => Instrument has to be correlated to the endogenous variable. In other words, in the first step of the IV model instrument has to be a statistically significant regressor. This is called instrument relevance
2) $\mathrm{E(Y|I)} = 0$ => The dependent variable of the original model cannot be related to the instrument. The only correlation allowed is through the endogenous variable. This is called the exclusion restriction.

Additionally, according to Hanck et al. (2020), when IV estimation is used the following assumptions are necessary (using notations from equations 3 and 4):

a) $E(u_i|X_{1i}, \dots, X_{k-1i}) = 0$ => Other regressors have to be uncorrelated with the error term otherwise there is another case of endogeneity.
b) $X_{1i}, \dots, X_{k-1i}, I_i, Z_i$ all have to be independent and indentically distributed extractions from their joint distribution.
c) Large outliers are unlikely – in our case need to restrict datasets for reasonable ages as well as numbers of children and grandchildren

Kridahl (2017) used an instrumental variable for her estimation in order to overcome the problem with the correlation between a regressor and the error term. She suggested that the gender of the first-born child of the respondents is a valid variable to serve as an instrument. When a first-born child is a girl on average it means earlier timing for grandchildren than when it is a boy. It is then more likely for grandchildren to come in a time period when a respondent is considering whether to retired or not. Additionally, parents on the mother´s side are usually more involved (according to evidence). From a statistics viewpoint it also satisfies the two conditions. It does not affect the retirement timing by itself and therefore is not correlated with the error term. But at the same time, it affects the retirement timing through the number of grandchildren. In the easySHARE dataset, there is no information on the genders of children. Another approach would be to use the age of a first-born child to determine the likelihood of grandchildren´s existence. Again, using the average age for the beginning of parenthood (for children) in society one can estimate how likely is any respondent to be a grandparent. Unfortunately, even the age of a first-born (or any child for that matter) is not available in the dataset. It is necessary to think outside of the box.

In our situation, the variable chosen to become the instrument is a dummy for residential proximity. It is a binary variable that equals 1 when at least one child lives within a one-kilometer radius from the respondent and 0 otherwise. Condition of validity 1) is satisfied when the significance of the variable is shown in the first step of the model. Additionally, it literally makes sense. The existence of a grandchild is a sign of a new part of the family. On average children leave respondents in order to start their own family. It is by no mean the only reason but certainly one of them. The second condition is difficult to test using R software, but a reasonable assumption can be sufficient. The distance that separates respondents from their children is alone irrelevant in the retirement decision-making process.

4.3 Step 3 – check for a better model

The Hausman specification test (Durbin-Wu-Hausman test) is a tool widely used to check a model for endogeneity through consistency of the problematic coefficient while comparing a linear regression with an Instrumental variable regression. The structure of the test is based on the higher efficiency of the OLS estimator combined with the ensured consistency of the 2SLS estimator. The null hypothesis suggests consistency of the estimator in the OLS model. Using the chi-squared distribution rejection of the null hypothesis means inconsistency of the OLS estimator and "promotes" usage of the less efficient but consistent 2SLS estimator.

Multicollinearity is not an issue for the 2SLS estimation. The model setup is designed to count with an evident connection between the regressors. The first stage of the 2SLS estimation requires to use also other regressors from the original OLS equation (besides the endogenous variable that the first step aims to explain). Therefore, in the fitted values from the first stage, a presence of statistically significant regressors is evident, and using them again in the second stage automatically means correlation. But the endogeneity problem has to be determined in the estimation part of the thesis. With no clear evidence of omitted variable bias OLS, can actually be a better fit and collinearity then be an issue.

5 Results and discussion

In this section, the first results are presented in order to determine which model has the best fit for the particular dataset structure. Tables are generated using the *Stargazer* package in R software provided by Hlavac (2018). Function "ivreg" from package *AER* is applied for the purposes of IV model estimation in later sections of this chapter. This package was published by Kleiber, Christian, and Zeileis (2020). Fox, Kleiber and Zeileis (2020) specify additional information about the *ivreg* function alone. All presented tables are simplified to present only the "interesting" variables. Whole tables including the fixed effects of countries and area of living are available in the Appendix section with respective functions codes from R.

5.1 Comparison of OLS and 2SLS

5.1.1 Step 1 – OLS model

As the empirical approach described in the Methodology section states, we start with a simple OLS and then build our way towards the "best" model. In Table 5.1 below results from two linear regression models are presented. The explanatory power of the model is decent likely caused by using country fixed effects or other standard characteristics such as age, gender, or education. To gather more information about the interdependencies within the model, we apply the estimation with and without the children variable. The first linear regression is performed without a variable for the number of children. The latter estimation includes this factor in the model. We encounter a few interesting details within these two models. First of all, the grandchild variable coefficient shifts significantly when the children variable is added. This supports the initial assumption that these variables are related. The effect of a grandchild´s existence increases because the estimated impact of the number of children is negative. Therefore, such an effect is included in the grandchild impact in the case of the first model. The negative sign of the children coefficients implies that an additional child on average decreases the likelihood of retirement by almost 2%. Expectations that the sign could be opposite and imply that children can provide financial support (enable parents to retired sooner) are not supported by our evidence. Multicollinearity itself seems to be absent from both models. Variance inflation factor (VIF) does not exceed the value of two for any variable in the OLS model. Therefore, the inclusion of the number of children is valid but it does not necessarily cure the whole endogeneity problem in the number of grandchildren variable.

Table 5. 1 – OLS with and without children

	Dependent variable:	
	retired	
	(1)	(2)
grandchild	0.041***	0.053***
	(0.004)	(0.004)
age	0.038***	0.038***
	(0.0002)	(0.0002)
female	-0.079***	-0.080***
	(0.003)	(0.003)
eduyears_mod	0.001***	0.001***
	(0.0003)	(0.0003)
children		-0.020***
		(0.001)
Constant	-1.773***	-1.723***
	(0.017)	(0.018)
Observations	51,001	51,001
R^2	0.443	0.445
Adjusted R^2	0.443	0.444
Residual Std. Error	0.371 (df = 50972)	0.371 (df = 50971)
F Statistic	1,446.921*** (df = 28; 50972)	1,407.902*** (df = 29; 50971)

Note: Standard errors in brackets bellow respective coefficients

The next step is the Instrumental variable regression and with that model, the Hausman test can be applied to compare the OLS and the IV for the best fit.

5.1.2 Step 2 – IV model

The information discussed in the previous subchapter (see Table 5.1) implies no relevant condition. Nevertheless, including variable children in the model is still necessary. When there is no evidence of multicollinearity it is a safer approach. No matter the model (OLS or IV) there is an obvious connection between the grandchild variable and the number of children. The first step of the IV model requires other regressors to explain variation in the grandchild dummy. Withdrawing children from the equation means the error term carries its effect. Exclusion of such variable could violate the second condition of an instrumental variable in case of an actual connection. The instrument remains uncorrelated with retirement and it changes with grandchildren. At least that is the main assumption of the thesis. In the Methodology chapter, we discussed the reasons for this particular choice of instrument. Now we test its strength.

Table 5. 2 - Relevance of residential proximity to grandchild

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	50,698.500	0.707	50,698	50,698.2	50,698.8	50,699
RSS	2	7,578.016	81.245	7,520.567	7,549.291	7,606.740	7,635.465
Df	1	1.000		1.000	1.000	1.000	1.000
Sum of Sq	1	114.898		114.898	114.898	114.898	114.898
F	1	774.554		774.554	774.554	774.554	774.554
Pr(> F)	1	0.000		0.000	0.000	0.000	0.000

Note: Anova function tests the first step OLS with and without residence. Our major interest lies in the fifth and sixth row: F statistics.

To test the strength and relevance of the instrument a few tests can be performed (Hanck et al., 2020):

1) The F-test performed to compare the first step OLS with and without variable residence yields a P-value severely smaller than 0,05 (Table 5.2). The null hypothesis (relevance is an insignificant factor in the model) is therefore rejected. In other words, the null hypothesis expects the coefficient to be equal to zero. Andrews (2019) warns that even rejecting the null hypothesis might not be enough since even values very close to zero can yield weak instruments.
2) The effect of the residence itself should generate at least a 10% change in the dependent variable of the equation – grandchild. The average value from the

dependent variable is 0,7. The coefficient is equal to -0,1 (Table 5.3) and that is sufficient.

