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Preface

This thesis presents three chapters in applied welfare economics. What links all of them is that they point towards the individuals' well-being under different perspectives, and offer insights on potentially vulnerable groups of individuals that experience welfare losses and need improvement in policies to support them. The first and the second chapters provide a complementary analysis of the retirement role on individual well-being, which is observed firstly as individual subjective health status, and secondly, as subjective well-being, namely as an indicator of life satisfaction and an indicator of quality of life. The third chapter aims at analysing the association of energy poverty on the individuals' well-being, clearly it differs to the first two chapters in focus, methods and policy implications. The vulnerable groups we consider are energy poor and retirees. Energy poor are increasing in European countries and one of the main challenges is to be able to target them, given the multidimensional composition of the phenomenon. The growth of the elderly share in the population is an undeniable objective fact that brings out some concerns. In fact, it contribute to add financial burden to welfare states and worries to policymakers who aim at improving the financial stability of healthcare systems while preserving both the welfare and the well-being of older workers and retirees.

The first chapter deals with the retirement impact on general, mental, and cognitive health. Retirement may worsen the individuals' health status when they experience, for instance, a reduction in intellectual or physical daily activities. At the same time, retirement might discourage investment in health by inducing negatively changes in health-related behaviours. Thus, it may affect health status by a direct effect, and by an indirect effect running through health-related behaviours. By using longitudinal SHARE data, and exploiting the mediation analysis in an instrumental variable framework, we built on a model for health and retirement to unpack this causal chain. We also model retirement as a two-stage process, namely, we consider both the status of being retired and the time spent into retirement.

In the second chapter, we turn the attention to a broader definition of individual well-being, and we focus on the impact of retirement on life satisfaction and quality of life. The individual well-being consists of several domains, which people are able to separately or overall evaluate. As an example, exiting the labour market may be beneficial for well-being due to the increase in leisure time, but at the same time, it can be detrimental because of the drop in health status. Thus, retirement may impact subjective well-being in both a positive or negative way, and it is likely that the transition into retirement might adjust in time. By using longitudinal SHARE data, we model the relationship of retirement and well-being in an instrumental variable framework, which accounts for potential endogeneity arising for reverse causality of retirement and subjective well-being, and unobserved individual heterogeneity.

In the third chapter, we investigate the relationship between energy poverty and life satisfaction. After constructing a multidimensional energy poverty index exploiting both subjective and objective indicators, we evaluate its effect on subjective well-being by using ITSILC cross-sectional data. By taking into account the ordinal nature of our variables of interest, we employ a bivariate order probit, to estimate the effect of energy poverty on well-being, and to investigate whether the welfare losses change for any severity level and life satisfaction. As both our main variables contain subjective information, we account for the endogeneity by imposing an exclusion restriction on the energy poverty determinants, namely the decades of the dwellings' construction.

Chapter 1

A life change for the better? The health consequences of retirement

Abstract

This chapter aims at assessing the total effect of retirement on individual health status by focusing on the causal mechanism through which retirement operates on individuals' health. We use longitudinal data for ten European countries to estimate the effects of being retired and of time spent into retirement, within a mediation analysis framework where the total retirement effect nests the indirect effect, running through the lifestyle channel. Our identification strategy exploits the exogenous variations of the statutory and early retirement ages over time and across countries. We employ an FE-IV estimator to control for potential reverse causality, time-varying and time-invariant unobservables that may cause retirement endogeneity. Findings show that the long-term effect of retirement is detrimental for any health outcome taken into consideration. A temporary protective role is played solely on general health. Heterogeneity effects between the ERA and the SRA retirees are found when considering specific set of instruments: the general health is more endangered after statutory retirement, while the cognitive health seems more affected for early retirees. Depending on the physical burden degree experienced in the past occupation, the general and the cognitive health are respectively more positively (physical burden) or negatively (psychosocial burden) affected by retirement. Some indirect effects exist especially for the general and the mental health. The role of lifestyles seems particularly relevant for the general and the mental health of men, the SRA retirees, and those who retired from physically demanding jobs.

JEL: J26, I10, C36

Keywords: Retirement; Health-Related Behaviours; Health; Mediation Analysis; Instrumental Variables

1.1 Introduction

Developed countries are experiencing a clear-cut demographic transition, which is mainly caused by lower birth rates and by longer life expectancy. Advances in medical sciences have contributed to the increase in life expectancy observed since the 19th century, and consequently, to the rapid global population ageing (OECD/EU, 2016). Despite the improvements in life expectancy, the elderly suffers the growing burden of multiple chronic disease and disability (DuGoff, Canudas-Romo, Buttorff, Leff, and Anderson, 2014). This fact, coupled with an increasing old-age dependency ratio (OECD, 2017b), is threatening welfare states sustainability. The share of retirees over the working population has increased also due to the fact that in the past decades many public pension systems have encouraged workers to opt for early retirement: in Europe, about 43.1% of old-age retirees receive an early retirement pension (Eurostat, data 2014). This creates pressure on national government and on public pension systems (e.g. Gruber and Wise, 1998). Many European countries, indeed, are quickly adapting to the demographic and socioeconomic changes. Measures of life expectancy, for example, are often used to define public pension schemes, thus leading to an increase in the effective retirement age.

For a long time, scholars have been devoting special attention to the relationship between health and retirement, providing extensive evidence of a significant effect of individual health status on retirement choice and early exit from the labour market, specifically due to the impact of health shocks on retirement behaviour (Giustinelli and Shapiro, 2019; Roberts, Rice, and Jones, 2010; Jones, Rice, and Roberts, 2010; Disney, Emmerson, and Wakefield, 2006; Bound, Schoenbaum, Stinebrickner, and Waidmann, 1999). More recently, the growing interest in the ageing of the working population has spurred more and more studies on the potential effect of retirement on individual health and well-being. The extant literature draws attention to various health outcomes for physical health, as measured by self-reported indicators of general health (i.e., self-assessed health) and specific health indicators (i.e., chronic conditions, physical limitations); mental health, measured using self-reported indicators (such as the Euro-D scale); and cognitive abilities, measured using *ad hoc* test scores (i.e., memory test score).[1] Although the empirical evidence produced so far is mixed, it suggests that workers' health is related to differences in socio-economic characteristics (e.g., Schaap, Wind, Coenen, Proper, and Boot, 2018) and on whether is present a physically demanding job (e.g.,Mazzonna and Peracchi, 2017). Moreover, stressing working conditions have been found to worsen health (Cottini and Ghinetti, 2017) thus decreasing labour productivity and potentially inducing an early exit from the labour market.

Few studies, however, have mentioned changes in health-related behaviours, and lifestyle in general, as a channel through which retirement might affect health. Dave, Rashad, and Spasojevic (2008) find that retirement has adverse effects on physical and functional limitations, illness conditions, and depression and argue that these effects are partly driven by changes in physical activity and social interaction. In a more recent study, Eibich (2015) shows that retirement affects health when health behaviours are included in the health production function. By inducing changes in health behaviours, retirement impacts on health investments, as implicitly suggested by the Grossman (1972) model. Research focusing on the mechanisms beneath the effect of retirement on health, however, has been sparse. This work adds to the empirical health economics literature that investigates the mechanisms through which retirement operates on health, by estimating the effect of retirement and by decomposing it into the direct and the indirect parts within a mediation analysis framework where health-related behaviours act as mediator.

We exploit a rich longitudinal dataset collected by the Survey of Health, Aging and Retirement in Europe (SHARE) project to unpack the causal chain that arises when retirement and lifestyle jointly determine health outcomes.[2] We differentiate the retirement effect into being retired (henceforth *status* effect; e.g. the reduction of daily activities might negatively affect the cognitive health)

[1]See, among others, Bonsang, Adam, and Perelman (2012), Celidoni, Dal Bianco, and Weber (2017), Coe and Zamarro (2011), Mazzonna and Peracchi (2012, 2017).

[2]We use data from DOIs 10.6103/SHARE.w1.610, 10.6103/SHARE.w2.610, 10.6103/SHARE.w4.610, 10.6103/SHARE.w5.610. See Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been primarily funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N.211909, SHARE-LEAP: N.227822, SHARE M4: N.261982). Additional funding from the German Ministry of Education and Research, the U.S. National Institute on Aging (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, R21 AG025169, Y1-AG-4553-01, IAG BSR06-11, OGHA 04-064) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

and time spent into retirement (henceforth *long-term* effect; e.g. the reduction in daily activities might also be associated with a lack of purpose that progressively in time affects mental health.) on several health outcomes, and investigate the mediating role played by health-related behaviours in the relationship between retirement and health.

For this purpose, we estimate a model of health, lifestyle and retirement that addresses the endogeneity of retirement on health status and health-related behaviours (lifestyles, for the sake of brevity) and accounts for individual-specific unobserved heterogeneity by using a fixed effect instrumental variable estimator. The relationship between health and retirement is characterised by reverse causality: individuals in poor health or individuals who experience negative health shocks tend to have a higher probability to select into retirement (for example, because of the onset of job inability). Likewise, endogeneity of retirement might be an issue also in the relationship between lifestyle and retirement. Furthermore, the presence of unobservable time-invariant (e.g., time preference, personality traits, genetic make-up) and time-varying factors that affect both health, health-related behaviours and the decision to retire may explain retirement endogeneity. To identify the retirement effect on health outcomes and lifestyles we exploit the exogenous variation over time and across countries of the *Statutory Retirement Ages* and *Early Retirement Ages* (henceforth *SRA* and *ERA*) at which workers can retire and obtain a public pension. Using information on eligibility ages we build a set of instruments for retirement status and for time spent in retirement.

Overall, the long-term effect of retirement is found to be detrimental for general, mental, and cognitive health. The status of being retired is associated with a positive effect on the probability of having good health, which means that a temporary protective role is played on the perceived health. The status of being retired is also associated to a positive effect on the probability of being engaged in physical activity, along with a decreasing rate during the time spent into retirement; likewise, an increase in the probability of abusing of alcohol which decreases during the time, and a beneficial effect on BMI level. Heterogeneity effects between the ERA and the SRA retirees are found when considering specific set of instruments: the general health is more endangered after statutory retirement, while the cognitive health seems more affected for early retirees. We also find that while for women the negative effect of retirement on cognitive health is larger than for men, the probability to be depressed increases more for men than for women. Heterogeneity analysis also seems to stress the importance of the type of the occupational burden they were expose. The individuals who were employed in physical demanding occupations report a larger positive status effect on general health, while those who were employed in psychosocial demanding jobs have a larger negative effect especially on cognitive health. The mediation analysis allows us to unpack the causal chain between health and retirement, showing that some indirect effects exist, especially for general and mental health. In other words, the total effect of retirement operates on the individuals health through shaping the health-related behaviours with both status and long-term indirect effects. The role of lifestyles seems particularly relevant for the general and mental health of men, the SRA retirees, and those who retired from physically demanding occupations.

The rest of the chapter is structured as follows: Section 2 outlines the salient literature. Section 3 sketches the conceptual framework of the empirical model, illustrates the identification strategy, and the empirical specifications. Section 4 describes the data and explains the most relevant variables. Section 5 reports and discusses the results of the econometric analysis. Section 6 concludes.

1.2 Retirement and Health

Many empirical studies have focused on the effect of retirement on various health outcomes, showing mixed results. Behncke (2012) shows that retirement significantly increases the risk of being diagnosed with chronic conditions, such as cardiovascular disease and cancer, and worsen both self-reported health and the latent health stock. There is large evidence on the consequences on cognitive abilities in a labour market exit stage. Coe, Gaudecker, Lindeboom, and Maurer (2012) find that retirement does not affect cognition of white-collar retirees but positively affects that of blue-collar retirees, indicating heterogeneity across different occupation. Bonsang, Adam, and Perelman (2012) find that retirement exerts a detrimental effect on cognitive test scores. Motegi, Nishimura, and Oikawa (2017) show evidence of a decline in workers' mathematical scores after

retirement and of a weak negative effect on cognitive function with the exception of workers with high body mass index and fat intake experience. Celidoni, Dal Bianco, and Weber (2017) confirm the detrimental effect on cognitive function, especially for those who retire at the full statutory age. Although findings are not univocal, the literature has shown that psychosocial demanding jobs might decelerate the process of cognitive decline (Salthouse, 2006, Rohwedder and Willis, 2010), thus suggesting a potential protective effect of working. Mazzonna and Peracchi (2012, 2017) find a detrimental long-term effect of retirement on general and cognitive health, which leads to a worsening of who worked in physically demanding jobs.
Other studies have shown that transition into retirement might be associated with a reduction in daily activities, contact with peers and lack of purpose, which in turn affects individuals' well-being and mental health. Physical and mental health status may be threatened in case of physically demanding occupation and when workers are exposed to adverse working conditions that might affect both physical and mental health such as safety, rotation shifts, excess of overtime hours, lack of job satisfaction, job worries, lack of support from colleagues (Robone, Jones, and Rice, 2011, Cottini and Ghinetti, 2017, Cottini and Lucifora, 2013). If this is the case, one would expect a beneficial effect of retirement on both physical and mental health because of reduced work-related stress and pressure. Indeed, Barnay and Defebvre (2018) find a beneficial effect on depressive episodes; Bertoni, Maggi, and Weber (2018) show, instead, a short-term protective effect of retirement on muscle strength that is not persistent; Coe and Lindeboom (2008) find no negative effect of early retirement on men's health. Findings in Belloni, Meschi, and Pasini (2016) indicate mental health improvement for men after retirement. Leimer (2017) shows a long-term preserving effect on various health outcomes furthermore, Apouey, Guven, and Senik (2017) provide evidence of a higher probability of having unexpected positive health shocks for males after retirement.

The aforementioned studies have also shown that retirement can be included into health models in different ways, and leading to different findings. One simple indicator of retirement used by the extant literature is a dummy variable that captures the effect on health variables in terms of gains (losses) associated to the status of being retired. For instance, retirees might be less anxious than employed individuals due to the lack of working pressures. Another indicator of retirement takes into consideration also the duration of retirement, that is the time spent out of the labour market with a pension benefit. This allows to capture potential cumulative changes in health that might occur and evolve in time. As an example, the feeling of loneliness due to the lack of peers might increasingly raise the probability of being depressed.[3] Ignoring the progressive gain (loss) of health status may lead to completely different results, or rather assign a positive (negative) impact to retirement when, instead, it has a negative (positive) long-term effect.

1.2.1 Retirement and Health behaviour

Among the extant studies on the relation between health and retirement, some of them have mentioned individuals' health behaviours (such as smoking, drinking, doing physical activity or eating well) as a potential channel through which retirement might affect health (see, e.g., Dave, Rashad, and Spasojevic (2008), Behncke (2012), Eibich (2015), and Atalay, Barrett, and Staneva (2019)).

From a theoretical perspective, there is no *a priori* assumption on the type of change in lifestyle caused by retirement. Nevertheless, one would expect some potential changes in health investment due to the exit of the labour market. Within the Grossman's framework, rational individuals will invest in their own health (e.g. through healthy lifestyles and health care utilisation) to maximise individual utility (Grossman, 1972) and the optimal level of health investment is chosen at any time, depending on economic incentives, individual time preference, future expectations, and personal traits. Exiting the labour market might determine the loss of incentives to invest in health because individuals no longer need to be healthy and productive workers. However, some levels of health investment are expected to counteract the natural depreciation of the health capital. Thus, the mechanism that operates on the demand for health after retirement is unclear. On the one hand, if the individual discount time rate is low, retirees should invest in their health through an enhanced adoption in healthy behaviours. On the other hand, a high discount rate for

[3] The set of potential retirement indicators can eventually include another dummy variable that captures the transition effect of leaving the job market, namely what Leimer (2017) define as the "honeymoon effect". In other words, the transition dummy might capture a different temporarily effect from the cumulative effect - e.g. leaving physically demanding occupation might cause an immediate beneficial effect on physical health.

the future would presumably drop the health investment because of the lack of economic incentive (e.g. consuming less healthcare and more sin goods).

To our knowledge, only few empirical studies have focused their attention on the link between retirement and health-related behaviours, as documented in Zantinge, Berg, Smit, and Picavet (2013) and Schaap, Wind, Coenen, Proper, and Boot (2018). Celidoni and Rebba (2017) find that the probability of not practising any activities decreases after retirement, and this effect is stronger for higher educated individuals. According to Bertoni, Brunello, and Mazzarella (2018), postponing retirement ages stimulates engagement in physical activity, reduces obesity and increases self-reported satisfaction with health. Kesavayuth, Rosenman, and Zikos (2018) provide new empirical evidence on how the link between lifestyle and retirement depends on gender, European geographic region, job type and baseline health behaviour. Retirement might affect health behaviours through increased leisure time, loss of restrictions, changing social contacts, stress and reorientation on health. It seems, however, that the literature on retirement and health has not explicitly examined the role of lifestyles in the underlying mechanism through which retirement influences individual health.

Bringing together the two perspectives, namely the relationship between retirement and health and retirement and health-related behaviours, might help in investigating the beneath causal mechanism of retirement on health. We argue that lifestyles, whose mediating effect has been studied in other models for health (see, e.g., Tubeuf, Jusot, and Bricard, 2012, Brunello, Fort, Schneeweis, and Winter-Ebmer, 2016), also play a crucial role in the relationship between retirement and health. Therefore, we seek to unpack the causal chain that arises when retirement and lifestyles jointly determine health outcomes. The graphical representation of the causal chain is summarised by the following diagram:

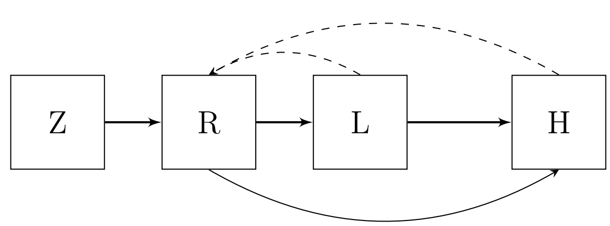


Figure 1.1 – The causal chain between retirement and health.

As shown by the graph, Z exogenously determines R. R causes H indirectly through L as well as directly, which is represented by the continuous arrows linking R and H. The potential reverse causality between H and R is represented by the dotted arrow from H to R. Simultaneously, the potential reverse causation between R and L is depicted by the dotted arrow from L to R. We argue that the causal pathway between retirement and health reflects a *total* effect that comprises a *direct* and an *indirect* parts. The former denotes the health status variation directly caused by retirement, and the latter corresponds to its variation induced by the variation of the lifestyle caused by retirement. However, the identification challenge is not effortless, given the endogeneity issues that occur.

1.3 The model

The identification strategy we follow to unpack the causal chain summarised by the Figure (1.1) is not straightforward because is composed by different steps, each characterised by different issues. Firstly, it is presented a model of health and retirement that describes the identification strategy for the retirement effect estimation on health. In a second moment, the model is extended to a mediation analysis specification, which finally enables to decompose the effect of retirement on different channels.

1.3.1 The retirement effect on health

The starting point is the specification of the health outcome equations. We model the individual health status including a set of two retirement indicators, respectively denoting the *status* effect and the *long-term* effect. As emerged in the literature review, the status indicator captures the potential effect induced by being retired, while the long-term indicator captures the potential cumulative changes that evolve for each year spent into retirement. In addition to previous works that focus on retirement, we also integrated the health status function with the health-related behaviours, which have been so far recognised as determinants of health (i.e. Balia and Jones, 2008). The health status function H can be written as follows:

$$H_{it} = \beta_1 R_{it} + \beta_2 TimeR_{it} + \gamma L_{it} + \lambda X_{it} + \tau_t + \epsilon_{it} \\ with \;\; i = 1, ..., N; t = 1, ..., T. \tag{1.1}$$

where H_{it} is an health outcome, R_{it} is a dummy variable associated to the *status* effect of retirement and $TimeR_{it}$ denotes the *long-term* effect of retirement. The distinction between the retirement effects imply that the overall impact of retirement is meant to be the sum of the two coefficients R_{it} and $TimeR_{it}$. L is a vector of health-related behaviours indicators, namely smoking, engagement in physical activities, drinking, and an indicator related to individuals' weight; X_{it} is a set of observable exogenous time-varying individual characteristics, such the age (assuming linearity because of the short time-span), the logarithm of the household income level, being married, living alone, the number of children and grandchildren; τ_t that denotes the interview date fixed effect; $\epsilon_{it} = \mu_i + e_{it}$ where μ_i indicates some unobserved heterogeneity, and e_{it} is the *i.i.d* error term.

It has been already discussed in previous works that using an Ordinary Least Squares (OLS) approach may produce biased results due to potential endogeneity issue. Endogeneity might arise because of the reverse causation between health and retirement. In fact, poor health or bad health shocks might induce retirement. As an example, severe diseases that cause mobility limitation might lead to job inability forcing the worker to opt for early retirement. Furthermore, unobservable time-invariant factors may simultaneously correlate with health and the retirement choice. For example, optimistic individuals tend to be less affected by anxiety and depression episodes, better handling work pressure, which may reduce the probability of early retirement. In order to control for constant individual heterogeneity, a FE estimator is often used, which allows for the correlation of the time-invariant unobservable and the other determinants. However, a FE estimator alone is not able to solve the reverse causality issue, which it can be overcome by using an instrumental variable approach (IV). Thus, the endogeneity issues are addressed by estimating the model in a FE-IV framework. Indeed, the equation (1.1) denotes the second stage of a standard

FE-IV estimator. The correspondent first stages for R_{it} and $TimeR_{it}$ can be written as:

$$\begin{aligned} R_{it} &= \alpha Z_{it} + \lambda X_{it} + \tau_t + v_{it} \\ TimeR_{it} &= \varphi Z_{it} + \lambda X_{it} + \tau_t + w_{it} \\ with\ \ i &= 1, ..., N; t = 1, ..., T. \end{aligned} \tag{1.2}$$

where Z is a vector of exogenous variables that determine the two indicators of retirement; the set of controls X_{it} contains all the other covariate of the second stage, v_{it} and w_{it} are the error terms.

1.3.2 Identification issues

As mentioned above, assessing the retirement effect on health is not effortless, given that within our framework, retirement and its duration are clearly endogenous variables leading to bias in standard OLS estimates. As already recognised by the literature as a good instrument for retirement decision, we exploit the exogenous variation over time, across countries, gender, and type of job of the change in the retirement rules for early and statutory ages. Thanks to the cross-country variation, we are able to disentangle the age effect to the retirement duration comparing same-age individual that are allowed to retire in some countries while in other countries are not given this possibility. Previous works argue that eligibility ages may be correlated to country-specific characteristics that jointly influence the health status, such as, for instance, the correlation between country-specific education system, pension eligibility ages, and their impact on cognitive health (Mazzonna and Peracchi, 2012, 2017; Bingley and Martinello, 2013). However, the FE estimator takes into account any time-invariant determinant of retirement, overcoming this issue.

Other works have extensively discussed the assumption of the linear relationship between age and health when the age-window is relatively short (Mazzonna and Peracchi, 2017, Coe and Zamarro, 2011). Nevertheless, country specific differences in the relationship may exist. As an example, individuals from different countries may have experienced differences in healthcare provisions, or more generally in the social welfare systems, which may return in different impact of age on health. To account for this potential issue, we test our model by allowing the age term and the country dummies.

Another source of bias is the potential simultaneously correlation of the unobserved heterogeneity with lifestyles and health. Indeed, it has been discussed in literature that lifestyles might reflect individual preferences, economic constrains, environmental, and personal circumstances (Balia and Jones, 2008). By exploiting the longitudinal nature of the data and, in particular, by employing a FE estimator, we allow for correlation between all covariates and the individual time-invariant unobservable factors, thus controlling for any unobservables which may simultaneously affect the propensity to engage in healthy behaviours and the probability of reporting good health. (e.g. time preference, individuals' personality traits, genetic make-up). With regards time-varying factors, we believe that conditional on the set of controls, we are controlling for any time-varying third factors that can correlate with lifestyle. Indeed, we argue that any potential event that might produce a potential variation on time preference or established habits is captured by the observable characteristics that we are including in the health equation (e.g. the socio-economic status might captures shocks due to personal circumstances as well as having grandchildren).[4] Although this model produces unbiased estimation of the retirement effect on health, it does not unpack the causal chain, which is the ultimate aim of the analysis. Rather, it allows us to estimate the *direct* effect of retirement on health, ignoring the *indirect* part, which is captured by the coefficients associated to lifestyle. Therefore, we build on a mediation model that takes into account the intermediate role of lifestyles.

1.3.3 Mediation analysis for the retirement effect on health

The mediation analysis is typically used in studies that aim to investigate the causal mechanisms behind socio-economic phenomena by unravelling the role of intermediate variables (the *mediators*) existent in the causal pathway between the treatment and the outcome variables. The traditional

[4] However, a potential limit of this assumption may be related to the recent empirical evidence about the individual attitude evolution towards risk. For instance, Banks, Bassoli, and Mammi (2019) show that the risk preferences are interrelated at older ages, among others, with retirement decisions, health shocks, and health behaviours. Thus, this gives some scopes for further controls on the time-varying unobservables. A possible check might be the inclusion of a proxy of risk attitude in the equation to control for its evolution.

approach to mediation analysis assumes that the mediator and the treatment are exogenous and that the parameters of interest in the causal pathway can be estimated by means of OLS (MacKinnon, 2012). If this is not the case, because either the treatment or the mediator is endogenous, or both of them are, standard IV estimators are used to unpack the causal chain. While some studies rely on the use of a single instrument, others use separate instruments for the treatment and the mediator (for an overview, see e.g. Frölich and Huber, 2017). More recently, Dippel, Gold, Heblich, and Pinto, 2019 have proposed a new identification strategy that relies on a single instrument by assuming that endogeneity of the treatment depends on omitted variables that affect the (endogenous) mediator.

Building on the mediating analysis framework proposed by Tubeuf, Jusot, and Bricard (2012), with the difference that the treatment is endogenous both in mediator and outcome equations, we are able to decompose the effect of retirement on health into[5]:

- A *Direct Effect (DE)* of R on H, namely the health outcome variation, keeping constant the lifestyle
- An *Indirect Effect (IE)* of R on H, namely the health outcome variation due to the lifestyle variation
- A *Total Effect (TE)* of R on H, namely the total variation of the health outcome due to retirement, which is the sum of the above effects.

In our framework, the decomposition is complicated by the fact that the "treatment" is differentiated in a set of two indicators. For each potential decomposed effect of the causal chain, we can differentiate into the status and the long-term part. In other words, the *DE* and the *IE* can be split, in turn, into status and long-term effect. As an example, the elimination of work-related distress exerts a beneficial impact on the probability of having good health (status effect), along with a cumulative loss that evolves in time due to the progressively lack of daily activities (long-term effect). The two parts compose the direct effect of retirement on health, because no intermediate

[5] Tubeuf, Jusot, and Bricard (2012) focus on the mediating role of lifestyle (and education) in the relationship between early-life conditions and health.

variable is taken into account. However, eliminating the work distress might simultaneously help a person to quit smoking adding an additional increase in the probability of having good health, which is the indirect effect. The indirect effect, in turn, can concern both the status and the long-term effects - e.g. the beneficial of having quitted smoking dissipates in time.
Consider the following set of equations that reflects the Figure (1.1):

$$H = h(R, L, X, e, \mu_H) \tag{1.3}$$

$$L = l(R, X, u, \mu_L) \tag{1.4}$$

$$R = r(Z, v, \mu_R) \tag{1.5}$$

where H is an health outcome function, L is the lifestyle vector, R is the retirement, X a vector of observable exogenous individual characteristics, Z is a set of exogenous determinants of R that contains X, μ_H,μ_L, and μ_R indicate unobservable factors which influence both the individual health status, the lifestyle, and the retirement; v, u and e are $i.i.d$ error terms. Given that we consider that L potentially mediates the causal relationship between R and H, the system extends the model (1.1) by including the intermediate equations of L that are auxiliary in estimating the mediating effects. As we have mentioned presenting the causal chain in Subsection 1.2.1, reverse causation may occur between R, H, and L, thus R is a reduced form for both H and L. Likewise, the L equations are meant to be reduced form for the H equation.
Now, to explain the intuition of the pathway between retirement and health, we simplify the notation assuming linear equations, one retirement indicator, one single lifestyle, omitting from notation both the vector of controls X and the subscript referring to individual and time. Define the lifestyle equation as:

$$L = \delta R + u \tag{1.6}$$

where δ is the effect of retirement on lifestyle. As extensively discuss in Section 1.3.1, the equation for health is defined as:

$$H = \beta_1 R + \gamma L + e \tag{1.7}$$

where β_1 reflects the direct effect of retirement on health, and L denote the lifestyle.[6] Next, to unpack the causal chain, substitute (1.6) into (1.7):

$$H = \beta_1 R + \gamma(\delta R + u) + e \tag{1.8}$$

$$H = (\beta_1 + \gamma\delta)R + \gamma u + e \tag{1.9}$$

$$H = \lambda R + \gamma u + e \tag{1.10}$$

$$H = \lambda R + \epsilon \tag{1.11}$$

where $\epsilon = \gamma u + e$ and $\lambda = (\beta_1 + \gamma\delta)$, which denotes the total effect of retirement.[7] As can be noticed by (1.9), λ is decomposable in the direct effect of retirement on health β_1 plus the indirect effect of retirement on health $\gamma\delta$, derived from the effect of retirement on lifestyle times the effect of lifestyle on health. However, neither the equation (1.10) nor the equation (1.11) allow to isolate β_1, which is possible, instead, by estimating the equation (1.7). Thus, the indirect effect can be obtained by the difference calculating $(\lambda - \beta_1)$.

Table 1.1 – Total, direct, and indirect effects of retirement on a health outcome

Total Effect	$\beta_1 + \gamma\delta$
Direct Effect	β_1
Indirect Effect	$\gamma\delta$

Notes: This decomposition reflects a model with a health outcome, a single lifestyle that acts as mediator, and a single binary treatment.

[6] As discussed in Subsection 1.3.2, when estimating the full model specification, lifestyles are considered exogenous conditional on a set of observables and the potential correlation with time-invariant heterogeneity is allowed by applying a FE estimator.

[7] In operational terms, estimating the equation (1.11) or (1.10), that is including the estimated residuals of the lifestyles model, does not produce different results in λ as the $\hat{u}$ are purged from any correlation with retirement.

1.3.4 Empirical specification of the mediation model

The estimation strategy is a two-step procedure, which is further complicated by the endogeneity issues that characterise each step. In fact, apart from the endogeneity of retirement in the health equation discussed in Subsection 1.3.2, retirement is potentially endogenous also in the lifestyle equations. Therefore, the adoption of a FE-IV estimator is required also on the mediating models. In operational terms, the first step of the mediation analysis is dedicated to the estimation of the mediating models to get the estimated residuals of lifestyles, which in our framework also allows to get rid of any correlation between the residuals and retirement. The second step, instead, focuses on the estimation of the equations of the health outcomes. They are estimated both in the TE and DE specifications, namely using respectively the estimated lifestyle residuals and the observed lifestyles.

In the regression analysis, we will use three different indicators for the health outcome (and five different indicators for robustness), a set of two retirement indicators, and a set of five health-related behaviours capturing the individual investment in health and mediating the effect of retirement. The mediating model functions are defined as follows:

$$\begin{aligned} &L_{ijt} = \theta_{1j} R_{it} + \theta_{2j} TimeR_{it} + \lambda X_{it} + \tau_t + u_{ijt} \\ &with\ \ i = 1, ..., N; t = 1, ..., 4; j = 1, ..., 5. \end{aligned} \tag{1.12}$$

where L_{ijt} is the vector of the j health-related behaviours, namely Smoker, Ex-Smoker, Alcohol Abuse, BMI, and No Activities, for each individual i at any wave t. Controls aim at taking into account confounding factors, such as the age, the logarithm of household income, being married, the number of children, grandchildren, living alone, the time fixed effect. Controlling for being married should be taking into account also for selection factors into lifestyle, as marriage appears to play a preserving role on health status. Married individuals tend to be happier, less susceptible to psychological disorders, wealthier, and generally more prone at investing in health (Espinosa and Evans, 2008). As stressed throughout the Section, the lifestyles equations are auxiliary in unpacking the causal chain. In fact, the coefficients associated to the retirement indicators in the mediating equations are included in the total effect of retirement on health, as the estimated residuals account for the lifestyle part independent from retirement. However, OLS estimator is not appropriate to get unbiased parameters. As discussed by literature (Celidoni and Rebba, 2017), endogeneity issues may arise due to time-invariant factors and reverse causation. Time preferences, genetic make-up may jointly correlate with retirement and lifestyle. Moreover, lifestyles may induce early exit from the labour market because of job inability. Thus, we overcome the reverse causation and unobserved individual heterogeneity by adopting an FE-IV approach. The equation (1.12) indicates the second stage of the model, while the first stages equations can be written as:

$$\begin{aligned} R_{it} &= \alpha Z_{it} + \lambda X_{it} + \tau_t + v_{it} \\ TimeR_{it} &= \varphi Z_{it} + \lambda X_{it} + \tau_t + w_{it} \\ with\ \ i &= 1, ..., N; t = 1, ..., T. \end{aligned} \tag{1.13}$$

where Z is a vector of exogenous variables that determine the two indicators of retirement; the set of controls X_{it} contains all the other covariate of the second stage, v_{it} and u_{it} are the error terms. Once estimated the models, we can get the residuals $\hat{u_{ijt}}$ from each health-related behaviour equation. This generated regressors will be integrated in the health status model instead of the observed lifestyles to estimate the total effect of retirement on health.

The next step is dedicated at estimating the health status function, which is done in two specifications, namely the DE and TE specifications. While the DE specification corresponds to the individual health status equation, where the observed lifestyles are included as determinants of the individual health stock (discussed in subsection 1.3.1 and 1.3.2), the TE specification replaces the observed lifestyles with the generated regression of the first step, the $\hat{u_{ijt}}$. In empirical terms, the two specification share the identification strategy with its issues and the set of controls except for the lifestyles. The models are defined as follows:

$$\begin{aligned} H_{TE,ikt} &= \beta_{TE,1k} R_{it} + \beta_{TE,2k} TimeR_{it} + \gamma_{TE,jk} \hat{u}_{ijt} + \lambda_{TE,k} X_{it} + \tau_t + \epsilon_{TE,ikt} \\ H_{DE,ikt} &= \beta_{DE,1k} R_{it} + \beta_{DE,2k} TimeR_{it} + \gamma_{DE,jk} L_{ijt} + \lambda_{DE,k} X_{it} + \tau_t + \epsilon_{DE,ikt} \\ with\ \ i &= 1, ..., N; t = 1, ..., 4; j = 1, ..., 5; k = 1, ..., 3. \end{aligned} \tag{1.14}$$

where the subscripts DE and TE indicate, respectively, the total and direct effect specifications. H_{ikt} are the k health outcomes for each individual i at any wave t. We include also the age (assuming linearity because of the relatively short time-span), the logarithm of the household income level, being married, living alone, the number of children, and grandchildren, indicated by X_{it}, and τ_t that denotes the interview date fixed effect. In robustness analysis, we allow age to interact with the country indicator. The covariates are potential confounders, having influence on retirement decision (e.g. taking care of grand children may induce retirement and the same time improving good health). Once estimated the two models, we can finally obtain the indirect effect IE for each health outcome such that:

$$\begin{aligned} R_{IE,k} &= \beta_{TE,1k} - \beta_{DE,1k} \\ TimeR_{IE,k} &= \beta_{TE,2k} - \beta_{DE,2k} \\ with\ \ k &= 1, ..., 3. \end{aligned} \tag{1.15}$$

We computed the standard error to test the significance level of each IE using a cross-model hypothesis test based on artificial nesting to calculate the covariance of the estimated coefficients.

1.4 Data and variables

1.4.1 SHARE and sample selection criteria

We use data from the first, second, fourth, and fifth waves of the SHARE, a multidisciplinary survey of individuals aged 50 years old and over, for a set of European countries including Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Spain, Sweden and Switzerland.[8][9] The standard questionnaire includes questions on health, socio-economic status, social and family

[8] In the first wave, all household members had to be born 1954 or earlier. From the second wave onwards, the age limit is set only for the selected respondent, although all members are asked to answer.

[9] We select all the countries that participate in the first wave except for Greece, which is missing in the fourth wave. Moreover, the representativeness of the Greek sample has been previously considered doubtfully (Mazzonna and Peracchi, 2017) and it has been often excluded from previous works. Thus, including Greece would have made partial uncomparable our results with previous findings.

network.[10]

We only keep records of individuals who declare to be retired, employee and self-employed, observed at least in two continuous waves. These criteria avoid confounding effects due to the comparison with permanent sick, home-maker, and unemployed individuals. In fact, the former never entered the labour market, and the latter might confound the retirement effect due to a similar impact of unemployment on health. We include in the analysis sample only individuals aged between 50 and 75 years old in order to contain the ageing effect on poor health and mortality selection. We also exclude all those individuals who declare to have moved from retirement back to employment, because we define retirement as an absorbing status. Thanks to these criteria, we can measure the status effect of being retired, and the cumulative effect of time spent into retirement on health outcomes. Our final sample is composed by 11,167 individuals (30,048 observations) who stayed in the survey for at least two and up to four consecutive waves. Table 1.2 provides the sample size by country and wave.

Table 1.2 – Sample Size by Country and Wave

Country	Wave 1	Wave 2	Wave 4	Wave 5	Total
Austria	499	534	694	615	2,342
Germany	808	927	601	408	2,744
Sweden	1,227	1,335	892	657	4,111
Netherlands	690	826	762	624	2,902
Spain	415	484	484	397	1,780
Italy	686	812	741	554	2,793
France	929	1,041	987	806	3,763
Denmark	648	841	731	609	2,829
Switzerland	361	447	622	543	1,973
Belgium	1,262	1,363	1,206	980	4,811
Total	7,525	8,610	7,720	6,193	30,048

Notes: SHARE data referring to 11,167 individuals aged between 50 to 75 that stayed in the survey from 2 up to 4 waves.

[10] The third wave, SHARELIFE, completely diverges as it is dedicated to the life history; likewise the seventh incorporates both the standard and retrospective questionnaires. These waves are not used because of the absence of questions which are key for our analysis.

1.4.2 Definition of retirement

Starting from Lazear (1986), there have been several definitions of the retirement status, each of them targeting a different group of individuals. In our analysis, an individual is defined as *Retired* if she self-declares to be retired and if she also declares not to have had paid jobs in the previous four weeks.[11]. In addition, we only consider individuals who have been in the labour force at age 50 to avoid early-retired aged less than 50. Table 1.3 describes our sample composition by retirement status and gender. The self-declared retired are almost 57% of the sample, but according to the definition adopted, this number drops down to 50%. Individuals who are not retired are considered employed, making no differences between employees and self-employed.

Table 1.3 – Sample Composition by Retirement Status and Gender

Variable	Overall		Female	Male
	Mean	Std. Dev	Mean	Mean
Retired	0.50		0.49	0.51
Self-declared Retired	0.57		0.55	0.59
TimeR	3.67	5.14	3.72	3.88
Self-declared TimeR	4.2	5.18	4.04	4.34

Notes: SHARE data referring to 11,167 individuals aged between 50 to 75 that stayed in the survey from 2 up to 4 waves. Sample size: 30,048. Female: 13,733; Male: 16,315. *Self-declared Retired* is an indicator based on respondents' answers, while the indicator *Retired* restricts the retirement status to individuals who are not involved in paid activities in the past four weeks.

TimeR refers to the time spent into retirement, defined as:

$$TimeR_{it} = Age_{it} - Age_{it}^{R} \tag{1.16}$$

where Age_{it}^{R} is the age at the retirement. For those individuals who did not meet the requirement of not receiving a pay in the previous for weeks, thus considered employed, the age at retirement is set as the mean age between the two waves in which they become retired under the constraint.

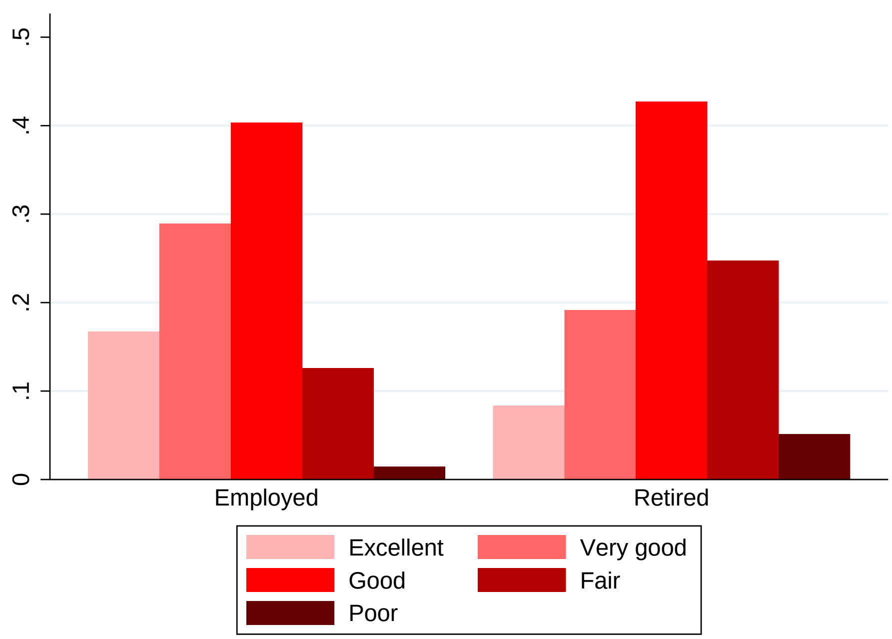
[11] See also Celidoni, Dal Bianco, and Weber (2017); Mazzonna and Peracchi (2017); Behncke (2012)

1.4.3 Health outcomes

We apply our model to three different measures of health status, indicating general, mental, and cognitive health. Table 1.4 reports some summary statistics.