3) First step OLS estimation gives R-squared equal to 26% (Table 5.3). The explanatory power is given by the inclusion of the original regressors as well as the instrument. A potential sign of a weak instrumental variable would be a very low R-squared. That is not relevant for this case.

Table 5. 3 - Statistical significance of residential proximity to grandchild

	Dependent variable:
	grandchild
residence	-0.101^{***}
	(0.004)
female	0.058^{***}
	(0.003)
age	0.020^{***}
	(0.0002)
eduyears_mod	-0.004^{***}
	(0.0003)
children	0.079^{***}
	(0.002)
Constant	-0.633^{***}
	(0.018)
Observations	51,001
R^2	0.263
Adjusted R^2	0.262
Residual Std. Error	0.385 (df = 50971)
F Statistic	626.333^{***} (df = 29; 50971)

Note: Standard errors located in brackets bellow respective coefficients

In conclusion, the chosen instrument should be performing well. After the IV model estimation is done, the Hausman test will provide additional information on the fit of the model compared to the original OLS estimation. Execution of the model yields interesting results presented in Table 5.4. As we can see, both OLS models provide slightly higher explanatory power using the same set of regressors as 2SLS. Grandchild variable carries four widely different coefficient estimators. As previously happened in a simple OLS setup (see table 5.1), an addition of the variable children changes the coefficients rapidly. Therefore, tests searching for potential problems are vital.

Table 5. 4 - OLS vs IV with respect to children

	Dependent variable:			
	retired			
	OLS		*instrumental variable*	
	(1)	(2)	(3)	(4)
grandchild	0.041***	0.053***	0.266***	0.197***
	(0.004)	(0.004)	(0.042)	(0.035)
age	0.038***	0.038***	0.033***	0.035***
	(0.0002)	(0.0002)	(0.001)	(0.001)
female	-0.079***	-0.080***	-0.091***	-0.089***
	(0.003)	(0.003)	(0.004)	(0.004)
eduyears_mod	0.001***	0.001***	0.003***	0.002***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
children		-0.020***		-0.031***
		(0.001)		(0.003)
Constant	-1.773***	-1.723***	-1.644***	-1.616***
	(0.017)	(0.018)	(0.030)	(0.031)
Observations	51,001	51,001	51,001	51,001
R^2	0.443	0.445	0.411	0.432
Adjusted R^2	0.443	0.444	0.410	0.432
Residual Std. Error	0.371 (df = 50972)	0.371 (df = 50971)	0.382 (df = 50972)	0.375 (df = 50971)
F Statistic	1,446.921*** (df = 28; 50972)	1,407.902*** (df = 29; 50971)		

Note: Standard errors in brackets bellow respective coefficients. OLS are columns 1,2 and IV 3, 4.

5.1.3 Step 3 – check for a better model

Firstly, we check for the endogeneity within the model using the Hausman test. We compare the OLS model where the children variable is included, and residence is excluded. In our case, the statistics equal 0,0001 therefore the null hypothesis is rejected. Due to the evidence of endogeneity the Instrumental variable regression is more feasible.

Another step is to test the IV model for other potential problems. The introduction of the number of children into the model raised the possible issue with multicollinearity. A high correlation between two or more regressors in a linear equation can disregard the statistical significance of an individual variable. The Variance inflation factor (VIF) divides variance of all coefficients in the model by the variance of the specific problematic coefficient in a hypothetical case when its related variable is the only regressor. Those factors that yield VIF value higher than 10 seem to be highly correlated. Magnitudes between 5 and 10 can be considered alarming. In Table 5.5 we have the first two columns presenting values for the first and second stages of the IV model (two linear regressions) with age included. As it turns out, age seems to be highly correlated with other regressors. Even larger VIF value appears with the fitted values saved from the first stage and used as a regressor in the second stage.

Table 5. 5 – VIF values for the first and second stage of IV

	First	Second	First	Second
residence (only first stage)	1.108		1.082	
grandchild_fitted (only second stage)		23.454		1.755
country	1.549	6.441	1.519	1.873
area of living	1.261	1.544	1.259	1.275
female	1.012	1.390	1.005	1.013
age	1.084	14.144		
eduyears_mod	1.152	1.485	1.122	1.227
children	1.041	4.644	1.041	1.313

Note: VIF values for first and second steps of IV estimation respectively with and without age. In this case even fixed effects of countries and area of living are included in the presented table.

Dropping out this variable would mean leaving out the most important value of the model (for the purposes of this thesis). Instead, no longer including the age variable seems to be solving the problem for all other variables in the model. In general datasets with no age restrictions, one would expect age to be likely correlated with the number of years of education. In this case, it is highly unlikely since the dataset consists of respondents of age at least 40. By then additional education is no longer of any concern for any individual. Since the highest values in the original second stage are related to grandchildren and age respectively, it is reasonable to assume that the correlation is mutual between them (not necessarily the only significant relationship among the regressors). The setup of the function "ivreg" in R is designed to count with the collinearity because the idea of including side regressors into both stages makes multicollinearity unavoidable. Finding multicollinearity within the model is a confirmation that the model estimation by R software was correctly performed.

Furthermore, excluding age from the model would not even be helpful in order to cure heteroskedasticity. The Non-constant Variance Score test rejects the null hypothesis that the variance of the error term is not related to levels of the dependent variable. Therefore, we have a presence of heteroskedasticity. Robust standards errors are an option regarding the statistical significance of individual explanatory variables.

5.2 Final model

Results from the previous subchapter yielded the right model for estimation. In this part, we estimate and interpret not only the significance and effect of the main variable but also other potentially interesting regressors. The dataset used for the estimations is restricted to people available in the survey who have at least one child. As explained before, the "choice" between zero and at least one grandchild automatically implies the existence of at least one child. Otherwise, the grandchild variable does not make any sense. Still, it is interesting to estimate the model on the unrestricted dataset for comparison. Either way, it is crucial to keep track of the datasets for interpretation. Of course, not all NAs that appear as values for the grandchild variable are caused by no children, but it represents the vast majority. Additionally, results from multiple estimations are discussed. We estimate not only the overall effect but also models estimated on further restricted datasets for four different age groups (40-50, 50-60,…,70-80), both female and male separately. All estimations are done for easySHARE wave 5 as well to compare the results to see potential consistency across the two waves and/or difference caused partly by (for example) fewer countries.

5.2.1 Age groups – wave 6

Table 5.6 provides five columns of results for IV estimates from models using datasets for four different age groups and the last column gives the overall results. Each of the five models offers a different view on the matter. The first column represents people with age from 40 (including) to 50 (not including).

Table 5. 6 – Final IV model with respect to age (wave 6)

	Dependent variable:				
	retired				
	(1) *[40,50)*	(2) *[50,60)*	(3) *[60,70)*	(4) *[70,80)*	(5) *[40,80)*
grandchild	-0.006	0.012	0.162*	0.237	0.197***
	(0.053)	(0.030)	(0.090)	(0.226)	(0.035)
female	-0.020	-0.012**	-0.059***	-0.178***	-0.089***
	(0.018)	(0.006)	(0.008)	(0.009)	(0.004)
age	0.0005	0.019***	0.066***	-0.002	0.035***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
eduyears_mod	-0.001	-0.001**	0.001*	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.0003)
children	-0.001	-0.004	-0.028***	-0.033***	-0.031***
	(0.003)	(0.004)	(0.008)	(0.012)	(0.003)
Constant	0.128*	-0.937***	-3.469***	1.044***	-1.616***
	(0.066)	(0.075)	(0.095)	(0.102)	(0.032)
Observations	816	14,254	20,770	15,069	51,001
R^2	0.093	0.102	0.268	0.110	0.432
Adjusted R^2	0.061	0.101	0.267	0.109	0.432
Residual Std. Error	0.107 (df = 787)	0.270 (df = 14225)	0.407 (df = 20740)	0.317 (df = 15040)	0.375 (df = 50971)

Note: Robust standard errors presented in brackets bellow respective coefficients

There are only 816 observations (see also Figures 3.1 – 3.4) and with the three-decimal difference between R-squared and Adjusted R-squared, it is certain that the model is poorly constructed. The reason for such a small number of observations is that initially the quaetionnaires are targeted on people above 50. For ages 50 (including) to 60 (not including), the model statistics yield slightly better performance of the model. Grandchild variable is (similarly to the number of children factor) statistically insignificant. It is reasonable to assume that people in their 50s usually do not think in general about an earlier retirement, especially not due to families of their children. It certainly does not mean that they are not involved in the grandchild care but on average their status (health, energy, money, free-time) enables them to remain unretired. Even when data are restricted for just these 10 years, age is still a significant factor with a positive impact. Since the common policy age for retirement in many countries is around 64, reaching 60 increases the likelihood of retirement definitely more than reaching 50. The third age group is arguable the most important/interesting one for retirement-related data estimation. Age interval [60,70) covers the period when people often retire. All regressors show statistical significance (all at least 5% percent interval). Even grandchild dummy appears to be significant not only due to the age interval being the most common retirement time (when more factors can influence the decision) but likely due to the higher probability of having any grandchildren. Data provided for estimation do not include the average ages of respondents (or their children) when they become parents for the first time. Therefore, we cannot claim that for example, 60 years is the most common age for a person to become a grandparent for the first time. But it is undeniable that people who belong to the age interval [60,70) either already are or will soon become grandparents of course if they were ever destined to become them.