The indicators of health stock used in the literature are several. Self-assessed health (SAH) is commonly exploited as an indicator of general health, defined as a binary variable that indicates *good health* or as an ordered variable generally evaluated by a 5-point scale from 1 to 5 (*excellent, very good, good, fair, poor*). Figure 1.2 displays a bar chart for SAH by retirement status. While the employed distribution is right-skewed, the retired one is left-skewed, indicating that, on average, working individuals declared to be healthier than retirees. However, we comprise the information into a dummy variable that takes value 1 for levels higher than good. As displayed in Table 1.4, nn average, 78% of the sample reports at least good health. The sub-sample of non-retired individuals reports higher level of health than retirees. In the robustness analysis, we also use an health index

Figure 1.2 – SAH distribution by retirement status



Notes: SHARE data referring to 11,167 individuals aged between 50 to 75 that stayed in the survey from 2 up to 4 waves.

to correct for the bias that can arise given the subjective nature of the SAH. Indeed, there are several issues linked to the use of SAH and the presence of measurement errors due to the personal perception of individuals. A common bias discussed by the literature is the *justification bias*, which mainly regards people who are not working. Indeed, they tend to declare worse perceived health to justify the lack of a job or early retirement. Besides, suffering from clinical depression may let people underestimate their purely physical condition. *Vice versa* individuals who have a chronic disease since long time may adapt to the conditions overestimating their level of general health.[12] To minimise these biases, we adopt the health index proposed by Bound, Schoenbaum, Stinebrickner, and Waidmann (1999) as a general health outcome. It is an index that corrects the measurement errors of subjective variables by means of objective indicators, and it indicates the probability of having good health. It is constructed by estimating the following equation by means of a pooled ordered probit estimated for each country and gender. Separate estimations allow us to control for the difference in perception across countries (Kapteyn, Smith, and Soest, 2007) and gender. Define:

$$H_i = \alpha + X\beta_i + \mu_t + \epsilon_i \tag{1.17}$$

where the subjective health stock H is the self-assessed health that ranks between 1, *excellent*, and 5, *poor*; $X\beta_i$ is a vector containing the maximum grip, 10 limitation in doing daily activities[13], 13 limitations in doing instrumental activities[14], a dummy for clinical depression (calculated on the basis of the Euro-D scale), 10 chronic conditions, μ_t, which is the interview date fixed effect. Then, we predict good health (outcome 3 of the ordered variable) and standardise the prediction between 0 and 1. Table 1.4 displays the main summary statistics.

To make an additional test for measurement errors and misclassification, we adopt an indicator of objective physical health, namely a measure of individual grip strength. Following Bertoni, Maggi, and Weber (2018), we generate a dummy indicator of low grip strength, which takes the value of 1 if the score of the grip test is lower than 20 for women and 30 for men.

Regarding mental health, the SHARE database offers the Euro-Depression scale as one of the

[12] Cubı-Mollá, Jofre-Bonet, and Serra-Sastre, 2017, Powdthavee, 2009, Groot, 2000

[13] In SHARE are ph048d1-ph048d4, ph048d6-ph048d10

[14] In SHARE are ph049d1-ph049d13

indicators of mental health.[15] It is a 12-points scale variable, constructed by summing all the contributing items by each. The items are sadness or depression; pessimism; suicidal thoughts; guilt; sleep trouble; lack of interest; concentration; appetite; irritability; fatigue; enjoyment and tearfulness. The average score of the Euro-D scale is 1.88. Retired individuals report more depression items than non-retired, with an average score around 2. Thus, we generate a dummy to measure the probability of suffering from mental health problem after retirement. It takes 1 if the Euro-D scale is larger than 4, which is the common threshold used in literature indicating depression . As shown in Table 1.4, the share of the depressed individuals is higher among the retired (10%).

The last outcome is built on the basis of the three main variables used to measure the cognitive ability level, which are numeracy, fluency, and memory test scores. The numeracy test consists of a set of numerical calculations (e.g. *If the chance of getting a disease is 10 per cent, how many people out of 1,000 (one thousand) would be expected to get the disease?*) and measures the respondents' mathematical performance. The memory indicator is a 10-words recall test, which aims at assessing cognitive impairment and dementia. The fluency indicator is a test of executive function. Respondents are asked to say as many animals as possible in 60 seconds. We drop the outliers in verbal fluency from the records. The original test score ranges from 0 to 100 words, we cut above 45.[16] Table 1.4 displays also the main descriptive statistics also of the single cognitive indicators.

To comprise the information of the three different cognitive items, we apply the principal component analysis (PCA) to have a single index of individual cognitive abilities. PCA has been already applied several times to exploit the information of cognitive and non-cognitive test in other works on return to education and wage differentials (e.g. Cawley, Heckman, and Vytlacil, 2001). All the three test report higher average score for non retired than retired, likewise the cognitive index.

[15] Blazer, 2002; Larraga, Saz, Dewey, Marcos, and Lobo, 2006; Prince, Reischies, Beekman, Fuhrer, Jonker, Kivela, Lawlor, Lobo, Magnusson, Fichter, et al., 1999.

[16] See also Mazzonna and Peracchi (2017).

Table 1.4 – Health Outcomes Summary Statistics

Variable	Mean	Std. Dev.	Non-Retired	Retired
SAH	0.78	-	0.86	0.70
Depression	0.10	-	0.09	0.12
Cognitive	0.003	1.31	0.33	-0.32
H-Index	0.71	0.21	0.70	0.72
Euro-D Scale	1.88	1.91	1.75	2.00
Memory test	9.84	3.32	10.57	9.12
Numeracy test	3.71	1.01	3.85	3.60
Fluency test	21.74	7.05	23.19	20.51
Low grip-strength	0.07	-	0.03	0.11

Notes: SHARE data referring to 11,167 individuals aged between 50 to 75 that stayed in the survey from 2 up to 4 waves. Sample size: 30,048. Non Retired: 15,037; Retired: 15,011.

1.4.4 Health-related behaviours

Regarding health-related behaviours, we use binary indicators for smoking habits, drinking, engagement in physical activity, and BMI level. Smoking habit is measured by two indicators that take value 1 if the individual is a current or former smoker, respectively denoted by *Smoker* and *Ex-Smoker*. *BMI* takes value 1 when the body mass index (BMI) is higher than 30. Although the BMI variable is not describing a behaviour, we choose the indicator as a proxy of a unhealthy diet. *No activities* that takes value 1 when the person declares never or seldom practising activities that require at least a moderate level of energy. In SHARE, alcohol consumption is mainly recorded in terms of drinking days and number of drinks when the individual drinks. To the purpose of building a proxy of excessive alcohol consumption, we construct an indicator of alcohol abuse merging the two different information. Therefore, *Alcohol Abuse* is a dummy variable that takes value 1 if the individual declares to drink at least 5/6 days per week and more than 2 drinks each time her drinks. Table 1.5 reports the statistics on health-related behaviours. The prevalence of smokers is higher among non-retired, while the retired are more ex-smokers. The share of individuals not engaged in physical activity is more present in the retired group; the same higher percentage can be observed when dealing with obese individuals. At last, the incidence of alcohol abuse is higher among retired people.

Table 1.5 – Lifestyles Summary Statistics

Variable	Mean	Min	Max	Non-Retired	Retired
Smoker	0.29	0	1	0.34	0.23
Ex-Smoker	0.33	0	1	0.34	0.35
No Activities	0.04	0	1	0.03	0.06
BMI	0.17	0	1	0.15	0.20
Alcohol Abuse	0.10	0	1	0.09	0.11

Notes: SHARE data referring to 11,167 individuals aged between 50 to 75 that stayed in the survey from 2 up to 4 waves. Sample size: 30,048. Non Retired: 15,037; Retired: 15,011.

1.4.5 Retirement ages and instruments

The *ERA* and *SRA* have been reconstructed by using mixed sources.[17] In particular, we integrate the retirement rules used in Angelini, Brugiavini, and Weber (2009) with the OECD reports(2007-2015), the MISSOC[18] tables updated at January 2018, and the country-specific social security systems direct information. We have always excluded the rules for the *ERA* due to permanent illness. With the aim of showing the variability of *ERA* and *SRA* across countries, we summarise the information in Figures 1.3 and 1.4. These histograms reflect the variability across countries and gender. The red bars indicate the SRA and the empty-black the ERA. The variability primarily arises due to the differences in country specific rules, which are based on gender, type of job (public, private, employee, or self-employed), years of potential fiscal contribution. As an example, Italy shows the higher variability, especially for *ERA*. On the contrary, Sweden has the lower variability. The Appendix A provides the detailed rules for every country. We construct four variables, $AboveERA_{it}$ and $AboveSRA_{it}$, which are the dummies that indicate respectively whether the person is above the minimum eligibility and the statutory age, and $DistERA_{it}$ and $DistSRA_{it}$ that are the distance in years to/from ERA and SRA, in the following way:

- $AboveERA_{it} = \mathbb{I}[Age_{it} \geq Age_{it}^{ERA}]$
- $AboveSRA_{it} = \mathbb{I}[Age_{it} \geq Age_{it}^{SRA}]$

[17] Although in the third wave SHARE provides a specific module for the job history with *ERA* and *SRA* of the respondents of the first two waves, the same information for the fourth and the fifth waves has been integrated in the 7 release of SHARE with the seventh wave. Thus, we have adopted the country-specific retirement rules to assign to each individual the potential *ERA* and *SRA* with the aim of covering a larger time-span.

[18] Mutual Information System on Social Protection

- $DistERA_{it} = Age_{it} - Age_{it}^{ERA}$
- $DistSRA_{it} = Age_{it} - Age_{it}^{SRA}$

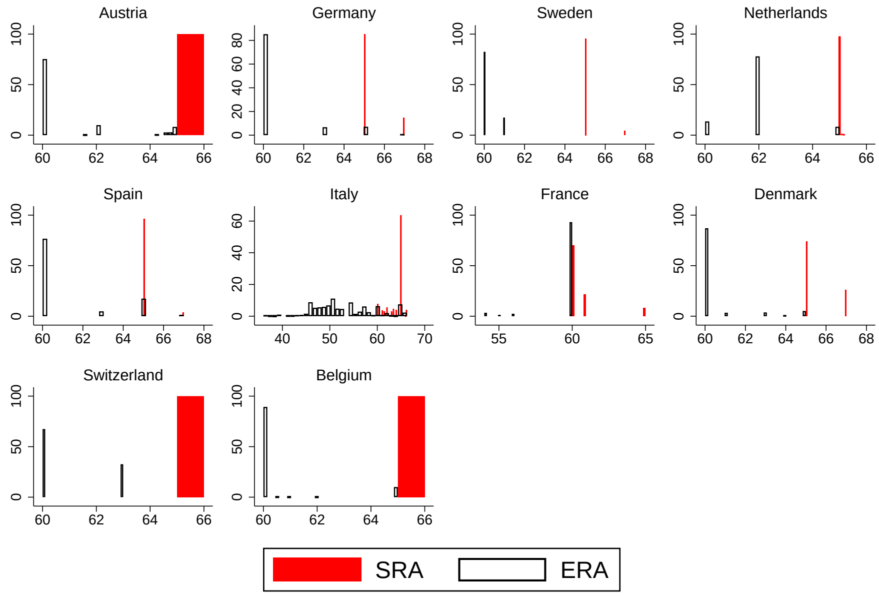
Table 1.6 reports the summary statistics. The share of the sample above ERA is 65% while above SRA is 46%. Given the fact we keep in our sample both individuals who were already retired and who retire during the survey, we can exploit a greater variability of retirement ages.

Table 1.6 – Eligibility Ages Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
ERA	59.86	3.19	36	67
SRA	63.90	2.23	55	67
AboveERA	0.65	-	0	1
AboveSRA	0.46	-	0	1
DistERA	3.03	8.19	-15.1	38.5
DistSRA	-1.01	7.00	-15.1	20

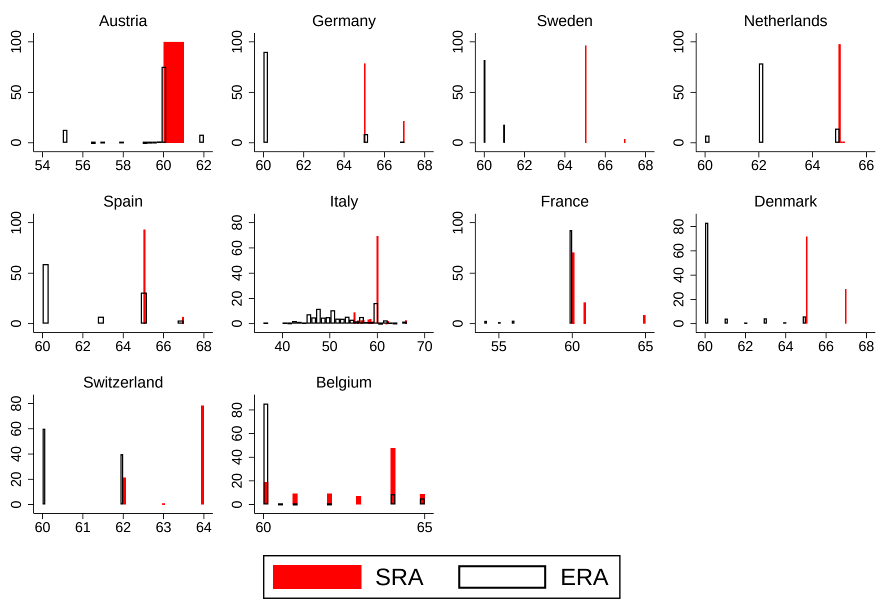
Notes: Era refers to early retirement ages. SRA refers to statutory retirement ages. AboveERA and AboveNRA refer to a dummy variable that takes 1 when the individual age is greater than ERA or SRA. DistERA and DistSRA refer to the years to/from the ERA and SRA. Sample size: 30,048. Non Retired: 15,037; Retired: 15,011. See Appendix A for the rule details.

Figure 1.3 – Distribution of men ERA and SRA by country



Notes: Era refers to early retirement ages. SRA refers to statutory retirement ages. Sample size: 30,048. Non Retired: 15,037; Retired: 15,011. See Appendix A for the rule details.

Figure 1.4 – Distribution of women ERA and SRA by country



Notes: Era refers to early retirement ages. SRA refers to statutory retirement ages. Sample size: 30,048. Non Retired: 15,037; Retired: 15,011. See Appendix A for the rule details.

1.5 Results

In this Section, we present the estimation results of the effect of retirement on the self-assessed health, depression and cognitive health from a mediation analysis model in an FE-IV framework, as presented in the Subsection 1.3.4. We also report the results of several robustness checks, and the investigation of the heterogeneity in the effects across different subsamples.

1.5.1 The decomposition of the effect of retirement on health

The DE outcome models are presented in Table 1.7, each columns reporting on a different health outcome, and for each outcome two specifications displayed side-by-side. In these models, the coefficients associated to health-related behaviours are capturing the potential IE of retirement on health status. The first specifications report overidentification issues, as indicated in the bottom panel by the p-value of the Sargan-Hansen J statistic for over-identification. The preferred specification includes the socio-economics individual characteristics, which are needed to overcome biases due to confounding factors.

With regards the SAH model, Column (2) shows that being retired increases the probability of reporting good health of 0.14, and that the long-term decrease values of -0.03. It other words, the cumulative effect would progressively increase for each year spent into retirement. Thus, this apparently protective role on the perceived health is only temporary. Moving to Depression Column (2), no status effect is detected, whereas the cumulative effect of retirement lowers the probability of being depressed of 0.01. Likewise, in Cognitive model Column (2), the cognitive index is negatively affected by the time spent into retirement, decreasing of -0.002 of a standard deviation. It appears that working has a protective role, especially in the long-run. Even if a beneficial initial effect exists, as in SAH model, the detrimental impact overcomes the positive element during the time. With regards to health-related behaviours, no engagement in physical activities has a negative effect on the three health outcomes. BMI is found to be detrimental for general health.

Table 1.7 – Estimation Results: DE Outcome Model

	SAH		Depression		Cognitive	
Retired	0.0471	0.1364***	-0.0389	-0.0085	0.0171***	0.0029
	(0.032)	(0.039)	(0.026)	(0.030)	(0.006)	(0.007)
TimeR	-0.0279***	-0.0127***	0.0052**	0.0096***	0.0000	-0.0023***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.000)	(0.001)
No Activities	-0.0990***	-0.1018***	0.0639***	0.0629***	-0.0068**	-0.0063**
	(0.017)	(0.017)	(0.015)	(0.015)	(0.003)	(0.003)
BMI	-0.0301**	-0.0290**	-0.0205**	-0.0193*	0.0011	0.0009
	(0.013)	(0.013)	(0.010)	(0.010)	(0.002)	(0.002)
Smoker	-0.0066	0.0030	-0.0198	-0.0185	0.0065	0.0050
	(0.036)	(0.036)	(0.024)	(0.024)	(0.006)	(0.006)
Ex-Smoker	-0.0422	-0.0278	0.0025	0.0056	0.0070	0.0049
	(0.038)	(0.038)	(0.025)	(0.025)	(0.006)	(0.006)
Abuse Alcohol	-0.0022	-0.0009	-0.0024	-0.0014	-0.0012	-0.0015
	(0.010)	(0.010)	(0.008)	(0.008)	(0.002)	(0.002)
Age		0.0954		0.0312		-0.0293**
		(0.081)		(0.065)		(0.014)
Log-Income		0.0003		-0.0025		0.0006*
		(0.002)		(0.002)		(0.000)
Married		0.0446**		-0.0682***		0.0061
		(0.023)		(0.024)		(0.004)
Live Alone		0.0280*		0.0161		0.0034
		(0.016)		(0.016)		(0.003)
Children		-0.0043		0.0041		0.0001
		(0.006)		(0.006)		(0.001)
Grandchildren		0.0005		0.0008		0.0001
		(0.003)		(0.002)		(0.000)
Interview Date	No	Yes	No	Yes	No	Yes
SH J p-value	0.0001	0.4672	0.0532	0.3637	0.0006	0.5253
Individuals	11167	11167	11167	11167	11167	11167
Obs.	30048	30048	30048	30048	30048	30048

Notes: interview date includes month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A somehow counter-intuitive sign is found, instead, in the Depression model, where BMI decrease the probability of being depressed. The remaining lifestyle indicators are non statistically significant. As expected, the age effect is negative for cognitive health. Being married is beneficial in SAH and Depression models. Surprisingly, Living alone is found to increase the probability of having good health, which is instead usually linked to feeling of loneliness and depression episodes that are expected to worsen health.

Before presenting the TE specification, we report our findings of the mediating models, which we need to get the estimated errors to put in place of the observed lifestyle in the TE specification. The auxiliary mediating models are reported in Appendix in Table A1. They show that retirement has no effect on nor smokers neither ex-smoker. The probability of not being engaged in physical activities is associated to a status effect of about -0.08, and to a long-term increase that values 0.01. Being obese appears to be positively affected by the long-term effect of retirement, with a point estimated coefficient of -0.01. Finally, the probability of abuse of alcohol increase of 0.08 with a decreasing cumulative effect of around -0.01. Overall, the gain in time due to having left the labour market seems to shape health-related behaviours positively, also thanks to the contribution of the physical activity, potentially coupled to more potential effort put to follow a healthier diet. On the contrary, the extreme alcohol consumption has a significant increase. It is likely that individuals either spend more time in socialising (e.g. having drinks with friends) or tend to be more addicted due to the reduction in daily activities. Other works argue that the regular consumption of alcohol does not necessary imply a negative effect on health (Ziebarth and Grabka, 2009; Eibich, 2015; Celidoni and Rebba, 2017). However, at this stage, we are accounting for the impact of retirement on the worsen behaviours (e.g. looking at a proxy of alcohol addiction or the probability of being obese) perhaps limiting to capture less extreme lifestyle changes. Moreover, as shown by Celidoni and Rebba (2017) heterogeneous retirement effect in shaping health-related behaviours may be observed.

The results of the TE model estimations are reported in Table 1.8, following the reporting scheme of the *DE* models in Table 1.7. The difference with respect to the DE is the way in which lifestyles enter in the regression. The results are qualitative equal. The time spent into retirement is associated with an increase in the probability of being depressed, and in a decrease of the cognitive index score. Moving to the perceived health, the retired individuals have a higher probability of having good health that nevertheless decreases with the time spent into retirement. Thus, working shows a protective role for individual health. The interesting element (already emerged in DE models) that individuals undergo through a transition period in which they perceive themselves as being in higher general health when retired is confirmed (also corroborating several works cited in Section 1.2). Coherent with other works, the reduction of daily activities accelerates the cognitive decline (Celidoni, Dal Bianco, and Weber, 2017; Mazzonna and Peracchi, 2017). The time spent into retirement also worsens the determinants of depressions such as lack of purpose or meaning in life. However, we do not find any significant status effect as in Barnay and Defebvre, 2018; Belloni, Meschi, and Pasini, 2016. Other works also show a detrimental negative effect on more objective proxies of physical health (Bertoni, Maggi, and Weber, 2018; Mazzonna and Peracchi, 2017).