Age has an even larger effect than for previous age interval which is connected to retirement policy setup about legally required age for retirement. The negative signs of female dummy for the three age intervals starting at 50 and ending at 80 cannot be necessarily explained identically for all three periods. For ages 50 to 70, a large impact on the sign has the structure of the dependent dummy variable itself. Retired equals one when a person is retired and zero otherwise. The latter value includes permanently disabled, homemakers, or people outside of the workforce. Historically, women were often fully engaged at home, and even though (as mentioned in the beginning) a lot has changed it still fairly common. Column number 4 can also be partly explained by that phenomenon but we must not forget that the life expectancy of women is over five years longer. The health status of women is on average better at the elder state which enables those few who desire to remain working longer. Years of education have a significant but mild effect on retirement. Sign change between the second and third column is not anything significant. The statistical significance of the grandchild variable across the first four columns complies with presumptions that reality offers. The effect of over 16% for people between 60 and 70 presents a reasonable estimate.

The fifth column provides results from the overall estimation and the impact of possession of at least one grandchild increases to almost 20%. With all other aspects kept constant an average person with at least one grandchild is 20% more likely to be retired than a person with none. It is worth mentioning that the number of children becomes statistically significant only for the top two age groups. The negative coefficients suggest a decrease in retirement likelihood with an increase in the number of children. An expectation that children could be a source of financial support and speed up the earlier retirement of parents is rejected by evidence in our model.

5.2.2 Gender – wave 6

Previous estimations showed a negative relationship between the female dummy (value 1 for woman and zero otherwise) and retirement when statistically significant. In this step, we compare the effect grandchild can have on retirement with respect to gender. Table 5.7 reports results for estimation on the dataset of only females, only males, and combination respectively. Dummy variable female is dropped from the estimation because it adds no additional information to the model after the dataset is restricted. Using the robust standard errors, we get very promising results that align with assumptions. All variables presented in the table are statistically significant throughout each estimation. The effect of a grandchild - 20,9% is almost 2% higher for females than for men. That is a satisfactory revelation because it aligns with theoretical predictions. As illustrated in Figure 5.1 below (especially the top left and bottom right graphs), women are generally expected to be more involved in grandchild care than men therefore it is reasonable to assume that women´s decisions are more sensitive to the impact of grandchildren.

Age also has a significant change in its effect based on gender (Table 5.7). One percent increase occurs in the case of males which is explained by poorer health conditions hand-to-hand with shorter life expectancy. An interesting pattern is formed in the case of the sign related to coefficients of variable children. 1,8% larger in magnitude is the negative effect for women. The same sign was also the case of estimating for various age groups (see Table 5.6) when statistically significant. These results indicate that the more children a person has the less likely she/he is retired.

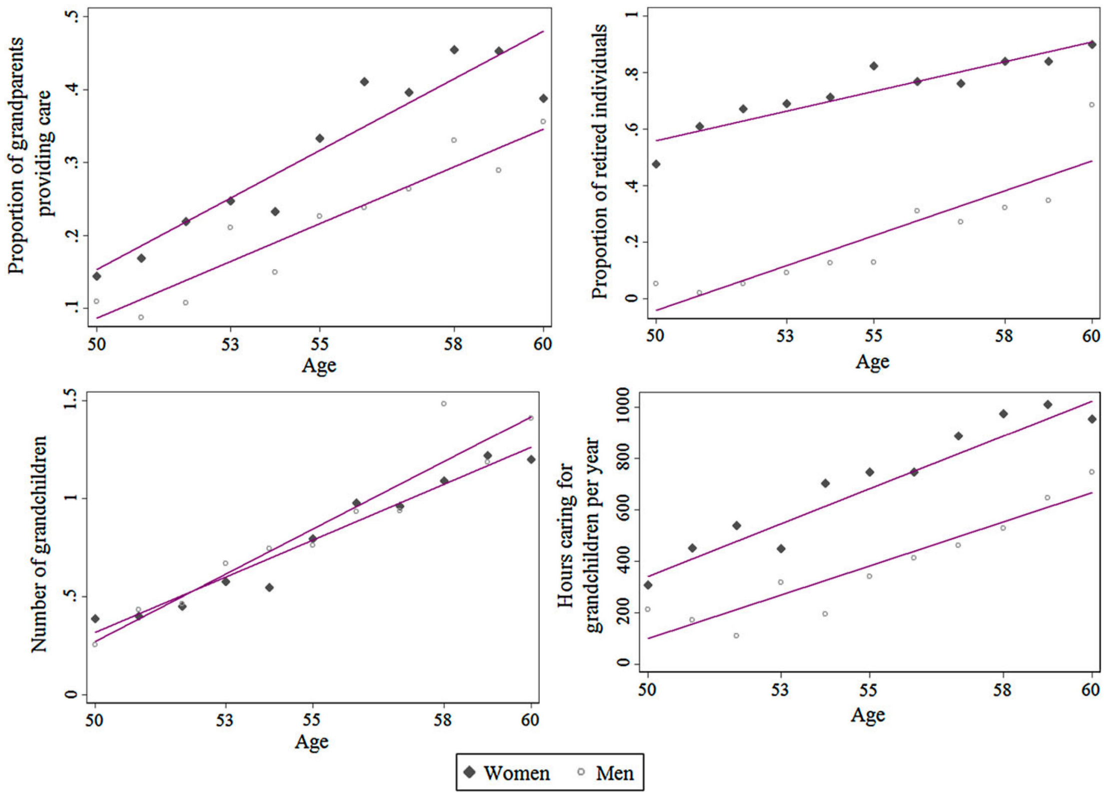

Figure 5. 1 – Compare involvement in grandchild care with respect to gender

Source: Feng and Zhang (2018)

Notes: Graphs are based on data from China (27 provincies). All four graphs apply age 50 to 60 on the horizontal line. The first graph shows the proportion of grandparents providing grandchild care (bottom line represents men). The second graph illustrates proportion of retired individuals (again bottom line respresents men). The third shows number of grandchildren and the fourth presents hours caring for a gnradchild per year (bottom line men again).

Evidence from these two tables combined does not support the hypothesis mentioned in the Literature review part that more children enable earlier retirement because they can provide for the pension-related expenses of their parents. Results presented here contradict the existence of such phenomenon and rather show that more children mean more expenses and extended work-life for parents. There is a large difference between the explanatory powers of each model. Over 10% increase in variance explained for male estimation when compared to the female model. That is fairly unexpected especially due to the magnitudes of coefficients being larger combined for women which is no proof of anything, of course. In reality, such gap is caused by having variables included that are more important for men in the decision-making process of retirement.

Table 5. 7 – Final IV model with respect to gender (wave 6)

	Dependent variable:		
	retired		
	(1) *female*	(2) *male*	(3) *combined*
grandchild	0.209***	0.191***	0.197***
	(0.052)	(0.045)	(0.035)
female			-0.089***
			(0.004)
age	0.031***	0.040***	0.035***
	(0.001)	(0.001)	(0.001)
eduyears_mod	0.004***	-0.001**	0.002***
	(0.0005)	(0.0004)	(0.0003)
children	-0.038***	-0.020***	-0.031***
	(0.005)	(0.004)	(0.003)
Constant	-1.393***	-2.065***	-1.616***
	(0.040)	(0.044)	(0.032)
Observations	28,953	22,048	51,001
R^2	0.398	0.508	0.432
Adjusted R^2	0.398	0.508	0.432
Residual Std. Error	0.388 (df = 28924)	0.341 (df = 22020)	0.375 (df = 50971)

Note: Robust standard errors located in brackets bellow respective coefficients

5.2.3 Age groups – wave 5

In this section, the first comparison between waves is presented. The first three columns in Table 5.8 present models estimated on data from wave 5 for age groups [50,60), [60,70), and [70,80) respectively. The other three columns follow the same logic for wave 6. From Table 5.6 we know that the first age group of people between 40 and 50 years old has unsatisfactory characteristics for valid estimation (not enough observations, small likelihood of grandchild´s existence, etc.). Consequently, results in Table 5.8 regard only people over 50 years old (including). The first value in the table is already unexpected. Not only is there a statistical significance of grandchild for people in their 50s (in case of wave 5) but also there is a negative effect present - 6,3%. An explanation could be that the children of respondents are likely not old enough to sufficiently support a family with little children therefore grandparents provide financial support. Since the impact is no longer significant in wave 6 it is safer to interpret it as an inconsistent result. Furthermore, the wave 5 model for age group [60,70) quantifies the larger effect of a grandchild by almost 5% than its counterpart in wave 6.

Table 5. 8 – Final IV model compare wave 5 and 6 with respect to age

	Dependent variable:					
	retired					
	(1) *[50,60)*	(2) *[60,70)*	(3) *[70,80)*	(4) *[50,60)*	(5) *[60,70)*	(6) *[70,80)*
grandchild	-0.063**	0.231**	0.022	0.012	0.162*	0.237
	(0.031)	(0.102)	(0.253)	(0.030)	(0.090)	(0.226)
female	0.004	-0.058***	-0.157***	-0.012**	-0.059***	-0.178***
	(0.005)	(0.009)	(0.007)	(0.006)	(0.008)	(0.009)
age	0.022***	0.065***	-0.001	0.019***	0.066***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
eduyears_mod	-0.002***	0.001	0.002***	-0.001**	0.001*	0.002***
	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.0004)
children	0.005	-0.043***	-0.018	-0.004	-0.028***	-0.033***
	(0.004)	(0.008)	(0.011)	(0.004)	(0.008)	(0.012)
Constant	-1.019***	-3.401***	1.111***	-0.937***	-3.469***	1.044***
	(0.077)	(0.103)	(0.134)	(0.075)	(0.095)	(0.102)
Observations	14,690	18,605	13,252	14,254	20,770	15,069
R^2	0.103	0.261	0.144	0.102	0.268	0.110
Adjusted R^2	0.102	0.259	0.142	0.101	0.267	0.109
Residual Std. Error	0.249 (df = 14664)	0.408 (df = 18578)	0.303 (df = 13226)	0.270 (df = 14225)	0.407 (df = 20740)	0.317 (df = 15040)

Note: Robust standard errors located in brackets bellow respective coefficients. The first three columns represent wave 5, the latter three columns wave 6.

Gender and age keep almost the same values and significance for both waves in respective age groups. Interesting aspects in favor of similarity between the datasets are model characteristics. The explanatory power of each model in wave 5 is closely similar to its counterpart in wave 6. Additionally, the number of observations does not change too rapidly.

5.2.4 Gender – wave 5

This part is devoted to the comparison of results from waves 5 and 6 based on gender. In the first two columns of Table 5.9 estimations using wave 5 are presented. Model characteristics seem to be following a very similar pattern in both waves. Obviously,

Table 5. 9 – Final IV model compare wave 5 and 6 with respect to gender

	Dependent variable:			
	retired			
	(1) *female*	(2) *male*	(3) *female*	(4) *male*
grandchild	0.155^{***}	0.216^{***}	0.209^{***}	0.191^{***}
	(0.049)	(0.046)	(0.052)	(0.045)
age	0.033^{***}	0.040^{***}	0.031^{***}	0.040^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
eduyears_mod	0.003^{***}	-0.001^{*}	0.004^{***}	-0.001^{**}
	(0.0004)	(0.0004)	(0.0005)	(0.0004)
children	-0.034^{***}	-0.026^{***}	-0.038^{***}	-0.020^{***}
	(0.004)	(0.004)	(0.005)	(0.004)
Constant	-1.514^{***}	-2.098^{***}	-1.393^{***}	-2.065^{***}
	(0.039)	(0.046)	(0.040)	(0.044)
Observations	26,914	20,554	28,953	22,048
R^2	0.439	0.540	0.398	0.508
Adjusted R^2	0.438	0.540	0.398	0.508
Residual Std. Error	0.375 (df = 26889)	0.334 (df = 20528)	0.388 (df = 28924)	0.341 (df = 22020)

Note: Robust standard errors located in brackets bellow respective coefficients. The first two columns are wave 5, the latter two are wave 6.

both datasets consist of fewer observations in the case of males which partly affects the R-squared, therefore, the explanatory powers of male estimations are higher in both cases. The effect of grandchild yields troublesome results when compared. The magnitude of the impact is different in each case ranging from 15,5% (wave 5 – female) to 21,6% (wave 5 – male). Furthermore, unlike wave 6, wave 5 produces the larger effect in the case of the male dataset. For male respondents in wave 5 existence of a grandchild increases the likelihood o retirement by 21,6%. Other variables seem to offer only small changes and appear to be very consistent across both waves.

5.2.5 Unrestricted vs restricted; wave 5 vs wave 6

The final estimation focuses on inter-wave changes as much as it examines the potential differences that appear from the inclusion of respondents that have no children at all. As was explained before, the overall effect of grandchildren can be better comprehended when only people with children are used in the model dataset. Zero values in the children variable mean not only non-available value for grandchildren but also residential proximity. A person with no children cannot have any distance from those children. In reality, we can hardly compare respondents in terms of having grandchildren when there are no children among them. From the point of view of econometrics, this difference can be quantified. In Table 5.10 we observe results from wave 5 in the first two columns (options “unrestricted” and “only with children” respectively). Columns 3 and 4 provide results for wave 6. A new “variable” appears in columns 1 and 3. It represents the potential effect even an NA value among grandchildren variable can have on retirement likelihood. Inclusion of this option through the unrestricted model creates changes in other variables´ coefficients. Since female, age, education and children are used in the first step of 2SLS estimation to describe variation in grandchild variable it should not be a surprise that a certain level of correlation between other regressors and grandchild fitted value occurs. When we focus on the grandchild NA factor, we realize that it serves as a dummy variable in which the default state is having at least one child (not include grandchild NA) and having zero children (add grandchild NA) is the alternative. In the latter case, variable children serves no purpose in the equation anymore because there is no child in existence. Therefore, the actual impact of children variable decreases for both models estimated on unrestricted data. Due to the existence of grandchild NA, the children variable still acts as the average effect of “one additional child” but no longer carries the impact of the difference between 0 and 1 children within its value. When grandchild NA appears for an observation, we automatically know that there is no child. That explains the drop in magnitude when we move from restricted data set to the unrestricted. The “traditional” grandchild variable keeps its effect almost leveled across all four estimations (range 1,1%). The general effect of having at least one grandchild on retirement likelihood seems to be around 19%.

Table 5. 10 – Final IV model compare wave 5 and 6 with respect to children

	Dependent variable:			
	retired			
	(1)	(2)	(3)	(4)
grandchild	0.204^{***}	0.189^{***}	0.175^{***}	0.197^{***}
	(0.034)	(0.034)	(0.033)	(0.035)
grandchildNA	0.105^{***}		0.063^{***}	
	(0.021)		(0.018)	
female	-0.070^{***}	-0.072^{***}	-0.084^{***}	-0.089^{***}
	(0.003)	(0.004)	(0.004)	(0.004)
age	0.036^{***}	0.036^{***}	0.036^{***}	0.035^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
eduyears_mod	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
children	-0.021^{***}	-0.032^{***}	-0.029^{***}	-0.031^{***}
	(0.002)	(0.003)	(0.003)	(0.003)
Constant	-1.763^{***}	-1.705^{***}	-1.676^{***}	-1.616^{***}
	(0.025)	(0.032)	(0.026)	(0.032)
Observations	57,617	47,468	58,147	51,001
R^2	0.465	0.467	0.439	0.432
Adjusted R^2	0.465	0.467	0.439	0.432
Residual Std. Error	0.365 (df = 57589)	0.365 (df = 47441)	0.373 (df = 58116)	0.375 (df = 50971)

Note: Robust standard errors located in brackets bellow respective coefficients. The first two columns represent wave 5, the latter two wave 6.