Table 1.8 – Estimation Results: TE Outcome Model

	SAH		Depression		Cognitive	
Retired	0.0484	0.1448***	-0.0420*	-0.0136	0.0176***	0.0031
	(0.031)	(0.040)	(0.025)	(0.030)	(0.005)	(0.007)
TimeR	-0.0295***	-0.0131***	0.0061***	0.0101***	0.0000	-0.0023***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.000)	(0.001)
Resid No Activities	-0.1784***	-0.1945***	0.1075***	0.1025***	-0.0140***	-0.0115***
	(0.027)	(0.028)	(0.024)	(0.024)	(0.004)	(0.004)
Resid BMI	-0.0365*	-0.0427**	-0.0304**	-0.0319**	0.0008	0.0017
	(0.021)	(0.021)	(0.015)	(0.015)	(0.003)	(0.003)
Resid Smoker	-0.0243	-0.0372	-0.0231	-0.0277	0.0041	0.0062
	(0.058)	(0.057)	(0.043)	(0.043)	(0.009)	(0.009)
Resid Ex-Smoker	-0.0775	-0.0930	0.0157	0.0102	0.0034	0.0059
	(0.061)	(0.060)	(0.045)	(0.046)	(0.010)	(0.010)
Resid Abuse Alcohol	0.0096	0.0171	-0.0072	-0.0049	-0.0004	-0.0016
	(0.017)	(0.018)	(0.014)	(0.014)	(0.003)	(0.003)
Age		0.0792		0.0427		-0.0302**
		(0.082)		(0.062)		(0.014)
Log-Income		0.0005		-0.0026		0.0007*
		(0.002)		(0.002)		(0.000)
Married		0.0404*		-0.0670***		0.0060
		(0.022)		(0.023)		(0.004)
Live Alone		0.0267*		0.0168		0.0033
		(0.016)		(0.016)		(0.003)
Children		-0.0044		0.0041		0.0001
		(0.007)		(0.006)		(0.001)
Grandchildren		0.0008		0.0006		0.0002
		(0.002)		(0.002)		(0.000)
Interview Date	No	Yes	No	Yes	No	Yes
SH J p-value	0.0000	0.3943	0.0998	0.3151	0.0002	0.5244
Individuals	11167	11167	11167	11167	11167	11167
Obs.	30048	30048	30048	30048	30048	30048

Notes: Interview date includes month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The effects on individuals health of smoking habits and alcohol abuse are never significant. Not being engaged in physical activities is negatively associated with the probability of having good health, increases the probability of being depressed, and reduces the cognitive index score. Likewise, BMI reduces the probability of reporting good health, and surprisingly is associated with a reduction of the probability of being depressed.

However, as stressed by the extant literature, the retirement effect is far to be constant across individuals as well as the effect on lifestyles, giving scope for the investigation of the heterogeneity in the effects that we present in the followings sections. The Appendix reports in Table A2 the first stage results for the TE and DE models. The instruments are significant and well predict both *Retired* and *TimeR*, as confirmed by the F-test for excluded instrument displayed at the bottom panel. Moreover, the p-values of the SH test reported in the bottom panel of the Table 1.8 confirm that the models are not affected by overidentification issues.

Despite the small difference, the coefficients associated to Retired and TimeR are not the same. As expected, this difference is due to the fact that the DE model does not capture the mediation effect of retirement that runs through lifestyles. In Table 1.9, we present the IEs, each column reporting on a health outcome estimation.

Table 1.9 – Indirect Effects: Main and heterogeneity effects specifications

SAH		Depression		Cognitive	
IE Retired	IE TimeR	IE Retired	IE TimeR	IE Retired	IE TimeR
0.0084***	-0.0004**	-0.0051***	0.0004**	0.0003	-0.0000
(0.0018)	(0.0002)	(0.0014)	(0.0001)	(0.0003)	(0.0000)

Notes: The IE are obtained respectively by subtracting $\beta_{TE,Retired,k} - \beta_{DE,Retired,k}$ and $\beta_{TE,TimeR,k} - \beta_{DE,TimeR,k}$ for each outcome. TE refers to estimation results displayed in Table 1.8. DE refers to estimation results displayed in Table 1.7. Standard errors in parenthesis. The significance level of each IE is tested by using a cross-model hypothesis test based on artificial nesting to calculate the covariance of the estimated coefficients. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

At first, we find that the mediating effects of retirement always have the same sign of the direct effects, namely they enlarge the either positive or negative direct effect. No significant IEs are found for cognitive health. Contrarily, the changes in health-related behaviour due to retirement induce a reduction in the probability of being depressed on those who retire, along with a long-term cumulative increase for each year spent into retirement. Likewise, the probability of having good health is higher for retirees, but this protective effect progressively dissipates in time. In other words, the retirement shapes the lifestyle in a way that it also induces additional individual health changes.

1.5.2 Robustness Analysis

Now, we test and show the robustness of our models with several checks. For the sake of brevity, we only present the results for the TE model estimations. Table A3, and A4 reported in Appendix show that our models are robust to different sample and specifications. Firstly, by exploiting the balanced longitudinal data we replicate the estimation on the balanced sample of 2,874 individuals (11,496 observation). The models report slightly different point estimations with respect to the estimations with the unbalanced panel. Therefore, dropping the individuals who are observed for less that 4 waves - that may induce underestimation (overestimation) of negative (positive) effects - shows that our results are stable for each outcome used. We also let the age term interact with the country dummies to check for any possible country-specific relation between health and age, as discussed in Section 1.3.2 (e.g. differences in healthcare provision). The estimation results are almost equal to the main specification. As the last test, we control for the household wealth instead of the logarithm of the household disposable income, as suggested in Alessie, Lusardi, and Aldershof (1997), Allin, Masseria, and Mossialos (2009), and Van Ourti (2003). They argue that using individuals' current income might be a less reliable and significant measure of socio-economic status when dealing with older individuals. However, as reported in Table A3, the models are stable. The coefficients associated to the wealth quartile (the reference is the fourth) are coherent in sign, but generally not significant.

Next, the model is tested to different dependent variables. The SAH variable is likely to be affected by measurement and misclassification errors that may lead to estimation biased (e.g. justification bias). To this purpose the model for SAH is re-estimated by using an health index that corrects the self-reported variable with more objective indicators, and a objective indicator of grip strength.[19] Likewise, it can be argued that using the depression dummy might be biased as it is based on the self-reported number of depression symptoms. For this reason, we test the mental health model by using as dependent variable the Euro-D scale, referring in this way to the number of symptoms associated with depression. Finally, we use the single indicators used to compute the

[19] See Subsection 1.4.3 for the details about the construction of the health index and for the indicator of low grip strength.

index of cognitive abilities, which we have presented in the data section, to test the contribution to the index. As displayed by the Table A4, Fluency and Numeracy equations do not display any significant effects of retirement. For the Memory test, we find negative strong significant effect for the time spent into retirement and a positive effect associated to being retired. The positive effect might be related to the reduction of work information, and feelings of overloading. With regard to mental health, findings show that the time spent into retirement causes an increase in the number of depression symptoms. The health index equation confirms the positive effect associated to being retired and the negative associated to the time spent into retirement on the probability of having good health. Likewise, the indicator of low grip strength confirm the pattern of SAH, also coherent with Bertoni, Maggi, and Weber (2018). Overall, the pattern of our results is robust across different health outcomes.

1.5.3 Heterogeneity Analysis

Our findings might be driven by some specific subgroup of individuals, and are not generally expected to be constant as extensively shown by mixed results of the previous literature. We investigate their heterogeneity among different set of instruments and among several sub-samples.[20]

Firstly, we look whether the results change when estimating the models by using alternatively the ERA and the SRA set of instruments. As discussed in Celidoni, Dal Bianco, and Weber (2017), when jointly employing the ERA and the SRA instrument together, we are grouping two type of individuals who are potentially quite different, namely those who leave work as soon as possible and those who leave the work as late as possible. Thus, this procedure allows us to distinguish, in our sample, between the retirement effect for those who comply with the ERA and for those who comply with the SRA. Table 1.10 displays the results.

[20]For the sake of brevity, we only report the results of the TE models, omitting the mediating models and the direct model for each estimated specification.

Table 1.10 – Estimation Results: TE Instrument Set Heterogeneity

	SAH		Depression		Cognitive	
	ERA	SRA	ERA	SRA	ERA	SRA
Retired	0.2816	0.1958***	-0.1613	0.0182	-0.0256	0.0003
	(0.172)	(0.063)	(0.142)	(0.051)	(0.032)	(0.010)
TimeR	-0.0018	-0.0261**	0.0014	0.0043	-0.0043*	-0.0013
	(0.012)	(0.013)	(0.011)	(0.010)	(0.002)	(0.002)
Resid No Activities	-0.2492***	-0.2715***	0.1466***	0.0912**	-0.0026	-0.0106
	(0.062)	(0.052)	(0.051)	(0.042)	(0.011)	(0.008)
Resid BMI	-0.0056	-0.0644***	-0.0526**	-0.0341*	-0.0017	0.0016
	(0.033)	(0.022)	(0.026)	(0.018)	(0.006)	(0.004)
Resid Smoker	-0.0878	0.0357	0.0166	-0.0302	0.0141	0.0075
	(0.079)	(0.067)	(0.060)	(0.049)	(0.014)	(0.010)
Resid Ex-Smoker	-0.1070	0.0332	0.0389	0.0165	0.0098	0.0070
	(0.068)	(0.084)	(0.051)	(0.063)	(0.012)	(0.013)
Resid Abuse Alcohol	0.0101	0.0318	-0.0084	0.0008	-0.0023	-0.0022
	(0.018)	(0.021)	(0.014)	(0.018)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	11167	11167	11167	11167	11167	11167
Obs.	30048	30048	30048	30048	30048	30048

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For the SAH equation, the estimated coefficients associated to the retirement indicators are not significant in the ERA model. This may denote the presence of individual characteristics in the ERA sub-groups of the retirees composition (e.g. the individuals who voluntary leave work as soon as possible may be affected by retirement in an opposite way with respect the individuals who unvoluntary exit from the labour market). The SRA retirees show, instead, either a stronger positive status effect or a stronger negative cumulative effect than the effects associated to the main findings. Moving to cognitive health, we find that who retires early is associated with a larger cumulative effect than the main specification. This result confirms the protective role of daily working activities in terms of counteracting against the natural decline of the cognitive abilities (Salthouse, 2006, Rohwedder and Willis, 2010). No activities and BMI remain significant and detrimental in SAH model. Contrarily, no activities looses the statistical significance. No heterogeneity effects of retirement are detected for mental health model determined by the set of the instrument.

Next, we look at the heterogeneity effect across several observable characteristics. We investigate heterogeneity of the effects in gender, education level, and type of occupations. The gender difference outlined is important to underline how the impact of retirement affects the health status under the different behaviours the individuals had in the labour market. The gender-gap implied (and still imply) that the participation in the labour market was larger for men than women. Table 1.11 displays gender heterogeneity estimations for the three outcomes. The probability of having good health is associated with a beneficial status effect while the cumulative effect is negative, alike the main specification. However, women seem to gain more in terms of perceived health, as they report a larger status effect and a smaller cumulative effect than men. This is somehow expected, as the sample considers all countries in which the social norm about labour market participation is quite similar. For instance, Eibich (2015) shows how this difference vanishes in East Germany where the social-political norm consisted of an equal participation to the labour market.

Table 1.11 – Estimation Results: TE Gender Heterogeneity

	SAH		Depression		Cognitive	
	Women	Men	Women	Men	Women	Men
Retired	0.1473***	0.1263**	0.0294	-0.0518	-0.0007	0.0063
	(0.055)	(0.057)	(0.049)	(0.038)	(0.009)	(0.010)
TimeR	-0.0103*	-0.0156**	0.0067	0.0119***	-0.0030***	-0.0015
	(0.006)	(0.007)	(0.005)	(0.004)	(0.001)	(0.001)
Resid No Activities	-0.1555***	-0.2246***	0.0906***	0.1171***	-0.0054	-0.0190***
	(0.038)	(0.043)	(0.035)	(0.034)	(0.006)	(0.007)
Resid BMI	-0.0464	-0.0392	-0.0602**	-0.0095	0.0056	-0.0019
	(0.030)	(0.027)	(0.028)	(0.018)	(0.005)	(0.004)
Resid Smoker	0.0525	-0.1335	-0.0221	-0.0160	0.0015	0.0097
	(0.080)	(0.087)	(0.057)	(0.062)	(0.014)	(0.014)
Resid Ex-Smoker	0.0762	-0.2400***	0.0102	0.0277	0.0061	0.0052
	(0.086)	(0.092)	(0.061)	(0.066)	(0.014)	(0.015)
Resid Abuse Alcohol	0.0284	0.0088	0.0044	-0.0096	-0.0064	0.0005
	(0.035)	(0.020)	(0.036)	(0.015)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.7985	0.0178	0.0465	0.5234	0.8182	0.4122
Individuals	5118	6049	5118	6049	5118	6049
Obs.	13733	16315	13733	16315	13733	16315

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Moving to mental health, we find that the time-spent into retirement is negatively associated to the probability of being depressed for men. The difference may be related to the lack of the social role, an issue that may arise with the progressive lack of daily activities. With respect to cognitive health, we find a significant point estimate only for women for the time spent into retirement. The non-significance effect for men is somehow unexpected, although a first explanation could be linked to the heterogeneity in retirement rules compliance and the type of job. The impact of not being engaged in physical activity is stronger for men across all the outcomes; being an ex-smoker decreases the probability of having good health only for men (with respect to those who never smoke), and the positive effect of being obese on the probability of being depressed is still confirmed for women, which is totally counter-intuitive and unexpected.

Another central role on our main findings is surely played by the past occupation. The health changes induced by retirement may differ depending on the degree of specialisation in skills needed for the job, which mainly differ in terms of physical or mental burden. Therefore, the lack of daily activities might affect in different way and size individuals who were exposed to different occupational roles. The investigation on job heterogeneity is presented in Tables 1.12, 1.13, and 1.14 and in the Appendix in Tables A6, A7, A8. In particular, it is explored dividing the sample in physical and psychosocial demanding occupations, and in the Appendix with the more general white and blue collars classification.[21] Our preferred focus is on individuals who were in physical and psychosocial demanding occupation (PDJ and PSDJ), by making this distinction on the information provided by the Job Exposure Matrix (JEM) by Kroll (2011).[22] The JEM lets us link the Isco-88 classification (2, 3, and 4 digits) to the two job exposure indexes that comprise respectively the physical and the psychosocial burden of each occupation. Those indexes range from 1 to 10, where the higher the value, the higher is the specific burden in the occupation. We classify among PDJ (I) if the Physical Job Index is higher than 7, and PSDJ (I) if the Psychosocial Job Index is higher than 7. Similarly, a less restrictive version of the classifications is considered, namely PDJ (II) and PSDJ (II), where the threshold on the index is set greater than 5. The sample is restricted to those individuals who provided the Isco-88 code at the first wave, were employed or retired and did change employment status during the waves, or retire during the waves.

[21] We follow ISCO-08 1 digit classification for white/blue collar definitions. Physical and psychosocial demanding jobs are defined on the basis of the Job Exposure Matrix by Kroll, 2011.

[22] Also Mazzonna and Peracchi (2017) employ the JEM to investigate heterogeneity in physical and less physical occupations.

Table 1.12 – Estimation Results: TE SAH Job Heterogeneity(I)

	SAH			
	PDJ (I) > 7	PDJ (II) > 5	PSDJ (I) > 7	PSDJ (II) > 5
Retired	0.1355*	0.0773	0.1081	0.0926
	(0.071)	(0.068)	(0.093)	(0.057)
TimeR	-0.0107	-0.0058	-0.0115	-0.0115**
	(0.008)	(0.007)	(0.010)	(0.006)
Resid No Activities	-0.2053***	-0.1510***	-0.1671***	-0.1464***
	(0.038)	(0.034)	(0.042)	(0.032)
Resid BMI	-0.0679**	-0.0664**	-0.0698**	-0.0379
	(0.028)	(0.028)	(0.031)	(0.025)
Resid Smoker	-0.1375	-0.0954	-0.0881	-0.0589
	(0.100)	(0.090)	(0.112)	(0.082)
Resid Ex-Smoker	-0.2236**	-0.1662*	-0.1619	-0.1273
	(0.108)	(0.098)	(0.123)	(0.089)
Resid Abuse Alcohol	0.0098	0.0225	0.0117	0.0315
	(0.025)	(0.025)	(0.028)	(0.022)
Controls	Yes	Yes	Yes	Yes
SH J p-value	0.1406	0.1138	0.2361	0.1115
Individuals	6524	6997	5760	8320
Obs.	16381	17784	14294	21669

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. PDJ and PSDJ (I) refer to individuals who have physical and psychosocial job indexes higher than 7. PDJ and PSDJ (II) refer to individuals who have physical and psychosocial job indexes higher than 5. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 1.12, our findings show that the probability of reporting good health is increased by the status of being retired only for those individuals who worked under a high physical burden. People who were exposed to many fatigues during the job careers are likely to improve their perceived health by the losing of the daily activities. They are also more affected by not being engaged in physical activities, which is the counterpart of the fact they were used to high level of "physical" job activities. In other words, stopping the occupational fatigues is beneficial to counteract the physical deterioration although it is important not to completely give up the physical exercise. Moving to the cumulative effect of retirement, it seems that is significant and detrimental for those people who worked in psychosocial demanding jobs, which again confirm previous works that support the theory of the protective role of working. Being obese is not found significant only for PSDJ(II), while being an ex-smoker is found detrimental for those individuals who had a physical burden in their job.

Table 1.13 – Estimation Results: TE Depression Job Heterogeneity(I)

	Depression			
	PDJ (I) > 7	PDJ (II) > 5	PSDJ (I) > 7	PSDJ (II) > 5
Retired	-0.0105	-0.0052	0.0119	-0.0515
	(0.055)	(0.054)	(0.065)	(0.042)
TimeR	0.0157**	0.0121**	0.0165**	0.0126***
	(0.006)	(0.006)	(0.007)	(0.004)
Resid No Activities	0.1250***	0.1043***	0.1012***	0.1140***
	(0.032)	(0.029)	(0.034)	(0.025)
Resid BMI	-0.0344	-0.0553***	-0.0476**	-0.0466**
	(0.022)	(0.021)	(0.024)	(0.019)
Resid Smoker	0.0561	-0.0060	0.0357	0.0537
	(0.058)	(0.062)	(0.063)	(0.051)
Resid Ex-Smoker	0.0939	0.0248	0.0659	0.0955*
	(0.063)	(0.066)	(0.067)	(0.054)
Resid Abuse Alcohol	-0.0229	0.0033	-0.0135	-0.0062
	(0.019)	(0.019)	(0.022)	(0.017)
Controls	Yes	Yes	Yes	Yes
SH J p-value	0.5324	0.5466	0.6047	0.4783
Individuals	6524	6997	5760	8320
Obs.	16381	17784	14294	21669

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. PDJ and PSDJ (I) refer to individuals who have physical and psychosocial job indexes higher than 7. PDJ and PSDJ (II) refer to individuals who have physical and psychosocial job indexes higher than 5. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

When looking to depression model estimations, presented in Table 1.13, no significant status effect is detected across the different specifications. Contrarily, the cumulative effect is found to increase the probability of being retired across any type of occupational burden. However, the effects are stronger for those retirees who worked in job with higher burden either physical or psychosocial. The reasons that lead to same effect are likely to be different between the two groups. However, we underline that for both of them working might have played a central role in their lives, and it might be that these individuals suffer from the lack of the daily activities and this leads them to experience loneliness and lack of meaning in their life. Not practising physical activities always increases the probability of being depressed. Finally, the Table 1.14 presents the results for the cognitive abilities. As in the main model, the cognitive index score is negatively affected by the cumulative effect of retirement. As expected, the most affected subgroup is the PSDJ(I), that is those individuals who had the higher mental burden in their occupation. However, the people in physically demanding occupations show a strong effect as well. This might be related to the fact that in their careers they tended to exercise less frequently their cognitive abilities compared to those who worked in psychosocial demanding occupations.

Table 1.14 – Estimation Results: TE Cognitive Job Heterogeneity(I)

	Cognitive			
	PDJ (I) > 7	PDJ (II) > 5	PSDJ (I) > 7	PSDJ (II) > 5
Retired	-0.0001	0.0085	0.0048	0.0100
	(0.012)	(0.011)	(0.015)	(0.009)
TimeR	-0.0040***	-0.0035***	-0.0046***	-0.0023**
	(0.001)	(0.001)	(0.002)	(0.001)
Resid No Activities	-0.0075	-0.0102*	-0.0087	-0.0108**
	(0.006)	(0.006)	(0.007)	(0.005)
Resid BMI	0.0014	0.0000	-0.0049	-0.0020
	(0.004)	(0.004)	(0.004)	(0.004)
Resid Smoker	0.0014	0.0046	0.0030	0.0107
	(0.016)	(0.015)	(0.017)	(0.013)
Resid Ex-Smoker	0.0037	0.0080	0.0070	0.0112
	(0.017)	(0.016)	(0.019)	(0.014)
Resid Abuse Alcohol	0.0019	0.0049	0.0071	0.0037
	(0.004)	(0.004)	(0.005)	(0.004)
Controls	Yes	Yes	Yes	Yes
SH J p-value	0.6437	0.7212	0.7923	0.6319
Individuals	6524	6997	5760	8320
Obs.	16381	17784	14294	21669

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. PDJ and PSDJ (I) refer to individuals who have physical and psychosocial job indexes higher than 7. PDJ and PSDJ (II) refer to individuals who have physical and psychosocial job indexes higher than 5. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Appendix, we present in the Tables A6, A7, and A8 the heterogeneity of the retirement effect on the health status based on the standard white/blue collar classification, decomposing each category for high and low skilled workers. With regards to the white collar group, the status of retired confirms the main pattern. However, the low-skilled white collar workers seem to experience a larger increase in the probability of reporting good health, while the high-skilled subgroup reports a higher detrimental cumulative effect. We do not find any significant effect for the blue collar group. Moving to mental health, the high skilled subgroup reports a positive status effect, which can reflect the fact that during their careers thet were exposed to a higher occupational pressure than the others workers. For cognitive health instead, we find only some significant cumulative effect for the blue collar. We also present in Table A5 the education heterogeneity. Individuals with higher education report the same pattern of the main estimation for the probability of having good health, and the probability of being depressed. This findings appear coherent between each other, although somehow the classifications based on occupational burden seem to go in the opposite direction. This issue may be related to compliance with the retirement rules among the white/blue collar.

To summarise, the status of being retired has a beneficial effect mainly on the probability of reporting good health for statutory retirees, more for women than men, for those worked that had a higher physical burden. The SAH is progressively negatively affected during the time spent into retirement for statutory retirees, more for men than women, for those individuals employed in psychosocial demanding occupation. With regards to mental health, we always find a significant detrimental cumulative effect, that is the depression episodes related to the lack of daily activities and the contact with peers progressively increase. This effect is detected especially for men and the individuals with both the highest physical and psychosocial occupational burden. Likewise, the cumulative effect of retirement for the ERA retirees has proven to have a negative effect on cognitive health. This has been observed for women and regardless of the kind of past occupation. In this scenario, it is interesting though to underline that the higher is the psychosocial burden registered, the higher is the effect.

As extensively stressed in the previous sections, these effects are the total effects of retirement on the health status. Thus, to fully investigate the mechanism through which the retirement operates on health, we suggest to consider the lifestyles as a mediator in the causal chain. In Table 1.15, we present the indirect effects for the three outcomes, each column reporting the status effect side-by-side the cumulative effect. The first panel reports the main specification effects for the ease of comparing. For each total effect presented previously, there is an indirect part that runs through the lifestyles channel, that is the health variation due to the lifestyle change caused by the retirement. The only specification that does not report any significant indirect effect for the three outcomes is the ERA used as single instrument set. The status of being retired through shaping the health-related behaviours induces a positive effect on the probability of having good health for individuals who retire with the SRA rules, both women and men, for those who worked both in the physically demanding occupations and in the psychosocial demanding jobs. When turning to the cumulative effect, the indirect effect is significant for the women subgroup and for those that suffer a more physical burden. For mental health, instead, the status indirect effect is always significant and positively associated with the reduction of the probability of being depressed. The cumulative indirect effect is always significant except for men and PSDJ(II). Overall, adjusting the lifestyle seems particularly relevant for the general and mental health of SRA retirees, individuals that were employed in physically demanding jobs, and men. With regards to cognitive health, we only find significant effects for the SRA used as single group specification. However, this result could be somewhat related to the type of lifestyle we are observing. It would need further investigation on social-related lifestyle such as time spent into reading or keep participating to cultural activities.

Table 1.15 – Indirect Effects: Heterogeneity in the effects I

SAH		Depression		Cognitive	
IE Retired	IE TimeR	IE Retired	IE TimeR	IE Retired	IE TimeR
Main Specification					
0.0084^{***}	-0.0004^{**}	-0.0051^{***}	0.0004^{**}	0.0003	-0.0000
(0.0018)	(0.0002)	(0.0014)	(0.0001)	(0.0003)	(0.0000)
ERA as single instrument					
0.0070	-0.0003	-0.0066	0.0003	0.0005	0.0000
(0.0072)	(0.0005)	(0.0041)	(0.0003)	(0.0007)	(0.0001)
SRA as single instrument					
0.0114^{***}	-0.0011	-0.0070^{***}	0.0008^{*}	0.0007^{*}	-0.0001^{*}
(0.0040)	(0.0008)	(0.0023)	(0.0004)	(0.0004)	(0.0001)
Female					
0.0041^{**}	-0.0006^{**}	-0.0038^{**}	0.0007^{**}	0.0001	9.83e-06
(0.0017)	(0.0003)	(0.0015)	(0.0003)	(0.0003)	(0.0000)
Male					
0.0152^{***}	0.0000	-0.0073^{***}	0.0001	0.0008	-20.01e-06
(0.0037)	(0.0003)	(0.0026)	(0.0002)	(0.0005)	(0.0000)
Physically Demanding Jobs I					
0.0070^{***}	-0.0003	-0.0074^{***}	0.0004^{**}	0.0003	-0.0000
(0.0025)	(0.0002)	(0.0018)	(0.0002)	(0.0004)	(0.0000)
Physically Demanding Jobs II					
0.0107^{***}	-0.0005^{**}	-0.0104^{***}	0.0004^{***}	0.00037	-0.0000
(0.0031)	(0.0002)	(0.0022)	(0.0001)	(0.0004)	(0.0000)
Psycho-social Demanding Jobs I					
0.0047^{*}	-0.0003	-0.0064^{***}	0.0002	-0.0000	-0.0000
(0.0024)	(0.0002)	(0.0017)	(0.0001)	(0.0004)	(0.0000)
Psycho-social Demanding Jobs II					
0.0033	-0.0001	-0.0066^{***}	0.0001	0.000254	-0.0001
(0.0025)	(0.0002)	(0.0017)	(0.0002)	(0.0004)	(0.0000)

Notes: The IE are obtained respectively by subtracting $\beta_{TE,Retired,k} - \beta_{DE,Retired,k}$ and $\beta_{TE,TimeR,k} - \beta_{DE,TimeR,k}$ for each outcome. TE refers to the total effect model. DE refers to the direct effect model. Standard errors in parenthesis. The significance level of each IE is tested by using a cross-model hypothesis test based on artificial nesting to calculate the covariance of the estimated coefficients. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.6 Discussion and conclusion

Assessing the impact of retirement on general, mental, and cognitive health is relevant to health policymakers who aim at improving the financial stability of healthcare systems while preserving both the welfare and the well-being of older workers and retirees. Health changes after retirement vary across health domains, depend on socio-economic status, type of job (physically versus psychosocial demanding occupations), and on the changes in lifestyle that are activated when exiting the labour market.

We use the longitudinal data of SHARE to measure the total effect of retirement on individual health status by focusing on the causal mechanism through which retirement operates on individuals' health. We employ an FE-IV estimator to estimate the effects of being retired and of time spent into retirement, within a mediation analysis framework where the total effect nests the indirect effect, running through the lifestyle channel.

Overall, the long-term effect of retirement is found to be detrimental for general, mental, and cognitive health. The status of being retired is associated with a positive effect on the probability of having good health, which means that a temporary protective role is played on the perceived health. The status of being retired is also associated to a positive effect on the probability of being engaged in physical activity, along with a decreasing rate during the time spent into retirement; likewise, an increase in the probability of abusing of alcohol which decreases during the time, and a beneficial effect on BMI level. Heterogeneity effects between the ERA and the SRA retirees are found when considering specific set of instruments: the general health is more endangered after statutory retirement, while the cognitive health seems more affected for early retirees. We also find that while for women the negative effect of retirement on cognitive health is larger than for men, the probability to be depressed increases more for men than women. Heterogeneity analysis also seems to stress the importance of the type of the occupational burden they were exposed to. The individuals who were employed in physical demanding occupation report a larger positive status effect for general health, while those who were employed in psychosocial demanding jobs have a larger negative effect especially on cognitive health. The mediation analysis allows us to unpack the causal chain between health and retirement, showing that some indirect effects exist, especially for general and mental health. In other words, the total effect of retirement operates on the individuals health through shaping the health-related behaviours with both status and long-term indirect effects. The role of lifestyles seems particularly relevant for the general and mental health of men, the SRA retirees, and those who retired from physically demanding occupations.

When planning policies that may affect the older workers health, it is thus necessary to take into account the lifestyle element which reshapes the individuals experience. In particular, the individuals' heterogeneity is important, because the lifestyle role may have more influence on the changes in health status for some individuals than others, among others depending on their occupation. Therefore, policymakers who aim at preserving the individuals well-being should be able to incentive, for instance, more flexible retirement schemes. In this scenario, policymakers might improve the overall system by facilitating the transition into retirement in terms of health-related behaviours. In other words, older workers may need to adjust their lifestyle without drastically leave the labour market to have the time to compensate the shocks produced by the retirement.

Chapter 2

Well-being in old age: what's the retirement role?

Abstract

This chapter investigates the role of retirement on individual well-being. By using the Survey of Health, Ageing and Retirement in Europe longitudinal data, we built on a model to assess the retirement effect on two measure of subjective well-being, and to test leads and lags effects on individuals' adjustment process to retirement. The identification strategy relies on the exogenous variation of cross-country pension eligibility ages. Potential reverse causality and unobserved heterogeneity are controlled by means of FE-IV estimator. Retirement is found to improve measures of individual welfare. Anticipation and adaptation effects are detected depending on the subjective well-being measure adopted. Opposite effects are found when studying geographical heterogeneity between people living in northern or southern countries, which are also confirmed by the differences in social security systems. This reflects social-cultural norms and habits heterogeneity, along with the role played by the differences in welfare systems.
JEL: I31, J26, C36

Keywords: Subjective Well-being; Retirement; Adaptation; Instrumental Variable

2.1 Introduction

An important issue that has become very high on the policy agenda across Europe is the rising share of the older population and its consequences. In particular, the European old dependency ratio is constantly increasing (i.e. in 2050 it will be 50 %. Eurostat, July 2019). The demographic-cut translates into a high financial burden on both pension and healthcare systems, given that also life expectancy is increasing. Policymakers have been progressively extending statutory ages in the attempt to make more sustainable financial choices to preserve social security systems.[1] However, postponing the retirement age might turn into a worsening of the individuals' quality of life. When retiring, individuals experience somewhat an increase in their vulnerability. They are exposed to detrimental income shrinks, which may induce consumption changes. On the contrary, they may enjoy their leisure time depending on their preferences, for instance investing more in healthcare and healthy behaviours to compensate the natural ageing process. The level of life satisfaction, or more generally of the quality of life, is also found to be positively correlated with physical and mental health (Steptoe, Deaton, and Stone, 2015). By definition, individual well-being comprises several domains, making unclear the effect of exiting the labour market on the individual welfare. This gives scope to further investigate the relationship between retirement and well-being. Furthermore, the achievement of individual well-being is becoming a primary challenge of developed countries since the global financial crisis of 2008, although most economists until recently were very skeptical about happiness economics (Van Praag, Ferrer-i-Carbonell, et al., 2011). To measure and monitor subjective well-being is an economic and social need that policymakers have been broadly started prioritising. Specific subjective well-being (henceforth SWB) indicators have started to be included as country-specific public policy priorities as well as global goals to be reached. Institutions such as OECD are already oriented in providing international proxy measures of subjective well-being to go beyond GDP, which is no longer recognised as a macro-economic statistic able to give detailed pictures of living conditions that people experience (OECD, 2017a). Despite criticisms and limitations about how to quantify, measure, and compare individual well-being across

[1] This is particularly important for pay as you go pension systems that are the more unstable. See, among others, Auerbach and R. Lee (2011).

countries, economics recognises that the self-reported measures of well-being can be used to elicit information on individuals' behaviours and tastes (Ferrer-i-Carbonell, 2013). Thus, investigating the links between utility and socio-economic factors is particularly helpful to all policy-makers who seek to include well-being indicators as policy outcomes. Net of all the concerns on using the satisfaction questions, over the last decades the happiness economic literature has covered many issues, in particular, among others, the association with income, unemployment, inflation, health, marital status (Clark and Oswald, 1994, Ferrer-i-Carbonell, 2013, Dolan, Peasgood, and White, 2008). The happiness economics not only studies the contemporaneous correlation with events but also focuses on anticipation effects of future events and the degree of adaptation, that is investigating the time profile of individual well-being around the significant labour market and life events (Clark and Georgellis, 2013). Thus, investigating the retirement effect on SWB is primarily relevant when seeking to ensure a high standard of quality of life to aged individuals. Nevertheless, little has been said about retirement and well-being of old aged individuals.

A first insight from the literature on satisfaction and elderly is surely the association between individual well-being and age. The SWB is found to follow a U-shape pattern in high-income English-speaking countries. Frijters and Beatton (2012) investigate this pattern, finding that the change around 50 years old might be related to socio-economic determinants. Likewise, a two-way relationship between physical health and subjective well-being exists; poor health is correlated with lower levels of SWB, while the high well-being is associated to improvements on physical health impairments. Finally, SWB is positively correlated with longer survival (Steptoe, Deaton, and Stone, 2015). Thus, late-life well-being is characterised by several issues that may induce changes and potential impairments. The existent studies on retirement and SWB show beneficial or no effect on overall life satisfaction, focus on within-country analysis, use cross-sectional data in cross-country analysis (Bonsang and Klein, 2012; A. Gorry, D. Gorry, and Slavov, 2018; Zhu and He, 2015; Horner, 2014) or point towards broader definitions of well-being as in Fonseca, Kapteyn, J. Lee, Zamarro, and Feeney (2014), which consider the probability of fall into poverty or depression. Moreover, little has been said about the adjustment process that an individual experiences when retires (Kesavayuth, Rosenman, Zikos, et al., 2016; Zhu and He, 2015). As an example, adapting to the condition may turn into remaining at the same pre-retirement level of SWB, (i.e. it would be long-term neutrality), or experiencing such an increase that the SWB changes staying structurally higher (i.e. a long positive long-term effect).

Thus, the present work seeks to investigate the retirement effect on subjective well-being by using European longitudinal data. It also devotes special attention to the question of whether the potential effect is anticipated and/or dissipated in time. In other words, individuals might experience an early effect of future retirement on welfare and/or adapt to it depending on their personal experience. The main empirical challenge in this SWB analysis is addressing the endogeneity due to unobservable variables and the possible reverse causality of retirement and the individual utility. For instance, unsatisfactory job conditions may select people into retirement, being job satisfaction one of the happiness domains (Van Praag, Ferrer-i-Carbonell, et al., 2004). Moreover, the satisfaction variables are by definition related to the individuals' perception of their own situations (e.g. people tend to compare themselves to their reference group) and personal traits (e.g. pessimism, fatalism, non-cognitive abilities). The identification strategy relies on exploiting the exogenous variations of cross-country pension eligibility ages to estimate a fixed effect instrumental variable model. Thus, we look at the time profile of SWB, modelling the anticipation and the adaptation within the same individual.

Despite following established techniques to estimate the impact of retirement on individual utility, the present work updates and adds to the previous economic literature on subjective well-being that seeks to understand the role of various life events on subjective utility, including on the strand that investigates adaptation/anticipation effects, and to the economic literature on retirement. Firstly, it exploits five waves of SHARE to assess the causal effect of retirement on SWB, despite other works that solely use the cross-sectional data.[2] Secondly, it investigates the retirement impact on individual well-being using different indicators of overall subjective utility. Third, it adds to the

[2]We use data from DOIs 10.6103/SHARE.w2.700, 10.6103/SHARE.w4.700, 10.6103/SHARE.w5.700 10.6103/SHARE.w6.700, 10.6103/SHARE.w7.700. See Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been primarily funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N.211909, SHARE-LEAP: N.227822, SHARE M4: N.261982). Additional funding from the German Ministry of Education and Research, the U.S. National Institute on Aging (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, R21 AG025169, Y1-AG-4553-01, IAG BSR06-11, OGHA 04-064) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

empirical findings about retirement in terms of anticipation and adaptation effects in Europe.

Retirement is found to positively affect life satisfaction (LS) and the quality of life (CASP indicator). For the CASP model, we find a weak adaptation process that starts before the transition up to three years after. We investigate the presence of heterogeneity effects on gender, education levels, European macro-regions, the difference in social security systems, and the difference in healthcare systems. The aim of the geographical heterogeneity is twofold. On the one hand, it may confirm a constant cross-country effect. On the other hand, it helps testing the robustness of the results in terms of the presence of heterogeneity in reporting bias. The findings suggest that the weak retirement adjustment we find in the main specification might be partly explained by heterogeneity effects. We find a strong adjustment pattern only for individuals living in the Mediterranean area. Moreover, retirement is found to negatively affect people living in the Northern Europe sub-group. This reflects not only geographical heterogeneity that might be rooted on different social-norms, but also a difference due to the social security systems - and in particular the healthcare system - which is thought to play a central role in the SWB of older individuals.
The rest of the chapter is structured as follows. Section 2.2 describes the background of the relevant literature. Section 2.3 describes the data and the main variables of interest. Section 2.4 illustrates the empirical model and the main econometric issues. Section 2.5 displays the results of the econometric analysis, and Section 2.6 concludes.

2.2 Background on Well-Being and Retirement

Economic literature adopts a SWB approach to better understand individuals' preferences and behaviours, in order to evaluate effects on welfare, and to help in designing public policies. Several labour market and life events have been analysed in their relationship with individual utility. As an example, from a macro perspective, inflation, unemployment, and GDP (Di Tella, MacCulloch, and Oswald, 2001, 2003; Easterlin, 1974); from a micro perspective, relative income, preference-based valuation methods, own and others unemployment, productivity, education, health, inequality, and poverty (Ferrer-i-Carbonell, 2005, Kuhn, Kooreman, Soetevent, and Kapteyn, 2011, Card, Mas, Moretti, and Saez, 2012; Luechinger, 2009a; Clark, Diener, Georgellis, and Lucas, 2008, Clark, Knabe, and Rätzel, 2010; Oswald, Proto, and Sgroi, 2015 ; FitzRoy and Nolan, 2018; Oswald and Powdthavee, 2008; Clark, D'Ambrosio, and Ghislandi, 2016).[3] Another central question in SWB studies is whether individuals experience the anticipation and the adaptation in well-being. This branch relies on the psychological original hypothesis of the life classified as hedonic treadmill by Brickman and Campbell (1971). More recent research has shown that individuals differ in their adaptation to events (Diener, Lucas, and Scollon, 2009). Clark, Diener, Georgellis, and Lucas, 2008 have been among the first to analyse the theory of the hedonic treadmill across economics, developing a model for leads and lags in life satisfaction for several life events, as e.g. unemployment, marriage, and layoff.

Retirement has been in-depth analysed under different perspectives, such as consumption, health care utilisation (e.g. Lucifora and Vigani, 2018; Battistin, Brugiavini, Rettore, and Weber, 2009), and health status (e.g. see, among others, Fonseca, Kapteyn, and Zamarro, 2017; Schaap, Wind, Coenen, Proper, and Boot, 2018). Surprisingly, there is little evidence on the retirement role on individuals' well-being in happiness economics. Among these studies, differing results are found in the effect on SWB, depending on the country, the SWB measure, the retirement definition chosen in the analysis, and methods. When leaving the labour market, retirees may experience a drop in the SWB due to fewer opportunities for success, social support, drop in disposable income. Contrarily, individuals may experience a higher quality of life due to the raised leisure time, and the elimination of occupational stress. Although the common belief that retirement is beneficial, it is unclear how each domain of the overall individual well-being (e.g. health, job, social life, marriage, financial, leisure use) is affected by exiting the labour market. Moreover, the transition into retirement is supposed to be a multi-stage process (Fonseca, Kapteyn, J. Lee, Zamarro, and Feeney, 2014; Horner, 2014), and the adjustment mechanism may be characterised by different patterns.

[3] See Ferrer-i-Carbonell (2013) for a complete review of subjective measures at glance, methods, and findings in happiness economics.