6 Conclusion

This thesis covers the impact of a grandchild´s existence on retirement timing using the IV regression applied on data provided by the SHARE project. Such combination is unique among the available literature and offers a specific estimation of the desired relationship. The empirical part contains multiple regressions estimated while restricting the dataset to get the effect for a specific group with respect to gender, age, or the existence of a child. Lastly, results are compared between two different waves of data (years of questionnaires provided by SHARE) that represent 15 and 18 nations (European countries and Israel). Besides an inspirative insight into the relationships between various factors of specific groups, the main purpose of multiple regressions on different sets of data is to ensure consistency and validity of presented results.

The effect of a grandchild´s existence is estimated to be statistically significant for the retirement timing decision-making process. In other words, on average two people´s likelihood of retirement is different when one has at least one grandchild while the other has none (when other characteristics are held constant). To be precise, the actual effect is around 19%. The reason for an approximate value is simple: it is difficult to determine the "best" of models. Each dataset represents a specific group of people each distinct from all the other datasets. Eventually, we can see that the estimated effects are statistically significant, and the impact of the grandchild´s existence converges around 19%. The variance of presented results is easily explained by characteristics of specific groups that the individual datasets represent. Therefore, we can conclude that an average grandparent is almost 19% more likely to be retired than an average non-grandparent (while other factors are held constant). There exists evidence among the SHARE data that retirement occurs, on average, sooner when a respondent is a grandparent.

Secondary outcomes of the thesis imply significant differences between results when controlling for gender, age, and even the existence of a child. The effect of a grandchild´s existence varies based on these specifications. Additionally, all three factors are statistically significant explanatory variables that impact the retirement likelihood. Unexpectedly, age has a positive effect (undeniably supported by reality).

More interesting is the negative result of the female factor even though it is largely caused by a specific structure of the initial variable that the dependent “retired” is derived from. Contradicting some presented literature, the estimated effect for an additional child is negative. A common prediction assumes the impact to be positive because children are expected to provide financial support for retired parents. A possible explanation is that children require financial support to some extend which on average prolongs the work-life of a parent. Evidence from SHARE data suggests that the potential *vice versa* effect (children can provide financial support and speed up the retirement timing of a parent) is either non existent or not strong enough to counter the costs that a child generates for a parent even when close to retirement age.

There are multiple directions further research can continue. Keeping the same model setup, it would be interesting to use widely different datasets (the whole SHARE dataset or something else entirely) to potentially replicate the results or even find a different instrumental variable than “residential proximity”. Additional techniques to test the strength of the instrument would increase the validity of the model. Furthermore, the same relationship can be examined using a distinct estimation technique (for example Matching). Based on the available literature, there are still plenty of new opportunities for relevant research related to the overall issue of retirement. Some papers focus entirely on a specific aspect of the matter narrowing down the field too much or apply the estimation only for a particular country, area, etc. To be fair, to sufficiently comprehend the decision-making process as a whole, each aspect should be examined.

In general, nations, governments and even ordinary people would benefit from a deeper exploration of the retirement timing matter and causes of its variance between individuals.

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Appendix A – Figures

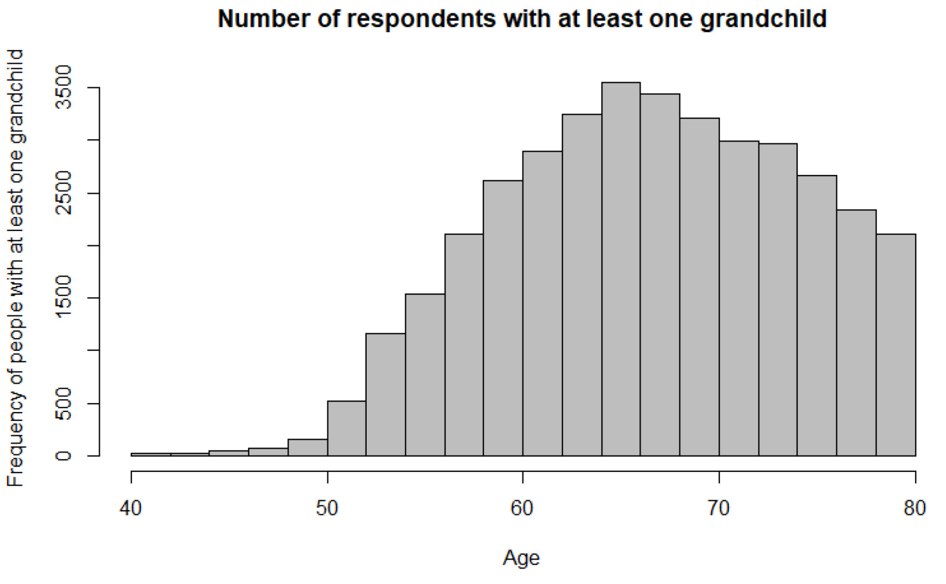

Figure Appendix A. 1 – Number of people with at least one grandchild (wave 5)

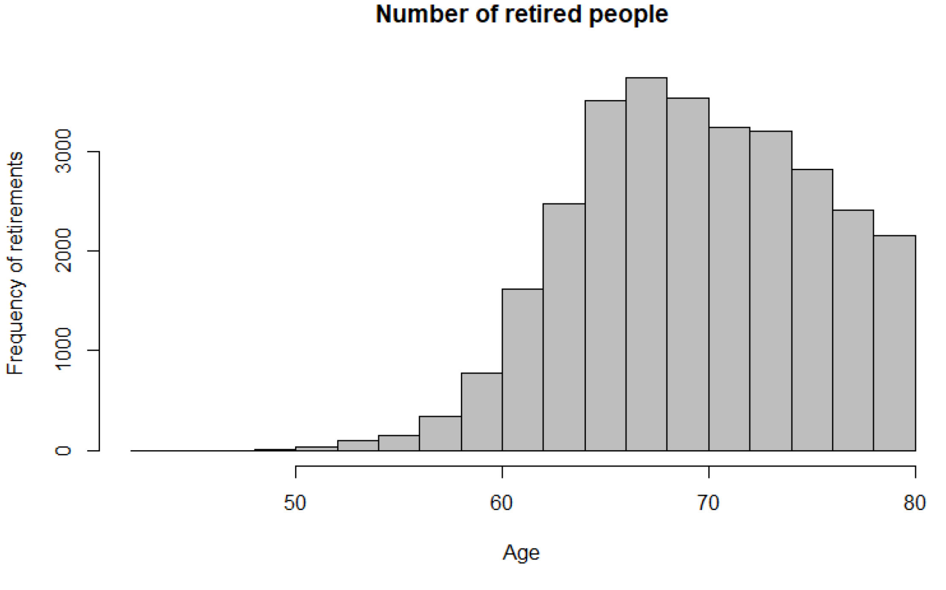

Figure Appendix A. 2 – Number of retired people with respect to age (wave 5)

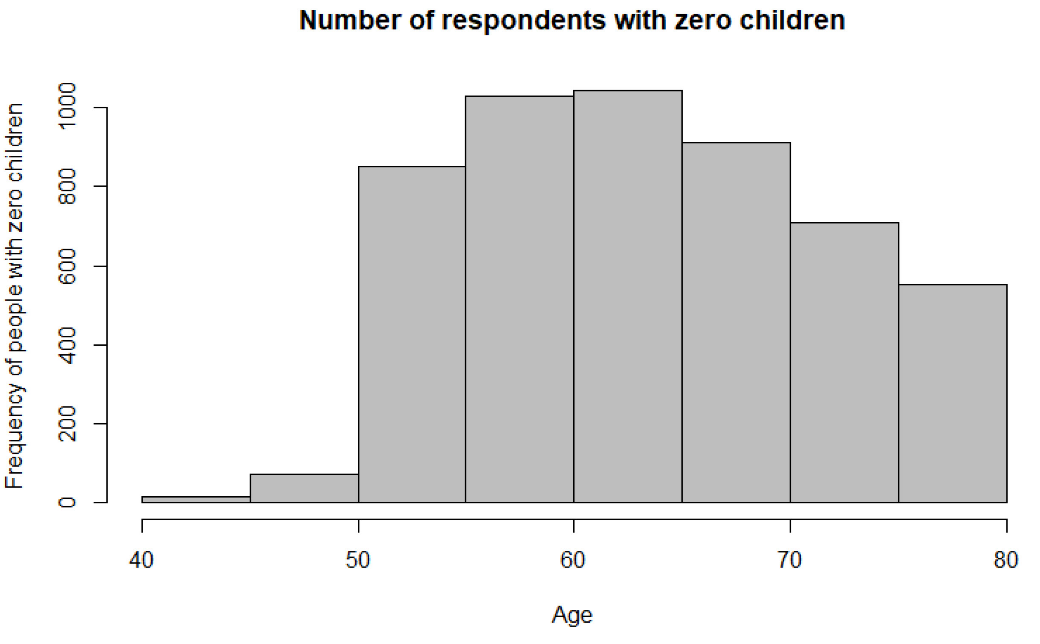

Figure Appendix A. 3 – Number of zero children with respect to age (wave 5)