One of the first work on retirement and well-being is by Börsch-Supan and Jürges (2006). They use the GSOEP data to compare the effect of early and normal retirement, finding a positive effect for those who opt for an early leaving of the labour market. However, they argue that the difference in happiness between early and normal retirees is mainly due to poor health. Using the same data, Bonsang and Klein (2012) show that the effect of retirement may differ depending on the well-being measure adopted. Their results fit with the prediction of the life cycle model, finding a negligible effect on overall satisfaction, a positive effect on leisure time satisfaction, and a negative effect on income satisfaction. However, involuntary retirement is associated with a negative effect on overall satisfaction, which is potentially motivated by a bigger drop in income satisfaction and a smaller increase in free time. Fonseca, Kapteyn, J. Lee, Zamarro, and Feeney (2014) examine the impact of retirement on the risk of poverty and depression, considering them determinants of financial and subjective well-being. By using three waves of SHARE, they find weak evidence that retirement may be protective against poverty and depression. A cross-sectional study by Horner (2014) investigates the relationship between retirement and subjective well-being in Western countries using SHARE, ELSA, and HRS data. They report a positive effect of retirement on overall life satisfaction and quality of life (i.e. CASP measure) that dissipates in a few years, reflecting long-term neutrality of retirement. The longitudinal nature of HRS data has been exploited also by A. Gorry, D. Gorry, and Slavov (2018) to assess the retirement effect on health and life satisfaction, arguing that occurs within the first 4 years of retirement. Likewise, Zhu and He (2015) provide evidence of a positive effect of retirement on women's overall life satisfaction in Australia, by using HILDA longitudinal data. Transition to retirement leads to an immediate increase in life-satisfaction and a decrease in its duration. However, the utility level post-retirement is always found higher than it was the pre-retirement stage.

The transition into retirement may be gradual and unfolds in several years (e.g. Atchley, 1982). Coherently with theoretical expectation, the aforementioned studies seem to indicate that retirement follows an adjustment process. However, as discussed in Clark and Georgellis (2013) and Qari (2014), when estimating a model of life satisfaction for predictable events, anticipation effect should be jointly taken into account. The only study we were able to find that model SWB integrating both anticipation and adaptation of retirement is by Kesavayuth, Rosenman, Zikos, et al. (2016). They investigate anticipation and adaptation of retirement on SWB, by using the BHPS data. They show that retirement increases satisfaction with life, health, and leisure domains of life up to three years before retiring. Post-retirement, individuals show a higher level of health, income, and leisure satisfaction. They detect almost complete adaptation for income satisfaction.

By using SHARE longitudinal data, this work wants to investigate on the effect of retirement on different well-being measures, and on the degree of dissipation of the effect and whether the phenomenon of adaptation may be generalised to European countries or if heterogeneity effects exist.

2.3 Data and Variables

The data are drawn on the Survey of Health, Aging and Retirement in Europe (SHARE). The longitudinal survey is composed by seven waves, which provides an extensive questionnaire about health, socio-economic status, social and family network. The third wave, SHARELIFE, is dedicated to the life history of respondents while the seventh integrates both standard and SHARELIFE questionnaires. However, we drop the third, which differs in informations, also the first, in which the subjective well-being variables are missing.[4] We pick the ten countries that where selected in first wave except for Greece, which is often excluded because of the representativeness that has been previously considered doubtfully (Mazzonna and Peracchi, 2017).[5]

The sample is also restricted to baseline and refreshment individuals between 50 to 75 years old. The definition of retirement is crucial to the definition of the sample. An individual is defined as retired by combining her current job self declaration with the intention to stay definitely out of the labour force.[6] Moreover, we drop from the sample all the individuals who declare to have moved from retirement back to employment, because we define retirement as an absorbing status. Thus,

[4]The period covered is 2006/2007 until 2017.

[5]The countries are Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Spain, Sweden and Switzerland. The Netherlands are missing after the fifth wave because of a change in the interview method.

[6]The intention is modelled by using information on paid work in the four past week and after retirement.

the sample is composed by individuals who enter as employed in the survey, remain employed or change their status into retired. All permanent sick, homemakers, rentiers, and unemployed are dropped.[7] Finally, all records with missing values for the variables used in the analysis are dropped as well. Table 2.1 diplays the sample size by country and gender. The final sample comprises 36,249 observation (12,774 individuals), whose 18,082 women and 18,167 men.

Table 2.1 – Sample Size by Country and Gender

Country	Women	Men	Total
Austria	1,240	1,210	2,450
Germany	2,051	1,857	3,908
Sweden	2,288	2,005	4,293
Netherlands	874	936	1,810
Spain	1,288	1,729	3,017
Italy	1,233	1,474	2,707
France	2,059	1,792	3,851
Denmark	2,718	2,633	5,351
Switzerland	2,108	2,086	4,194
Belgium	2,223	2,445	4,668
Total	18,082	18,167	36,249

Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

2.3.1 Individual Subjective Well-being

The work focuses on measures of SWB, and among the measures that the SHARE includes, we pick two indicators of individual well-being. The first is *life satisfaction* (henceforth LS), which is a typical measure of experienced utility (also hedonic well-being). The second is, instead, a proxy measure for quality of life (QoL) developed by Hyde, Wiggins, Higgs, and Blane (2003) based on the satisfaction on four domains, which are *Control, Autonomy, Pleasure, Self-realization* (also eudamonic well-being, henceforth CASP).[8] In fact, CASP is a more complete indicator of SWB, and McMahan and Estes (2011) suggests that predicts well-being better than the LS, giving reasons to test the empirical model on both measures.

[7] Unemployment may lead to confounding effect being by definition the temporarily exit from the labour market.

[8] See Deci and Ryan (2008) for an extensive focus on the conceptual differences, complementarity, and overlapping of the two measures.

In the questionnaire, respondents are asked to answer to the question "*How satisfied are you with your life?*", which ranges on a Likert scale from 0 (completely dissatisfied) to 10 (completely satisfied), whereas the CASP-12 scale comprises the satisfaction of the four domains on a Likert scale from 12 to 48.[9]

Table 2.2 – Life Satisfaction Distribution by Gender

Life Satisfaction	Women	Men	Total
0	25	14	39
1	10	24	34
2	19	12	31
3	51	46	97
4	111	96	207
5	718	522	1,240
6	814	675	1,489
7	2,692	2,686	5,378
8	6,546	6,790	13,336
9	3,979	4,271	8,250
10	3,117	3,031	6,148
Total	18,082	18,167	36,249

Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

These measures of subjective utility have been broadly used in literature to elicit information on individual perceived losses caused by social exclusion, health deprivation, or more generally material deprivation, with the ultimate goal of better designing appropriate public policies for support.[10] Despite the standard assumption of the absence of heterogeneity in the way people interpret the satisfaction scale, Bertoni (2015) and Clark, Etilé, Postel-Vinay, Senik, and Van der Straeten (2005) have underlined that might be affected by heterogeneity in reporting style, limiting its reliability. For instance, personality traits such as optimism and pessimism may influence the reported level of satisfaction, even though there is no difference in their level.[11]

Table 2.2 and Figures 2.1-2.5 report some statistics on the SWB measures distributions on country, gender, and retirement status. [12] The country-specific distribution of both SWB measure are

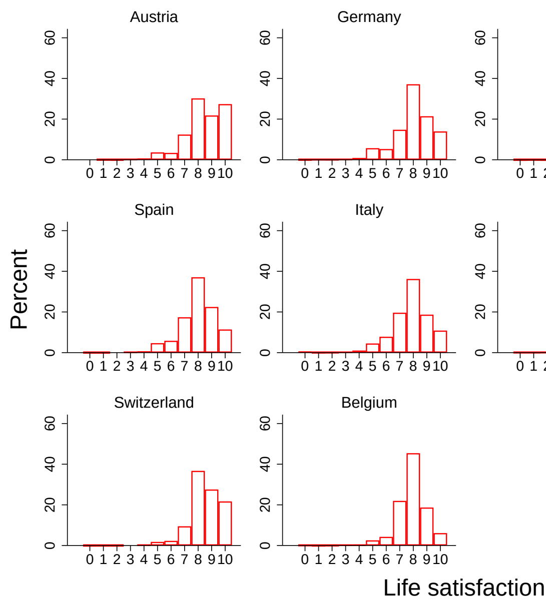
[9]Appendix A1 reports the single items of each domain.

[10]For a broader review of the SWB approach see Ferrer-i-Carbonell, 2013

[11]A procedure to test to what extent the reporting bias might affect empirical analysis might be normalising LS and CASP within country, alike in Horner (2014).

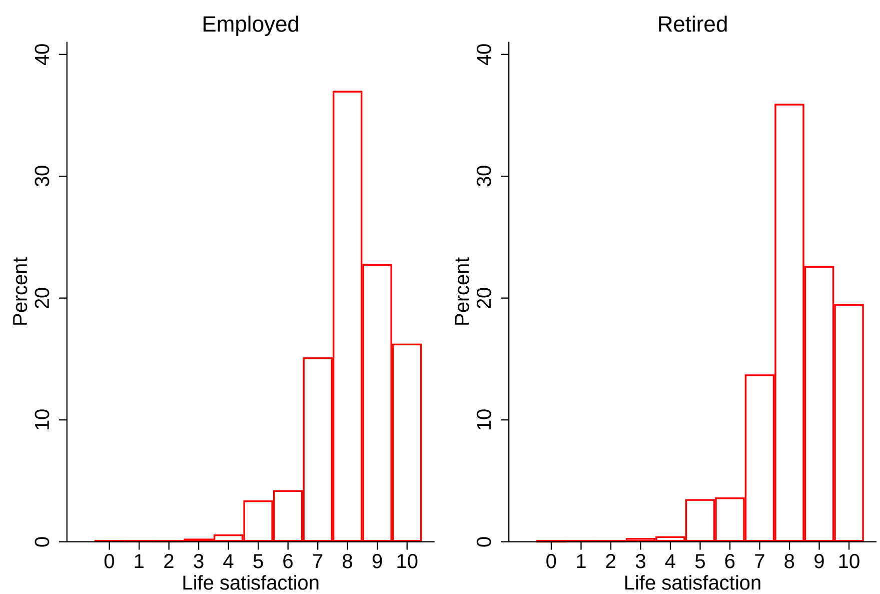
[12]As somewhat expected from the previous literature that studied the relationship between age and SWB, it is possible to notice the under-representation of the low levels of life satisfaction and CASP. From psychological

Figure 2.1 – Life Satisfaction Distribution by Country



Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

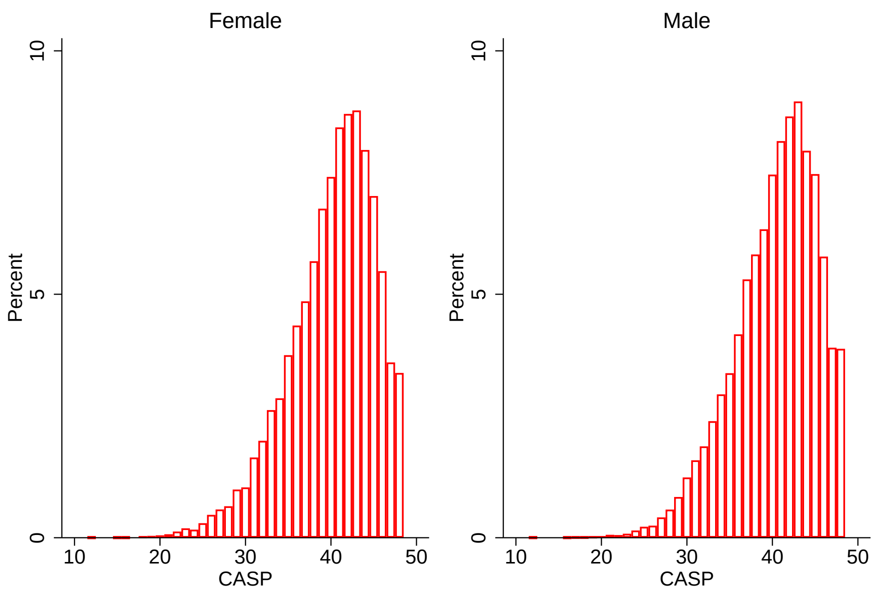
Figure 2.2 – Life Satisfaction Distribution by Retirement Status



Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

studies, we know that the Likert-scales might be potentially biased due to the socalled social desirability tendency (Greenwald and Satow, 1970). In other words, individuals may lie to look better than their real situation. There is some empirical evidence that the life satisfaction and quality of life assessments in late adulthood are not impacted by the social desirability biased (Fastame, Penna, and Hitchcott, 2015; Kozma and Stones, 1988). However, this left-skewed, as typical in Western countries, although the rough graphical analysis suggests that Northern countries are more left-skewed than the others, and men and employed report higher values of both Life Satisfacion and CASP.

Figure 2.3 – CASP Distribution by Gender



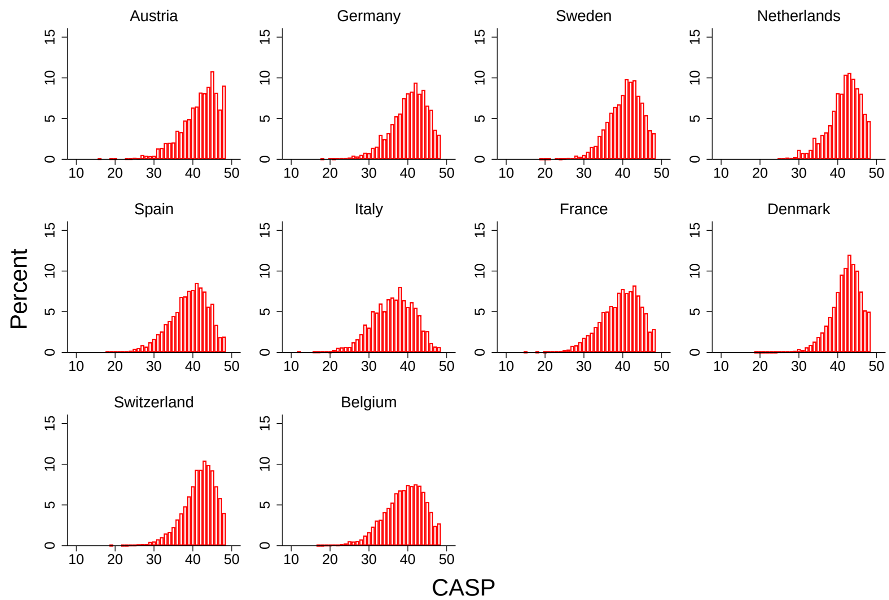
Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

2.3.2 Other control variables

Previous works on SWB broadly examine its determinants, which we use to control for time-varing factors that are likely to be correlated both with SWB and the retirement choice. These controls consist of household and individual characteristics as a set of dummy for marital status, a set of dummy for home ownership, the household size, the number of grandchild, the years of education, age and age squared, an indicator of daily activities limitation as physical health proxy, a wave fixed effect, and the income. Following the previous literature that has extensively examined the association between income and SWB and states the importance of the relative position with respect to a reference group (Ferrer-i-Carbonell, 2005, Kuhn, Kooreman, Soetevent,

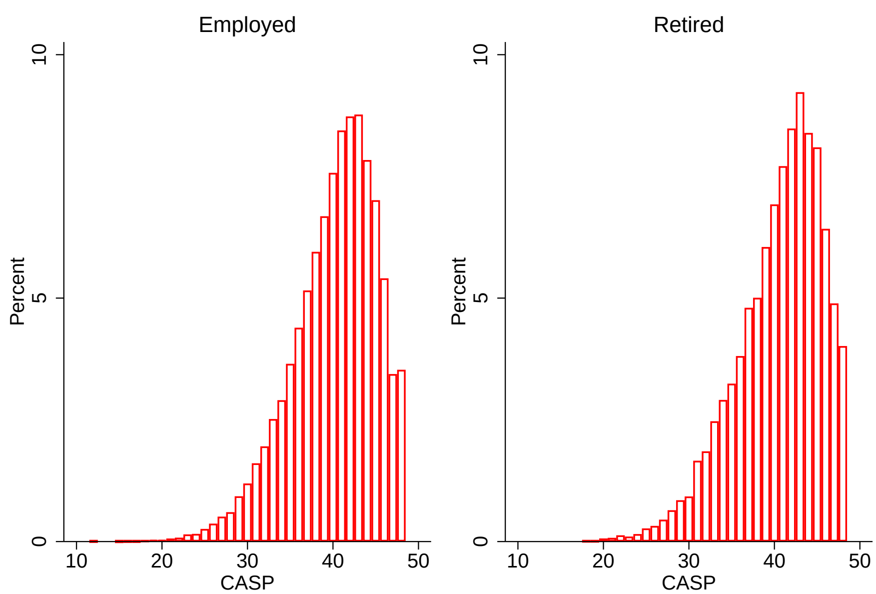
give scope to further test our findings (e.g. re-estimating the models with a different age window).

Figure 2.4 – CASP Distribution by Country



Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

Figure 2.5 – CASP Distribution by Retirement Status



Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

and Kapteyn, 2011, Card, Mas, Moretti, and Saez, 2012, and Clark, Frijters, and Shields, 2008b for an extensive review), we control for both the logarithm of the household income and, after creating a reference group on the basis of age, education, and country, the logarithm household difference to the average income of the reference group. The main summary statistics are reported in Table 2.3. The sample is balanced in gender,the 50% of the participants being female. 75% of individuals is married, average aged around 59 years old with an household size of around 2 individuals. Besides, 78% of the sample is homeowner, on average has 2 children and around 2 grandchildren. Around 13% of the sample is retired, and the average value of adl is 0.45, meaning less than one limitation. On average, the years of education are around 12. The average sample income is around 36.6 thousand of Euros, while the average difference compared to the average reference group is around 4 thousand of Euros, meaning that on average the household are richer than the reference group.

Table 2.3 – Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Life Satisfaction	8.177	1.341	0	10
CASP	40.218	4.971	12	48
Male	0.501	0.5	0	1
Age	59.351	5.317	50	75
Retired	0.134	0.340	0	1
Married	0.752	0.432	0	1
Separated/Divorced	0.13	0.336	0	1
Single	0.076	0.266	0	1
Widowed	0.042	0.2	0	1
Income	36.577	49.005	0	2528796
Income diff. with the ref. group	4.379	37.388	-671.592	1998.534
Homeowner	0.782	0.413	0	1
Tenant	0.17	0.375	0	1
Rentfree	0.02	0.139	0	1
Household size	2.32	0.976	1	10
N. children	2.082	1.24	0	17
N. grandchildren	1.528	2.196	0	23
Physical Health	0.045	0.303	0	6
ERA	61.422	2.704	46	67
SRA	64.438	1.916	60	67
ERA dummy	0.388	0.487	0	1
NRA dummy	0.214	0.41	0	1

Notes: SHARE data. The sample referred to 12,774 individuals aged between 50 and 75, that stayed in she survey from 2 up to 5 waves.

2.4 An Empirical Model of SWB and Retirement

To assess the retirement effect on SWB we define the individual utility as follows:

$$
\begin{aligned}
&S_{it} = s(R_{it}, X_{it}, \delta_c, \tau_t, \eta_i, u_{it}) \\
&with \;\; i = 1, ..., N \;\; and \;\; t = 1, ..., T
\end{aligned}
\tag{2.1}
$$

where R_{it} is the retirement indicator, X_{it} individual characteristics (e.g. income, education, health, family situation, house information, and so forth); δ_c is a country dummy, τ_t a time fixed effect, which are controlling for all the country-specific macro-factors that might correlate with the individual utility (e.g. inflation, unemployment level); η_i is capturing the time-invariant unobserved effect such as genetics and personality traits, and u_{it} is the time-variant idiosyncratic error.

As shown by Ferrer-i-Carbonell and Frijters (2004), assuming cardinal or ordinal utility in operational terms does not change the qualitative results of the analysis. Thus, although our measures of SWB are ordinal variables, the SWB model could be estimated by using a standard Ordinary Least Squares (OLS) model for panel data without loosing general information. Nevertheless, a OLS estimator can only provide biased results, because it is not addressing significant endogeneity issues with both the impact of retirement on SWB and the more general SWB analysis. Given the subjective nature of our measures of life evaluation, it is likely that the observed variable are not sufficiently accounting for any unobserved individual characteristics that may correlate with the covariates. Specifically, personality traits and time preference may play a role in determining the perceived utility and the retirement choice. Besides, subjective variables are affected by measurement errors, also due to country-specific reporting scale. If it is the case, the interested point estimates would be biased. Moreover, isolating the causal effect of retirement on SWB is not effortless, as the the individuals' retirement choice is not random and may arise potential reverse causation. For instance, the dissatisfied individuals (e.g. with job, lifestyle or leisure) might be more likely to retire, or to retire earlier.