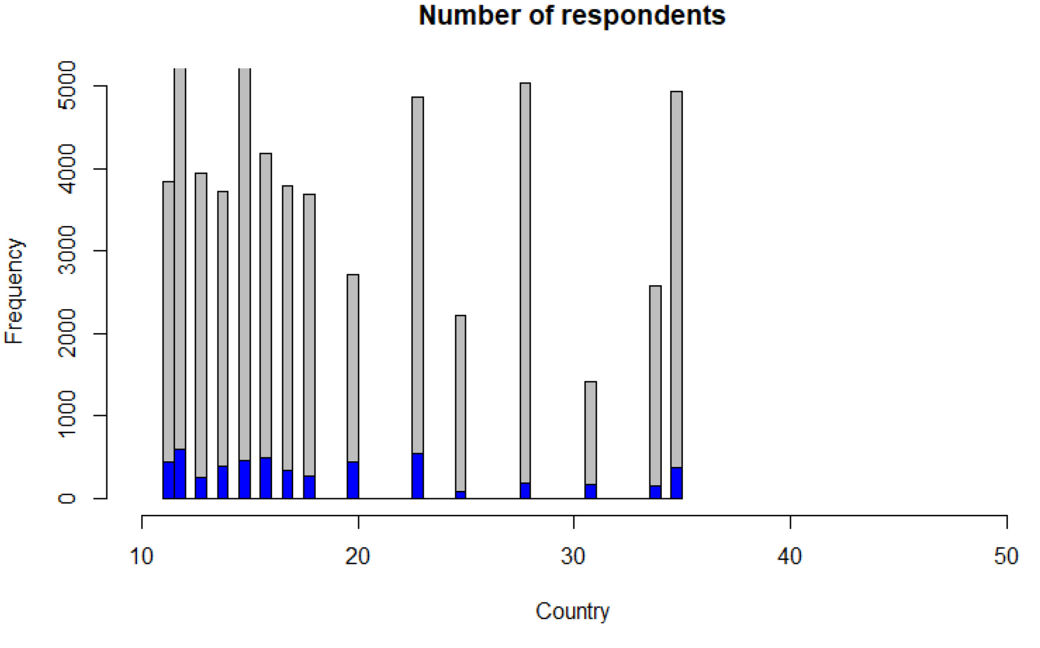

Figure Appendix A. 4 – Zero children vs all with respect to country (wave 5)
Note: Blue illustrates amount of zero children observations. Gray reflects all observations of the particular country.

Appendix B – Tables and formulas

Table Appendix B. 1 – OLS with and without children

$$Formula: lm(retired \sim grandchild + relevel(as.factor(country), ref = 28) + relevel(as.factor(iv009_{mod}), ref = 1) + age + female + eduyears_{mod} + children, data = wave\_6)$$

	Dependent variable:	
	retired	
	(1)	(2)
grandchild	0.041***	0.053***
	(0.004)	(0.004)
country, ref = "28")11	-0.061***	-0.061***
	(0.010)	(0.010)
country, ref = "28")12	-0.192***	-0.192***
	(0.009)	(0.009)
country, ref = "28")13	-0.175***	-0.171***
	(0.009)	(0.009)
country, ref = "28")15	-0.307***	-0.303***
	(0.009)	(0.009)
country, ref = "28")16	-0.243***	-0.245***
	(0.009)	(0.009)
country, ref = "28")17	-0.084***	-0.081***
	(0.009)	(0.009)
country, ref = "28")18	-0.213***	-0.210***
	(0.009)	(0.009)
country, ref = "28")19	-0.251***	-0.252***
	(0.009)	(0.009)
country, ref = "28")20	-0.246***	-0.243***
	(0.010)	(0.010)
country, ref = "28")23	-0.162***	-0.159***
	(0.008)	(0.008)
country, ref = "28")25	-0.316***	-0.295***
	(0.012)	(0.012)
country, ref = "28")29	-0.119***	-0.114***
	(0.011)	(0.011)

country, ref = "28")31	-0.165***	-0.165***
	(0.012)	(0.012)
country, ref = "28")33	-0.143***	-0.143***
	(0.012)	(0.012)
country, ref = "28")34	-0.013	-0.018**
	(0.009)	(0.009)
country, ref = "28")35	-0.207***	-0.208***
	(0.008)	(0.008)
country, ref = "28")47	-0.107***	-0.111***
	(0.010)	(0.010)
	(0.011)	(0.011)
iv009_mod, ref = "1")2	0.019***	0.021***
	(0.007)	(0.007)
iv009_mod, ref = "1")3	0.015**	0.016**
	(0.006)	(0.006)
iv009_mod, ref = "1")4	0.023***	0.025***
	(0.006)	(0.006)
iv009_mod), ref = "1")5	0.019***	0.024***
	(0.005)	(0.005)
age	0.038***	0.038***
	(0.0002)	(0.0002)
female	-0.079***	-0.080***
	(0.003)	(0.003)
eduyears_mod	0.001***	0.001***
	(0.0003)	(0.0003)
children		-0.020***
		(0.001)
Constant	-1.773***	-1.723***
	(0.017)	(0.018)
Observations	51,001	51,001
R^2	0.443	0.445
Adjusted R^2	0.443	0.444
Residual Std. Error	0.371 (df = 50972)	0.371 (df = 50971)
F Statistic	1,446.921*** (df = 28; 50972)	1,407.902*** (df = 29; 50971)

Note: IV009_mod is a variable for area of living. Based value is big city. Other levels are big city suburbs, large town, small town and village.

Table Appendix B. 2 – Compare OLS and IV with respect to children

$$Formula\ IV: ivreg(retired \sim grandchild + relevel(as.factor(country), ref = 28) + relevel(as.factor(iv009_{mod}), ref = 1) + age + female + eduyears_{mod} + children \mid residence + relevel(as.factor(country), ref = 28) + relevel(as.factor(iv009_{mod}), ref = 1) + age + female + eduyears_{mod} + children, data = wave\_6)$$

	Dependent variable: retired			
	OLS		*instrumental variable*	
	(1)	(2)	(3)	(4)
grandchild	0.041***	0.053***	0.266***	0.197***
	(0.004)	(0.004)	(0.042)	(0.035)
country, 11	-0.061***	-0.061***	-0.022*	-0.037***
	(0.010)	(0.010)	(0.012)	(0.011)
country, 12	-0.192***	-0.192***	-0.151***	-0.167***
	(0.009)	(0.009)	(0.012)	(0.011)
country, 13	-0.175***	-0.171***	-0.151***	-0.154***
	(0.009)	(0.009)	(0.010)	(0.010)
country, 15	-0.307***	-0.303***	-0.262***	-0.273***
	(0.009)	(0.009)	(0.012)	(0.011)
country, 16	-0.243***	-0.245***	-0.180***	-0.208***
	(0.009)	(0.009)	(0.015)	(0.012)
country, 17	-0.084***	-0.081***	-0.060***	-0.064***
	(0.009)	(0.009)	(0.010)	(0.010)
country, 18	-0.213***	-0.210***	-0.190***	-0.193***
	(0.009)	(0.009)	(0.010)	(0.010)
country, 19	-0.251***	-0.252***	-0.178***	-0.208***
	(0.009)	(0.009)	(0.016)	(0.014)
country, 20	-0.246***	-0.243***	-0.181***	-0.203***
	(0.010)	(0.010)	(0.016)	(0.014)
country, 23	-0.162***	-0.159***	-0.133***	-0.141***
	(0.008)	(0.008)	(0.010)	(0.010)
country, 25	-0.316***	-0.295***	-0.308***	-0.278***
	(0.012)	(0.012)	(0.013)	(0.013)
country, 29	-0.119***	-0.114***	-0.116***	-0.109***
	(0.011)	(0.011)	(0.012)	(0.012)
country, 31	-0.165***	-0.165***	-0.114***	-0.134***
	(0.012)	(0.012)	(0.016)	(0.014)
country, 33	-0.143***	-0.143***	-0.123***	-0.131***
	(0.012)	(0.012)	(0.013)	(0.013)