To the purpose of addressing the observed and unobserved time-invariant individual heterogeneity, a Fixed-Effect(FE) estimator has been employed. However, the possible reverse causality between retirement and individual utility depends also on time-varying factors, and the FE model is not enough to unsure unbiased estimation. Thus, the problem is tackled by means of a standard FE-IV estimator. We exploit the exogenous variations of pension eligibility ages and Table 2.3 displays the main summary statistics. These instruments have been extensively used both in previous works on SWB and retirement and health economics, specifically because these variations are crucial in disentangling the age to the retirement effect; indeed, the cross country variations compare individuals with the same age that are eligible in some countries but not in others. We assign to each individual the ERA and SRA depending on the country-specific rules, integrating the rules followed in Angelini, Brugiavini, and Weber (2009) with the OECD reports(2007-2015), the MISSOC[13] tables updated at January 2018, and the country-specific social security systems direct information. We build a set of two dummy instrument, where the first indicates the threshold for the early eligibility ages (ERA), and the second the threshold for the normal eligibility ages (SRA) such that:

$$
\begin{aligned}
ERA_{it} &= \mathbb{I}[Age_{it} \geq Age_{it}^{ERA}] \\
SRA_{it} &= \mathbb{I}[Age_{it} \geq Age_{it}^{SRA}]
\end{aligned}
\tag{2.2}
$$

Thus, the following system denotes the baseline specification of an instrumental variables model for individual well-being and retirement, with one endogenous variable:

$$
\begin{aligned}
SWB_{it} &= x_{it}'\beta + \gamma R_{it} + \tau_t + e_{it} \\
R_{it} &= x_{it}'\beta + z_{it}'\delta + \tau_t + u_{it}
\end{aligned}
\tag{2.3}
$$

where the second stage equation of SWB_{it} is the individual utility, whereas R_{it} the first stage equation, namely the is the probability to retire; z_{it} is the set of instruments; x_{it} is the vector of time-varying and time-invariant individual characteristics as age, age squared, marital status, relative household income position, household size, having children and grandchildren, health status; τ is the wave fixed effect; e_{it} and u_{it} idiosyncratic errors.

However, this baseline specification does not allow to investigate whether the retirement effect

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dissipates in time because it does not take into account any lagged effects. As argued by Clark and Georgellis (2013) and Qari (2014), when investigating any predictable and programmable event, it is also necessary controlling for any lead effects to the correct interpretation of the adaptation effects. To this end, the baseline model should be augmented to capture those effects within a determined time-span. The hypothesis of adaptation states that the individual who adapt to the initial effect is neutral to retirement in the long-run.

We extend the specification to test the presence of lead or lagged effect of retirement. Thus, a set of dummies to capture anticipation and adaptation is added to the baseline specification, and the single *retired* dummy is dropped to avoid multicollinearity. Previous works consider mainly 4 years before retirement and 5 years or more afterwards (e.g. Qari, 2014; Kesavayuth, Rosenman, Zikos, et al., 2016). However, as our panel is considerably shorter than the ones used in literature, we consider up to 3 years before and until more than 5 years after retirement.

The set of dummy is define as follows:

$$R_{s,it} = \mathbb{I}[-3 \leq Age_{it} - Age_i^R t < 0)] \tag{2.4}$$

$$R_{s,it} = \mathbb{I}[0 \geq Age_{it} - Age_i^R t < 1)] \tag{2.5}$$

$$R_{s,it} = \mathbb{I}[1 \geq Age_{it} - Age_i^R t \geq 5)] \tag{2.6}$$

$$with \;\; i = 1, ..., N \;\; and \;\; t = 1, ..., T \;\; and \;\; s \in \{-3, ..., 5\} \tag{2.7}$$

where Age^R is the age at retirement, and s denotes the year to/from the retirement. The 2.4 indicates the years leading to retirement, 2.5 reflects the year of the observed transition, and 2.6 indicates the years adjusting to retirement. As an example, if a person will retire in 2 years, $R_{-2,it} = 1$ and all the other dummies would be 0. Likewise, if a person has been retired for more than 5 years, $R_{5,it} = 1$ and all the others 0. The reference category refers to all respondents with 3 or more years of retirement anticipation.

The potential endogeneity of the baseline model is extended to the set of indicators that identify the retirement adjustment. Based on the *ERA* and *SRA*, we construct also a second set of instruments such that:

$$\begin{aligned} ERA_{s,it} &= \mathbb{I}[Age_{it} - Age_{it}^{ERA} = d] \\ NRA_{s,it} &= \mathbb{I}[Age_{it} - Age_{it}^{NRA} = d] \\ &\quad with \;\; d \in \{-3, ..., 5+\} \;\; and \;\; s \in \{-3, ..., 5\} \end{aligned} \tag{2.8}$$

where d denotes the years from/to retirement threshold, s indicates each specific year in the considered transition period. The following system reflects the specification of an instrumental variables estimator for lead and lag effects of retirement on individual well-being, with 5 endogenous variables:

$$\begin{aligned} SWB_{it} &= x'_{it}\beta + R_{s,it} + \tau_t + e_{it} \\ R_{s,it} &= x'_{it}\beta_s + z'_{it}\delta_s + \tau_t + u_{s,it} \\ &\quad with \;\; s \in \{-3, ..., 6\} \end{aligned} \tag{2.9}$$

where $R_{s,it}$ is the vector of auxiliary equations, and SWB_{it} is the second stage that produces unbiased estimation of the lead and lag effects. One would expect no adaptation if all the coefficient of $R_{s,it}$ with $s \in \{2..., 5\}$ maintain the same sign and magnitude of R_{it}, namely γ in 2.3. Contrarily, adaptation would be denoted by the same sign of the betas associated to decreasing magnitude. Complete adaptation means to find non-significant coefficient of lag indicators. Anticipation would be, instead, significant effects before the transition, in $R_{s,it}$ with $s \in \{-3..., -1\}$.

2.5 Results

2.5.1 Main Results

Table 2.4 displays the main results, each variable-specific column reporting both *Baseline* and *Leads and Lags* specifications estimated employing FE and FE-IV estimators.

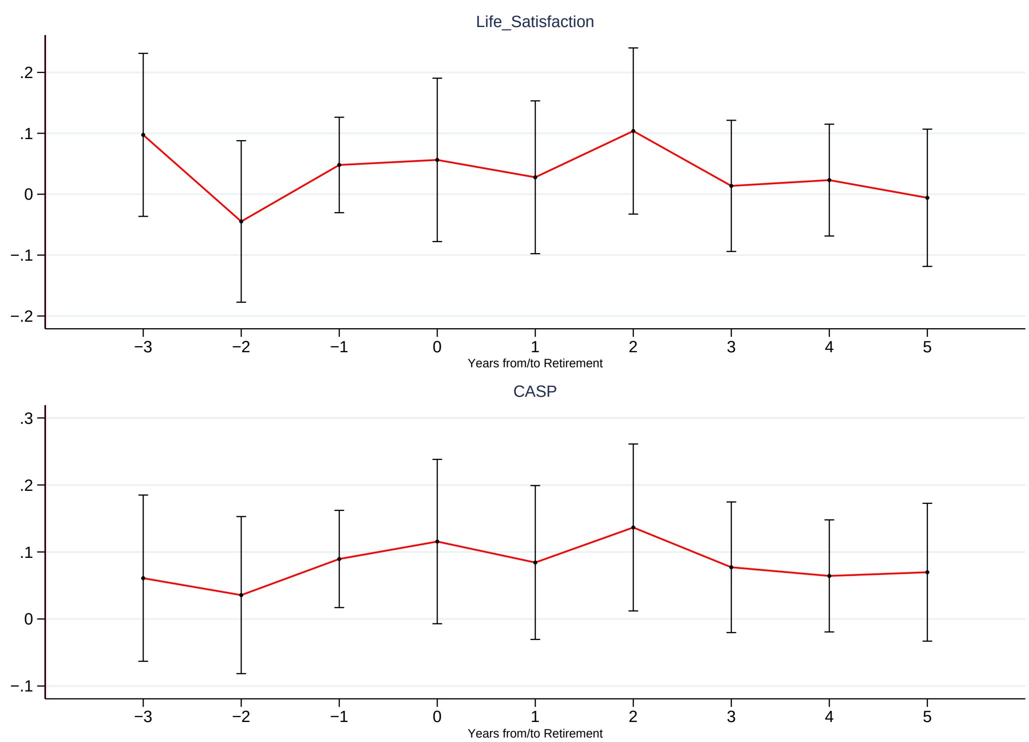
Table 2.4 – The effect of retirement on SWB

	Life Satisfaction				CASP			
	FE		FE-IV		FE		FE-IV	
	Baseline	Leads-Lags	Baseline	Leads-Lags	Baseline	Leads-Lags	Baseline	Leads-Lags
Retired	-0.005*		0.195**		0.002		0.398***	
	(0.003)		(0.099)		(0.003)		(0.124)	
3 years before		0.015***		0.097		0.013***		0.061
		(0.004)		(0.081)		(0.004)		(0.075)
2 years before		0.025***		-0.045		0.007		0.036
		(0.008)		(0.081)		(0.007)		(0.071)
Within 1 year		0.012***		0.048		0.015***		0.090**
		(0.004)		(0.048)		(0.003)		(0.044)
0-1 year		0.009*		0.056		0.024***		0.116
		(0.005)		(0.082)		(0.004)		(0.075)
1-2 years		0.010**		0.028		0.014***		0.084
		(0.004)		(0.076)		(0.004)		(0.070)
2-3 years		0.011*		0.104		0.016***		0.137*
		(0.006)		(0.083)		(0.006)		(0.076)
3-4 years		0.009		0.014		0.013**		0.077
		(0.006)		(0.065)		(0.006)		(0.059)
4-5 years		0.009		0.023		0.010*		0.064
		(0.006)		(0.056)		(0.006)		(0.051)
More than 5 years		0.012***		-0.006		0.008*		0.070
		(0.004)		(0.069)		(0.004)		(0.063)
Age	0.002	0.004	0.072**	-0.004	0.012***	0.012***	0.150***	0.019**
	(0.004)	(0.004)	(0.035)	(0.009)	(0.003)	(0.003)	(0.044)	(0.009)
Age2	-0.001	-0.003	-0.066**	0.004	-0.008***	-0.007***	-0.138***	-0.014*
	(0.003)	(0.003)	(0.033)	(0.008)	(0.003)	(0.003)	(0.041)	(0.008)
Log-Income	0.001	0.001	0.003*	0.001	0.000	0.000	0.004*	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Diff. with Ref. Group	-0.000	-0.000	-0.002	0.000	0.000	0.000	-0.004*	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Widowed	-0.045***	-0.045***	-0.050***	-0.048***	-0.007	-0.007	-0.016	-0.010
	(0.013)	(0.013)	(0.014)	(0.013)	(0.009)	(0.009)	(0.015)	(0.010)
Separated-Divorced	-0.021*	-0.020*	-0.012	-0.018	-0.009	-0.009	0.008	-0.005
	(0.011)	(0.011)	(0.013)	(0.012)	(0.010)	(0.010)	(0.014)	(0.010)
Single	-0.031	-0.031	-0.030	-0.029	-0.010	-0.010	-0.008	-0.009
	(0.021)	(0.021)	(0.022)	(0.022)	(0.018)	(0.018)	(0.022)	(0.019)
HH size	0.002	0.002	0.001	0.002	-0.003*	-0.003*	-0.005**	-0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Homeowner	-0.001	-0.001	-0.001	0.001	0.008*	0.008*	0.008	0.010**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.005)
Tenant	-0.004	-0.004	-0.007	-0.003	0.005	0.005	-0.002	0.006
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.008)	(0.005)
N. Children	-0.001	-0.001	0.000	-0.000	-0.000	-0.000	0.002	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
N. Grandchildren	-0.001	-0.001	-0.001*	-0.001	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Physical Health	-0.006*	-0.006*	-0.007*	-0.007**	-0.012***	-0.012***	-0.012***	-0.013***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value			0.384	0.434			0.036	0.086
Individuals	12774	12774	12774	12774	12774	12774	12774	12774
Obs.	36249	36249	36249	36249	36249	36249	36249	36249

Notes: Wave includes the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In the *Baseline* specification, we found a negative and non-significant effect of retirement on SWB, respectively for LS and CASP, using the FE estimator. However, these results are likely to be biased due to endogeneity. When using the FE-IV estimation, instead, retirement is found to be beneficial for SWB, respectively by 0.2 and 0.4 of a standard deviation. These findings are in line with the previous studies that analyse the association of retirement and well-being in a cross-country framework (Fonseca, Kapteyn, J. Lee, Zamarro, and Feeney, 2014; Horner, 2014). Moving to the "leads and lags" specification for LS, we find a positive and significant anticipation/adaptation pattern, which starts 3 years before and ends at the third lag. However, when correcting for endogeneity these effects vanish. With regards to CASP, the FE estimates suggest a positive adaptation process starting three years before retirement, reaches its pick in magnitude the year of the transition into retirement and gradually decreases. However, the FE-IV estimation results show a weak following retirement effect. Indeed, we find a positive effect the year within the transition of 0.09 of a standard deviation, and a stronger effect of 0.14 of a standard deviation 2-3 years after. For the sake of easier reading, we also plot the coefficients of the lead and lags specifications in Figure 2.6. At this stage of the paper, these findings should be considered

Figure 2.6 – The effect of retirement on SWB - Life Satisfaction and CASP



Notes: Graph (a) plots estimated coefficients associated with leads and lags in Life Satisfaction and CASP. The 0 reflects the year of the retirement; -3,-2,-1 denote up to three years before retirement; 1, 2, 3, 4, 5 up to more than 5 years after retirement. The entire sample referred to 12,774 individuals (36249 observations) aged between 50 and 75 that stayed in she survey from 2 up to 5 waves.

as preliminary. It emerges that overall people improve their perceived utility after retirement, especially when looking at the quality of life measure although the adjustment path is weak. Only for CASP, findings indicate a weak adjustment process up to three years after retirement that starts before the transition. It means that the reduction of the individual roles turns into relief for retirees (Duxbury et al. 1994; Kimand and Moen 2001). The CASP model also seems to better predict the SWB as suggested by McMahan and Estes (2011), confirming social and psychological evidence that life-course have an impact on the perceived well-being of older individuals (Blane 2006). On the other side, the weakness of the pattern may be due to differences between early and statutory retirees. As argued by Börsch-Supan and Jürges (2006), early retirees might experience different effects with respect to statutory retirees and always present a lower level of SWB, due for instance to poor health. Moreover, the difference in social security, pension, and healthcare systems might, in turn, cause heterogeneity across individuals. The SH test for over-identification is always passed at 10%, but when looking to the first stage results in Table 2.5, the F-tests for excluded instruments suggest weak identification for some lead and lags.

Table 2.5 – First Stage Results

	Baseline	Leads and Lags								
	Retired	Lead 3	Lead 2	Lead 1	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
ERA	0.028***									
	(0.007)									
NRA	0.001									
	(0.010)									
Lead Era 1		-0.006	0.000	0.062***	0.010*	0.021***	0.006*	0.000	0.003	-0.074***
		(0.008)	(0.004)	(0.010)	(0.006)	(0.006)	(0.003)	(0.004)	(0.003)	(0.009)
Lead Era 2		0.002	0.014***	0.032***	0.011**	0.018***	-0.002	0.002	-0.001	-0.047***
		(0.007)	(0.004)	(0.008)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)	(0.007)
Lead Era 3		-0.004	-0.002	0.019***	0.008**	0.003	0.000	-0.004*	-0.002	-0.020***
		(0.007)	(0.003)	(0.007)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.007)
Lead SRA 1		0.025**	0.006	0.100***	-0.014	-0.018*	-0.003	-0.011	0.017**	-0.044***
		(0.010)	(0.005)	(0.014)	(0.010)	(0.011)	(0.005)	(0.007)	(0.008)	(0.011)
Lead SRA 2		0.012	0.040***	0.036***	-0.011	-0.021**	0.001	0.009	-0.002	-0.034***
		(0.009)	(0.006)	(0.010)	(0.008)	(0.009)	(0.005)	(0.006)	(0.004)	(0.008)
Lead SRA 3		0.039***	0.005	0.011	-0.006	-0.012	0.004	-0.001	0.001	-0.018**
		(0.009)	(0.004)	(0.009)	(0.006)	(0.008)	(0.005)	(0.004)	(0.004)	(0.007)
Lag Era 1		-0.023***	0.003	0.079***	0.054***	0.019***	0.010***	0.001	-0.001	-0.101***
		(0.008)	(0.005)	(0.010)	(0.007)	(0.006)	(0.003)	(0.004)	(0.003)	(0.010)
Lag Era 2		-0.034***	-0.001	0.074***	0.040***	0.071***	0.016***	0.010**	0.004	-0.146***
		(0.009)	(0.005)	(0.011)	(0.008)	(0.009)	(0.004)	(0.005)	(0.004)	(0.011)
Lag Era 3		-0.032***	-0.009	0.074***	0.052***	0.078***	0.055***	0.008	0.003	-0.161***
		(0.011)	(0.006)	(0.012)	(0.009)	(0.011)	(0.007)	(0.006)	(0.005)	(0.012)
Lag Era 4		-0.031**	0.015*	0.071***	0.056***	0.084***	0.030***	0.044***	0.019***	-0.196***
		(0.012)	(0.008)	(0.014)	(0.011)	(0.012)	(0.006)	(0.008)	(0.006)	(0.014)
Lag Era 5		-0.080***	-0.018***	0.133***	0.059***	0.073***	0.040***	0.041***	0.058***	-0.200***
		(0.012)	(0.005)	(0.016)	(0.012)	(0.013)	(0.007)	(0.009)	(0.009)	(0.016)
Lag Era 6		-0.088***	-0.015**	0.130***	0.076***	0.091***	0.035***	0.025***	0.042***	-0.157***
		(0.011)	(0.006)	(0.016)	(0.012)	(0.014)	(0.007)	(0.008)	(0.008)	(0.018)
Lag SRA 1		0.028	0.019*	0.054	0.021	-0.017	0.016	0.003	-0.040**	-0.009
		(0.037)	(0.010)	(0.036)	(0.034)	(0.034)	(0.024)	(0.017)	(0.017)	(0.032)
Lag SRA 2		-0.032***	-0.005	0.014	0.048***	0.094***	0.026***	0.008	-0.007	-0.089***
		(0.011)	(0.005)	(0.013)	(0.014)	(0.017)	(0.009)	(0.009)	(0.009)	(0.015)
Lag SRA 3		-0.042***	-0.004	0.029**	0.008	0.061***	0.063***	0.043***	0.019*	-0.124***
		(0.009)	(0.004)	(0.012)	(0.014)	(0.017)	(0.011)	(0.011)	(0.011)	(0.015)
Lag SRA 4		-0.035***	-0.002	0.040***	0.016	0.013	0.013	0.126***	0.032**	-0.123***
		(0.010)	(0.005)	(0.014)	(0.015)	(0.018)	(0.008)	(0.016)	(0.013)	(0.019)
Lag SRA 5		-0.028***	-0.005	0.065***	-0.027*	-0.006	-0.004	0.003	0.118***	-0.056**
		(0.011)	(0.005)	(0.015)	(0.016)	(0.020)	(0.008)	(0.011)	(0.019)	(0.023)
Lag SRA 6		-0.032***	0.020***	0.208***	-0.011	-0.042***	0.024***	0.003	-0.023***	-0.069***
		(0.008)	(0.004)	(0.012)	(0.011)	(0.012)	(0.006)	(0.005)	(0.005)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F										
Individuals	12774	12774	12774	12774	12774	12774	12774	12774	12774	12774
Obs.	36249	36249	36249	36249	36249	36249	36249	36249	36249	36249

Notes: Controls includes age, age2, log-income, difference with the reference group, a set of dummies on marital status, household size, homeowner, tenant, number of children and grandchildren, physical health, and the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Now, we test the robustness of the model to issues linked to the age specification, the inclusion of the Netherlands in the sample due to the fact they are present in the last two waves, and to a less restrictive definition of retirement. The results are presented in Table 2.6.

Frijters and Beatton (2012) argue that SWB experiences a positive upwards shift of SWB from 50 years old, particularly significant at the age of 60, that turns into a decrease around 70 years old. Thus, to the purpose of checking for any misspecification of the age term that may confound especially the effect of the adjustment process, we substitute the second degree age polynomial with two dummies, *50-60* years old and *61-70* years old, with the reference group *71-75* years old. The group aged between 61-70 is expected to have higher SWB than the reference group while the 50-60 might have lower SWB respect to the older group, depending on how fast is the shrink around 70. The model for LS shows no effects in the baseline specification, whereas a weak adjustment process is found, up to the second year of retirement. The CASP model keeps better predicting SWB. Looking a the SH test, the specification seems actually improved by including the year dummies instead of the second-degree polynomial. In the baseline specification, the positive effect of retirement on CASP is confirmed; likewise, the dummy for the group aged 61-70 is positively associated with SWB. There is also a clearer long-lasting adjustment process, with no evidence of complete adaptation. Next, we re-estimate the model dropping the Netherlands records, restricting the sample to 12039 individuals. In both LS and CASP models, the baseline effects are confirmed, similar in magnitude, and statistical significance. Moreover, the weak dynamic adjustment of retirement is confirmed in the CASP model. In the LS model, instead, the coefficient associated with the third lag is significant at 10%. Thus, there is still no evidence of complete adaptation in CASP and almost no effect on LS.