country, 34	-0.013	-0.018**	0.003	-0.011
	(0.009)	(0.009)	(0.010)	(0.009)
country, 35	-0.207***	-0.208***	-0.199***	-0.204***
	(0.008)	(0.008)	(0.009)	(0.008)
country, 47	-0.107***	-0.111***	-0.081***	-0.097***
	(0.010)	(0.010)	(0.011)	(0.011)
iv009_mod, -15	-0.025*	-0.022*	-0.033**	-0.025*
	(0.013)	(0.013)	(0.013)	(0.013)
iv009_mod, -12	-0.420	-0.430	-0.503	-0.485
	(0.371)	(0.371)	(0.382)	(0.375)
iv009_mod, -9	-0.065***	-0.063***	-0.064***	-0.061***
	(0.011)	(0.011)	(0.011)	(0.011)
iv009_mod, 2	0.019***	0.021***	0.009	0.015**
	(0.007)	(0.007)	(0.007)	(0.007)
iv009_mod, 3	0.015**	0.016**	0.004	0.010
	(0.006)	(0.006)	(0.007)	(0.006)
iv009_mod, 4	0.023***	0.025***	0.008	0.017***
	(0.006)	(0.006)	(0.006)	(0.006)
iv009_mod, 5	0.019***	0.024***	0.0001	0.014**
	(0.005)	(0.005)	(0.007)	(0.006)
age	0.038***	0.038***	0.033***	0.035***
	(0.0002)	(0.0002)	(0.001)	(0.001)
female	-0.079***	-0.080***	-0.091***	-0.089***
	(0.003)	(0.003)	(0.004)	(0.004)
eduyears_mod	0.001***	0.001***	0.003***	0.002***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
children		-0.020***		-0.031***
		(0.001)		(0.003)
Constant	-1.773***	-1.723***	-1.644***	-1.616***
	(0.017)	(0.018)	(0.030)	(0.031)
Observations	51,001	51,001	51,001	51,001
R^2	0.443	0.445	0.411	0.432
Adjusted R^2	0.443	0.444	0.410	0.432
Residual Std. Error	0.371 (df = 50972)	0.371 (df = 50971)	0.382 (df = 50972)	0.375 (df = 50971)
F Statistic	1,446.921*** (df = 28; 50972)	1,407.902*** (df = 29; 50971)		

Note: Default level for country is 28 – Czech Republic (as in the previous table).

Table Appendix B. 3 – IV age groups wave 5 and 6

	Dependent variable:

	retired					
	(1)	(2)	(3)	(4)	(5)	(6)
grandchild	-0.063**	0.231**	0.022	0.012	0.162*	0.237
	(0.031)	(0.102)	(0.253)	(0.030)	(0.090)	(0.226)
country, 11	0.025	-0.001	-0.113***	0.012	-0.002	-0.091***
	(0.019)	(0.020)	(0.030)	(0.023)	(0.020)	(0.026)
country, 12	-0.113***	-0.238***	-0.057*	-0.124***	-0.245***	-0.040
	(0.014)	(0.020)	(0.029)	(0.016)	(0.019)	(0.026)
country, 13	-0.133***	-0.309***	-0.019	-0.138***	-0.314***	-0.025**
	(0.014)	(0.016)	(0.015)	(0.016)	(0.017)	(0.011)
country, 14	-0.154***	-0.325***	-0.159***			
	(0.015)	(0.018)	(0.019)			
country, 15	-0.119***	-0.390***	-0.280***	-0.125***	-0.365***	-0.249***
	(0.015)	(0.023)	(0.026)	(0.018)	(0.021)	(0.026)
country, 16	-0.115***	-0.239***	-0.214***	-0.102***	-0.290***	-0.192***
	(0.016)	(0.026)	(0.031)	(0.018)	(0.027)	(0.027)
country, 17	-0.095***	-0.037**	-0.026	-0.081***	-0.033**	-0.018
	(0.014)	(0.015)	(0.019)	(0.016)	(0.015)	(0.019)
country, 18	-0.138***	-0.287***	-0.052***	-0.120***	-0.304***	-0.046***
	(0.012)	(0.015)	(0.013)	(0.015)	(0.015)	(0.010)
country, 19				0.018	-0.322***	-0.275***
				(0.021)	(0.033)	(0.039)
country, 20	-0.182***	-0.288***	-0.104***	-0.161***	-0.329***	-0.097***
	(0.018)	(0.034)	(0.033)	(0.021)	(0.031)	(0.032)
country, 23	-0.073***	-0.187***	-0.169***	-0.070***	-0.165***	-0.112***
	(0.013)	(0.015)	(0.020)	(0.016)	(0.014)	(0.020)
country, 25	-0.085***	-0.450***	-0.222***	-0.062**	-0.415***	-0.210***
	(0.017)	(0.020)	(0.022)	(0.025)	(0.022)	(0.023)
country, 29				-0.051***	-0.134***	-0.058***
				(0.019)	(0.018)	(0.016)
country, 31	-0.054***	-0.163***	-0.232***	-0.042*	-0.125***	-0.251***
	(0.021)	(0.030)	(0.035)	(0.022)	(0.026)	(0.031)
country, 33				-0.056**	-0.194***	-0.084***
				(0.022)	(0.020)	(0.020)
country, 34	0.141***	0.026*	-0.116***	0.071***	0.045***	-0.088***
	(0.019)	(0.014)	(0.014)	(0.019)	(0.012)	(0.012)
country, 35	-0.111***	-0.271***	-0.063***	-0.117***	-0.288***	-0.066***
	(0.012)	(0.014)	(0.012)	(0.014)	(0.014)	(0.014)
country, 47				0.081***	-0.131***	-0.193***
				(0.021)	(0.017)	(0.018)

iv009_mod, -15	0.002	-0.057**	-0.015	0.023	-0.018	-0.031
	(0.020)	(0.028)	(0.024)	(0.018)	(0.024)	(0.021)
iv009_mod, -12		-0.371***			-0.384***	
		(0.028)			(0.034)	
iv009_mod, -9	-0.018*	-0.105***	-0.051**	0.013	-0.077***	-0.041**
	(0.010)	(0.020)	(0.025)	(0.012)	(0.020)	(0.020)
iv009_mod, 2	0.013	0.015	0.025*	0.022**	0.020	-0.002
	(0.008)	(0.014)	(0.014)	(0.009)	(0.013)	(0.013)
iv009_mod, 3	0.018**	0.031**	0.012	0.029***	0.017	-0.013
	(0.008)	(0.014)	(0.013)	(0.009)	(0.012)	(0.012)
iv009_mod, 4	0.026***	0.032**	0.022*	0.025***	0.037***	-0.009
	(0.007)	(0.013)	(0.012)	(0.007)	(0.011)	(0.014)
iv009_mod, 5	0.038***	0.033**	0.005	0.037***	0.027**	-0.006
	(0.008)	(0.014)	(0.014)	(0.007)	(0.012)	(0.012)
female	0.004	-0.058***	-0.157***	-0.012**	-0.059***	-0.178***
	(0.005)	(0.009)	(0.007)	(0.006)	(0.008)	(0.009)
age	0.022***	0.065***	-0.001	0.019***	0.066***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
eduyears_mod	-0.002***	0.001	0.002***	-0.001**	0.001*	0.002***
	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.0004)
children	0.005	-0.043***	-0.018	-0.004	-0.028***	-0.033***
	(0.004)	(0.008)	(0.011)	(0.004)	(0.008)	(0.012)
Constant	-1.019***	-3.401***	1.111***	-0.937***	-3.469***	1.044***
	(0.077)	(0.103)	(0.134)	(0.075)	(0.095)	(0.102)
Observations	14,690	18,605	13,252	14,254	20,770	15,069
R^2	0.103	0.261	0.144	0.102	0.268	0.110
Adjusted R^2	0.102	0.259	0.142	0.101	0.267	0.109
Residual Std. Error	0.249 (df = 14664)	0.408 (df = 18578)	0.303 (df = 13226)	0.270 (df = 14225)	0.407 (df = 20740)	0.317 (df = 15040)

Note: Country has default value 28, iv009_mod is area of living. Individual models are estimated on limited datasets with respect to age groups.

Table Appendix B. 4 – IV gender wave 5 and 6

	Dependent variable:			
	retired			
	(1)	(2)	(3)	(4)
grandchild	0.155***	0.216***	0.209***	0.191***

	(0.049)	(0.046)	(0.052)	(0.045)
country, 11	-0.090***	0.077***	-0.088***	0.044***
	(0.014)	(0.015)	(0.016)	(0.015)
country, 12	-0.211***	-0.050***	-0.222***	-0.082***
	(0.013)	(0.014)	(0.013)	(0.014)
country, 13	-0.165***	-0.113***	-0.160***	-0.130***
	(0.012)	(0.013)	(0.012)	(0.014)
country, 14	-0.318***	-0.065***		
	(0.014)	(0.014)		
country, 15	-0.431***	-0.061***	-0.427***	-0.068***
	(0.015)	(0.015)	(0.016)	(0.016)
country, 16	-0.320***	0.006	-0.327***	-0.044**
	(0.016)	(0.017)	(0.017)	(0.017)
country, 17	-0.128***	0.035***	-0.121***	0.024*
	(0.012)	(0.013)	(0.013)	(0.013)
country, 18	-0.201***	-0.137***	-0.210***	-0.150***
	(0.011)	(0.013)	(0.012)	(0.013)
country, 19			-0.358***	0.0004
			(0.019)	(0.021)
country, 20	-0.235***	-0.100***	-0.245***	-0.133***
	(0.019)	(0.019)	(0.020)	(0.019)
country, 23	-0.258***	-0.008	-0.228***	-0.011
	(0.012)	(0.012)	(0.012)	(0.013)
country, 25	-0.305***	-0.247***	-0.301***	-0.243***
	(0.015)	(0.018)	(0.018)	(0.021)
country, 29			-0.114***	-0.095***
			(0.015)	(0.017)
country, 31	-0.320***	0.107***	-0.299***	0.087***
	(0.021)	(0.021)	(0.021)	(0.020)
country, 33			-0.207***	-0.029*
			(0.017)	(0.017)
country, 34	-0.047***	0.074***	-0.054***	0.056***
	(0.013)	(0.014)	(0.011)	(0.012)
country, 35	-0.210***	-0.148***	-0.232***	-0.159***
	(0.009)	(0.012)	(0.010)	(0.012)
country, 47			-0.171***	0.014
			(0.015)	(0.016)
iv009_mod, -15	-0.017	-0.038*	-0.018	-0.006
	(0.019)	(0.022)	(0.017)	(0.020)
iv009_mod, -12		-0.501***	-0.575***	
		(0.019)	(0.023)	

iv009_mod, -9	-0.079***	-0.078***	-0.070***	-0.051***
	(0.014)	(0.017)	(0.014)	(0.017)
iv009_mod, 2	0.018*	0.018*	0.019**	0.014
	(0.010)	(0.010)	(0.010)	(0.010)
iv009_mod, 3	0.019**	0.012	0.002	0.020**
	(0.009)	(0.010)	(0.009)	(0.009)
iv009_mod, 4	0.013	0.028***	0.003	0.037***
	(0.009)	(0.009)	(0.008)	(0.008)
iv009_mod, 5	0.012	0.029***	0.009	0.025***
	(0.008)	(0.009)	(0.008)	(0.008)
age	0.033***	0.040***	0.031***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)
eduyears_mod	0.003***	-0.001*	0.004***	-0.001**
	(0.0004)	(0.0004)	(0.0005)	(0.0004)
children	-0.034***	-0.026***	-0.038***	-0.020***
	(0.004)	(0.004)	(0.005)	(0.004)
Constant	-1.514***	-2.098***	-1.393***	-2.065***
	(0.039)	(0.046)	(0.040)	(0.044)
Observations	26,914	20,554	28,953	22,048
R^2	0.439	0.540	0.398	0.508
Adjusted R^2	0.438	0.540	0.398	0.508
Residual Std. Error	0.375 (df = 26889)	0.334 (df = 20528)	0.388 (df = 28924)	0.341 (df = 22020)

Note: Country has default value 28, iv009_mod is area of living. Individual models are estimated on limited datasets with respect to gender.

Table Appendix B. 5 – IV children restrict wave 5 and 6

	Dependent variable:			
	retired			
	(1)	(2)	(3)	(4)
grandchild	0.204***	0.189***	0.175***	0.197***
	(0.034)	(0.034)	(0.033)	(0.035)
grandchildNA	0.105***		0.063***	
	(0.021)		(0.018)	

country, 11	-0.013	-0.021**	-0.030***	-0.037***
	(0.010)	(0.010)	(0.010)	(0.011)
country, 12	-0.141***	-0.144***	-0.165***	-0.167***
	(0.009)	(0.010)	(0.009)	(0.010)
country, 13	-0.147***	-0.147***	-0.148***	-0.154***
	(0.008)	(0.009)	(0.009)	(0.009)
country, 14	-0.209***	-0.209***		
	(0.009)	(0.010)		
country, 15	-0.266***	-0.272***	-0.272***	-0.273***
	(0.010)	(0.011)	(0.011)	(0.011)
country, 16	-0.167***	-0.180***	-0.206***	-0.208***
	(0.011)	(0.012)	(0.011)	(0.012)
country, 17	-0.065***	-0.061***	-0.062***	-0.064***
	(0.008)	(0.009)	(0.009)	(0.009)
country, 18	-0.180***	-0.178***	-0.188***	-0.193***
	(0.008)	(0.009)	(0.009)	(0.009)
country, 19			-0.217***	-0.208***
			(0.013)	(0.014)
country, 20	-0.179***	-0.178***	-0.206***	-0.203***
	(0.012)	(0.014)	(0.013)	(0.014)
country, 23	-0.148***	-0.153***	-0.136***	-0.141***
	(0.008)	(0.009)	(0.009)	(0.009)
country, 25	-0.296***	-0.281***	-0.278***	-0.278***
	(0.010)	(0.012)	(0.013)	(0.014)
country, 29			-0.109***	-0.109***
			(0.011)	(0.011)
country, 31	-0.123***	-0.135***	-0.121***	-0.134***
	(0.014)	(0.015)	(0.014)	(0.015)
country, 33			-0.129***	-0.131***
			(0.012)	(0.012)
country, 34	0.003	-0.0003	-0.006	-0.011
	(0.009)	(0.010)	(0.008)	(0.008)
country, 35	-0.179***	-0.184***	-0.192***	-0.204***
	(0.007)	(0.007)	(0.007)	(0.008)
country, 47			-0.093***	-0.097***
			(0.011)	(0.011)
iv009_mod, -15	-0.038***	-0.028*	-0.035***	-0.025*
	(0.013)	(0.015)	(0.013)	(0.013)
iv009_mod, -12	-0.398***	-0.392***	-0.480***	-0.485***
	(0.021)	(0.014)	(0.015)	(0.016)
iv009_mod, -9	-0.069***	-0.078***	-0.070***	-0.061***

	(0.010)	(0.011)	(0.010)	(0.011)
iv009_mod, 2	0.022***	0.016**	0.010	0.015**
	(0.006)	(0.007)	(0.007)	(0.007)
iv009_mod, 3	0.017***	0.015**	0.005	0.010
	(0.006)	(0.007)	(0.006)	(0.007)
iv009_mod, 4	0.020***	0.018***	0.015***	0.017***
	(0.006)	(0.006)	(0.006)	(0.006)
iv009_mod, 5	0.017***	0.017***	0.013**	0.014**
	(0.006)	(0.006)	(0.005)	(0.006)
female	-0.070***	-0.072***	-0.084***	-0.089***
	(0.003)	(0.004)	(0.004)	(0.004)
age	0.036***	0.036***	0.036***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)
eduyears_mod	0.001***	0.001***	0.001***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
children	-0.021***	-0.032***	-0.029***	-0.031***
	(0.002)	(0.003)	(0.003)	(0.003)
Constant	-1.763***	-1.705***	-1.676***	-1.616***
	(0.025)	(0.032)	(0.026)	(0.032)
Observations	57,617	47,468	58,147	51,001
R^2	0.465	0.467	0.439	0.432
Adjusted R^2	0.465	0.467	0.439	0.432
Residual Std. Error	0.365 (df = 57589)	0.365 (df = 47441)	0.373 (df = 58116)	0.375 (df = 50971)

Note: Country has default value 28, iv009_mod is area of living. Individual models are estimated on limited datasets with respect to children.