Finally, we test the model with a less restrictive definition of retirement, namely removing the paid-job constrain. The baseline specifications report a positive effect although the size is strongly reduced. The shift may reflect the partial change in the life of those who keep working. If the effect on SWB is strictly interrelated with, for instance, the income satisfaction or free time, this specification may underestimate the effect. In addition, the same argument of different adjustment process for a different type of retiree is valid that may underestimate the true effects of retirement.

Table 2.6 – The effect of retirement on SWB - Robustness checks

	(Life Satisfaction)						(CASP)					
	Age Dummy		No Netherlands		Retired II		Age Dummy		No Netherlands		Retired II	
Retired	0.011		0.206^{*}		0.009^{*}		0.047^{***}		0.334^{***}		0.027^{***}	
	(0.009)		(0.113)		(0.099)		(0.005)		(0.127)		(0.005)	
3 years before		0.118^{*}		0.106		0.074		0.116^{*}		0.047		0.034
		(0.066)		(0.084)		(0.055)		(0.061)		(0.078)		(0.050)
2 years before		-0.023		-0.034		0.033		0.032		0.028		0.035
		(0.079)		(0.084)		(0.044)		(0.072)		(0.073)		(0.038)
Within 1 year		0.076^{***}		0.052		0.084^{*}		0.105^{***}		0.083^{*}		0.061
		(0.029)		(0.049)		(0.045)		(0.027)		(0.045)		(0.041)
0-1 year		0.046		0.064		0.038		0.108		0.107		0.040
		(0.088)		(0.080)		(0.035)		(0.079)		(0.073)		(0.032)
1-2 years		0.076^{*}		0.032		0.065		0.125^{***}		0.076		0.070^{*}
		(0.046)		(0.077)		(0.046)		(0.043)		(0.070)		(0.041)
2-3 years		0.138		0.146^{*}		0.064^{*}		0.104		0.147^{*}		0.070^{**}
		(0.084)		(0.086)		(0.039)		(0.076)		(0.077)		(0.035)
3-4 years		0.043		0.018		0.051		0.090^{**}		0.071		0.071^{*}
		(0.046)		(0.068)		(0.046)		(0.041)		(0.061)		(0.042)
4-5 years		0.054		0.041		0.028		0.059		0.061		0.040
		(0.053)		(0.056)		(0.042)		(0.049)		(0.050)		(0.037)
More than 5 years		0.014		0.002		0.031		0.080^{**}		0.064		0.038
		(0.038)		(0.070)		(0.053)		(0.035)		(0.063)		(0.047)
Age 50-60	-0.003	-0.003					-0.003	-0.005^{*}				
	(0.003)	(0.003)					(0.003)	(0.003)				
Age 61-70	0.004	-0.005					0.006^{**}	0.002				
	(0.002)	(0.004)					(0.002)	(0.004)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.913	0.523	0.147	0.517	0.072	0.681	0.126	0.212	0.003	0.034	0.001	0.045
Individuals	12774	12774	12039	12039	12774	12774	12774	12774	12039	12039	12774	12774
Obs.	36249	36249	34439	34439	36249	36249	36249	36249	34439	34439	36249	36249

Notes: Controls includes age, age2, log-income, difference with the reference group, a set of dummies on marital status, household size, homeowner, tenant, number of children and grandchildren, physical health, and the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As for the main models, the adjustment process is weak but found also for the LS model. However, the identification worsens for both baseline specification, as suggested by the SH test.
On the one hand, robustness tests somehow confirm the main findings of a beneficial effect of retirement on SWB, and a weak adaptation process identified in the CASP model. On the other hand, they potentially suggest further investigation of the age specification and the type of retirees.

2.5.2 Heterogeneity Analysis

The consequences of retirement on SWB may affect the several SWB domains in different and opposite ways depending on specific characteristics, thus making unclear whether the average findings reflect specific subgroups of individuals.

Table 2.7 – The effect of retirement on SWB - Heterogeneity in Life Satisfaction I

	(1)		(2)		(3)		(4)	
	Female		Male		Low Skilled		High Skilled	
Retired	0.135		0.198*		0.007		0.018	
	(0.130)		(0.108)		(0.077)		(0.075)	
3 years before		0.104		0.065		0.054		0.015
		(0.129)		(0.080)		(0.134)		(0.086)
2 years before		-0.154		0.053		-0.152		-0.006
		(0.114)		(0.114)		(0.120)		(0.102)
Within 1 year		0.077		0.006		0.052		0.011
		(0.067)		(0.056)		(0.078)		(0.053)
0-1 year		0.005		0.023		0.010		0.022
		(0.102)		(0.079)		(0.155)		(0.079)
1-2 years		0.065		0.016		0.045		-0.016
		(0.134)		(0.075)		(0.160)		(0.075)
2-3 years		0.004		0.173		-0.046		0.064
		(0.126)		(0.108)		(0.134)		(0.092)
3-4 years		0.063		-0.085		-0.012		0.001
		(0.087)		(0.101)		(0.110)		(0.073)
4-5 years		-0.013		0.041		-0.114		0.047
		(0.078)		(0.077)		(0.090)		(0.070)
More than 5 years		0.021		-0.079		-0.089		-0.035
		(0.102)		(0.087)		(0.113)		(0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.583	0.134	0.175	0.969	0.111	0.013	0.010	0.641
Individuals	6386	6386	6388	6388	2857	2857	9899	9899
Obs.	18082	18082	18167	18167	8033	8033	28146	28146

Notes: Controls includes age, age2, log-income, difference with the reference group, a set of dummies on marital status, household size, homeowner, tenant, number of children and grandchildren, physical health, and the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As we are employing an FE-IV estimator and are not able to exploit the information of time-invariant personal characteristics, we firstly investigate the heterogeneity in the effect of being retired and in the dynamic of adaptation/anticipation with respect to gender, education level, and geographic area of residence. For instance, gender differences may arise because of the gender gap in the job market, and the consequent differences in both the life-course and the role-in-life impacts on SWB. In the same way, the implication of different level of education reflects somehow the differences in the pre-retirement occupation. Low-skilled individuals are potentially who work more hours, perhaps bearing more physical burden, and are likely to enjoy more leisure time. Another important difference in the consequence of retirement may arise due to socio-cultural differences related to the way in which both labour market and life events impact SWB. At this stage, we control for geographical heterogeneity aggregating the countries in three macro-European regions, namely Northern, Central, Southern European countries.[14] Tables 2.7, 2.8, and B1 display the estimation results for LS and CASP. The first two columns refer to gender heterogeneity. We find a positive effect of retirement for male in the baseline specification LS models, which confirms the average result. For CASP instead, while a positive effect of retirement is found only for female in the baseline specification, a weak adjustment is found only for males. Moving to education heterogeneity, we do not find any effect on the LS model. Contrarily, a positive effect is found for low-skilled individuals in the CASP model, with no dynamics pattern. As expected, lower education people are expected to be employed in the more fatiguing occupation with respect to higher educated individuals. Thus, it is more likely that they enjoy more the free time, and generally experience a boost in perceived utility in most of its domains due to the elimination of occupational stress.

[14] Northern comprises individuals from Denmark and Sweden. Central is composed of individuals from Austria, Belgium, Germany, the Netherlands, and Switzerland. Finally, Southern includes France, Italy, and Spain.

Table 2.8 – The effect of retirement on SWB - Heterogeneity in CASP I

	(1)		(2)		(3)		(4)	
	Female		Male		Low Skilled		High Skilled	
Retired	0.527**		0.157		0.211**		0.095	
	(0.226)		(0.097)		(0.087)		(0.072)	
3 years before		0.044		0.079		0.034		0.006
		(0.116)		(0.075)		(0.125)		(0.085)
2 years before		0.008		0.048		0.092		-0.014
		(0.097)		(0.098)		(0.110)		(0.095)
Within 1 year		0.096		0.092*		0.127*		0.047
		(0.061)		(0.053)		(0.074)		(0.052)
0-1 year		0.043		0.140*		0.030		0.140*
		(0.092)		(0.076)		(0.156)		(0.076)
1-2 years		0.130		0.084		0.135		0.012
		(0.119)		(0.070)		(0.154)		(0.074)
2-3 years		0.090		0.159		0.089		0.112
		(0.110)		(0.100)		(0.127)		(0.086)
3-4 years		0.081		0.058		0.086		0.040
		(0.077)		(0.092)		(0.106)		(0.070)
4-5 years		0.041		0.066		0.030		0.065
		(0.067)		(0.071)		(0.083)		(0.065)
More than 5 years		0.083		0.041		0.036		0.039
		(0.091)		(0.080)		(0.105)		(0.073)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.883	0.019	0.001	0.781	0.663	0.412	0.000	0.031
Individuals	6386	6386	6388	6388	2857	2857	9899	9899
Obs.	18082	18082	18167	18167	8033	8033	28146	28146

Notes: Controls includes age, age2, log-income, difference with the reference group, a set of dummies on marital status, household size, homeowner, tenant, number of children and grandchildren, physical health, and the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The geographical heterogeneity investigation shows important differences. Indeed, both LS and CASP models display a negative effect of retirement on SWB for individuals who live in northern European countries. Contrarily, only for the CASP model, a beneficial effect is found for those individuals who live in the south of Europe. Moreover, a strong anticipation/adaptation process is detected, which reflects the last-longing association of retirement with SWB. This result is clearly associated with strong differences in social-rules, life-course impact. However, it should be further investigated in terms of the difference in social security systems might have some effects in terms of the dynamic adjustment (e.g. the anticipation of the retirement effect might be stronger in those countries where more constant retirement ages are guaranteed by the stability of policy-making). Besides, the healthcare systems may have an important role in the retirement effect on SWB, as the perceived health status is an important domain in overall individual welfare. Finally, the generosity of pension systems may be relevant to capture different incentive to retire earlier or later that may result in weak instruments issue. At this stage of the work, the last point is left for future scope. Tables B2 and B3 present the estimation results. For LS, we do not find any significant point estimation, except for a negative leading effect for those who live in a country with SSH. For CASP model, a negative effect for people who live in countries that have a so-called Nordic social security system, while a weak positive adjustment process is detected for who live in countries that adopt both the Continental and the Mediterranean systems. With regards the healthcare systems, we find that people who live in both subgroups have a positive effect of retirement on SWB, although the one of NHS model is almost double the SSH model. With respect to the anticipation/adaptation dynamics, in the SSH model is found a weak positive adjustment process that lasts until 3-4 years after leaving the labour market. As for the main estimation models, in Figures 2.7 and 2.8 we plot all leads and lags sub-sample estimation to facilitate the reading of the adjustment process.

Overall, the weak retirement adjustment dynamics we find in the main specification might be partly explained by heterogeneity effects, which however reflects stronger patterns only for individuals living in the Mediterranean area. This reflects not only geographical heterogeneity that might be rooted on different social-norms, along with the role played by the differences in welfare systems, and in particular the healthcare system, which is thought to play a central role in the SWB of older individuals.

2.6 Discussion, limits, and future scope

Understanding whether retirement affects individual utility is important as for individuals who want to decide when exiting from the labour market as well as for policy-makers who design retirement policies to ensure the sustainability of pension and healthcare systems. On top of that, including well-being in policymaking is becoming a primary issue for those policy-makers who aim at preserving and improving the overall welfare and well-being of individuals.

Leaving the labour market is an important transition that may substantially change the individuals quality of life, impacting all the specific domain of the subjective well-being, e.g. health, income, and leisure time satisfaction. The elimination of the occupation pressure, the increase in leisure time might boost the SWB, for instance, enjoying the family time. On the other hand, losing the role played for the whole life at work might cause a sharp decline in perceived individual utility. Moreover, individuals tend to experience a decline in disposable income, as the pension substitutes the job income. All these reasons suggest that retirement might follow a multi-stage adjustment (Atchley, 1982) that can start even before the retirement itself.

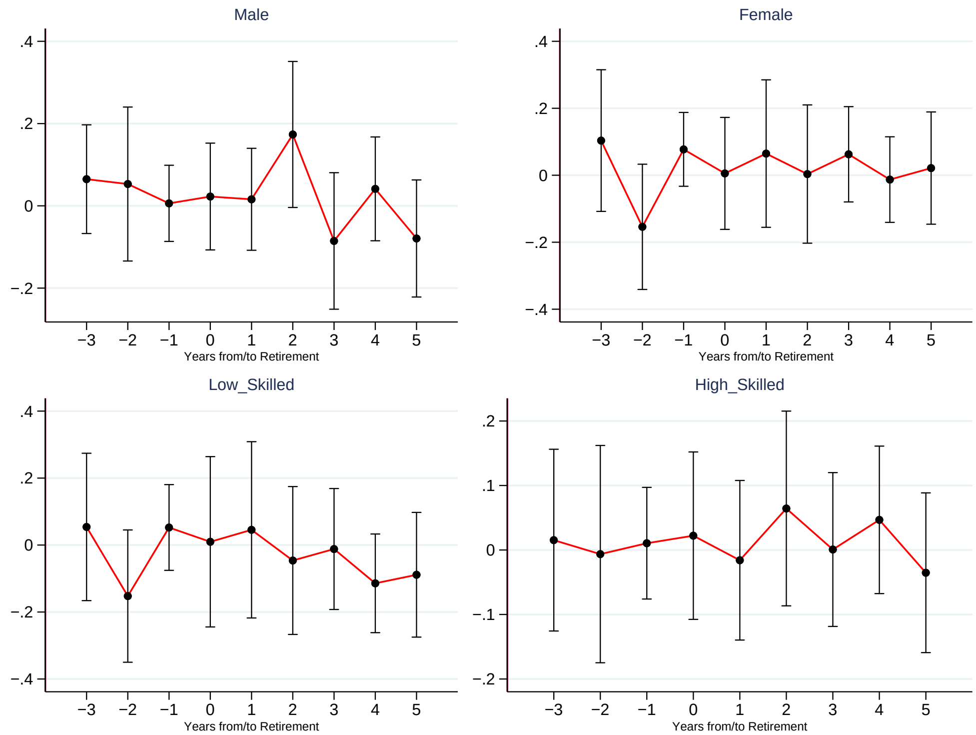
This paper seeks to provide new evidence to address the effect of retirement on SWB and to identify some pattern in terms of anticipation and adaptation of the individuals to retirement. As argued by Diener, Lucas, and Scollon (2009), SWB is not an hedonic treadmill implying that it is an empirical challenge to understand whether a life event effect such retirement completely dissipates. Moreover, it is important whether these effects can be generalised for different countries with similar characteristics, e.g. European countries that try to go in the same directions to overcome the consequences of the demographic-cut that are experiencing. Thus, we use the longitudinal data of SHARE to measure the effect of retirement on SWB in several European countries and to investigate the anticipation/adaptation patterns. We employ an FE-IV estimator to address endogeneity issues related to the potential reverse causation of retirement and SWB and to take into account measurement error/misclassification due to the subjective nature of the data. We use two different measure of individual well-being, namely life satisfaction and CASP.

Overall, retirement is found to positively affect LS and CASP. However, we find a weak adaptation process only for the CASP model. We investigate the presence of heterogeneity effects on gender, education levels, European macro-regions, the difference in social security systems, and the difference in healthcare systems. The weak retirement adjustment we find in the main specification might be partly explained by heterogeneity effects, which however reflects stronger patterns only for individuals living in the Mediterranean area. This reflects not only geographical heterogeneity that might be rooted on different social-norms but also a difference due to the social security systems and in particular the healthcare system, which is thought to play a central role in the SWB of older individuals.

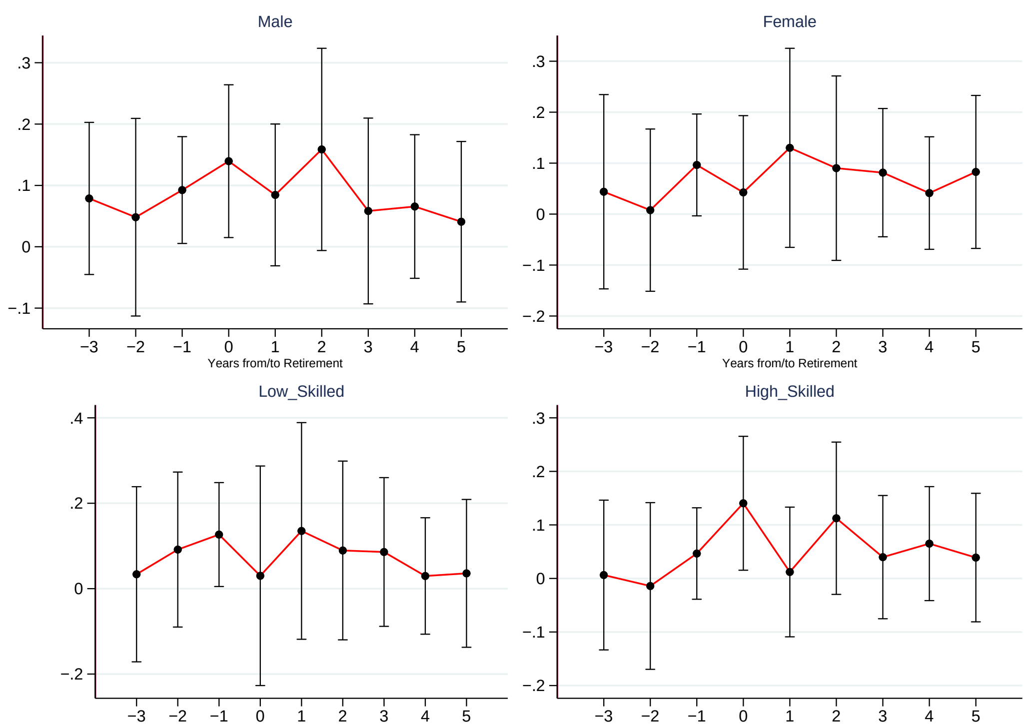
The policy suggestion that may be drawn from these findings is about the design of pension schemes. When increasing the retirement ages to ensure the financial sustainability of pension systems, policy-makers should consider heterogeneous incentives for more flexible retirement schemes to allow older workers to alleviate the work pressure, gaining leisure time, and at the same time, avoiding lack of meaning in life. Moreover, policies should be designed considering cross-crountry differences, as the type of social security system.

However, the findings should be taken as the result of a preliminary stage of this work. A first limitation may rely on the duration of the panel. The other studies that address the anticipation/adaptation of labour market and life events use very large panel data. A significant issue is related to the subjective nature of the proxy of well-being. Indeed, larger panel data potentially ensure to control for time-invariant unobservables. Another issue is linked to the heterogeneity of the effects between early and statutory retirees. In this sense, a role may be played by the net pension replacement rates, which can induce incentives in choosing to retire at statutory or early ages. This is a central issue because it can cause weak instruments problems. To correctly address this issue, a solution may be estimating the models separately for early and statutory retirees. To this end, the next step to improve the work will be retrieving the information on the job history of the SHARELIFE respondent. Moreover, it might be useful to test the model also using the perceived health, the satisfaction with income, which can be potentially constructed by exploiting the SHARE information on the income and wealth sphere. The implications of analysing also the single domains may results extremely valuable in terms of policymaking.

Figure 2.7 – The effect of retirement on SWB - Heterogeneity in Life Satisfaction and CASP



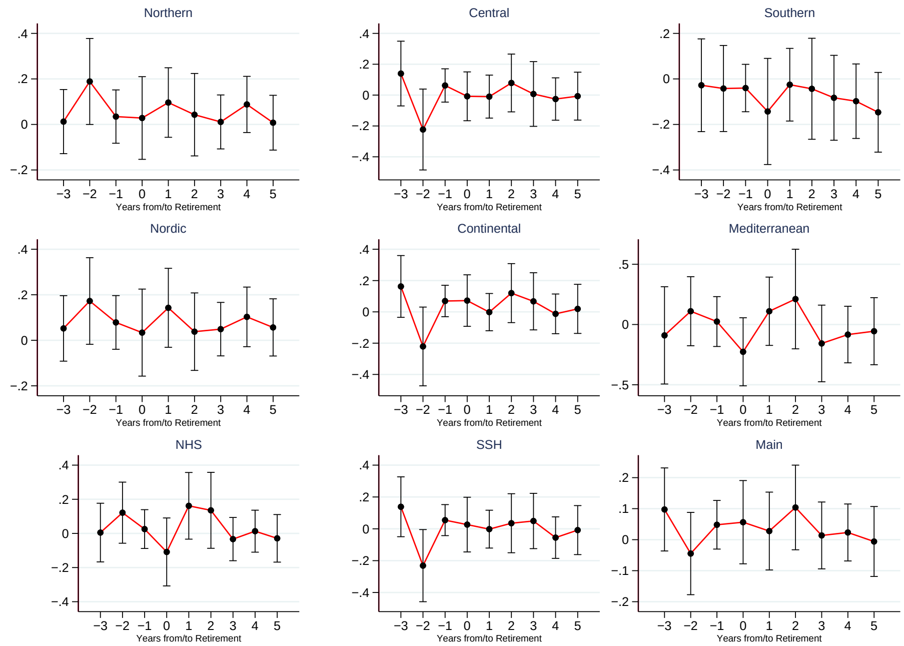
(a)



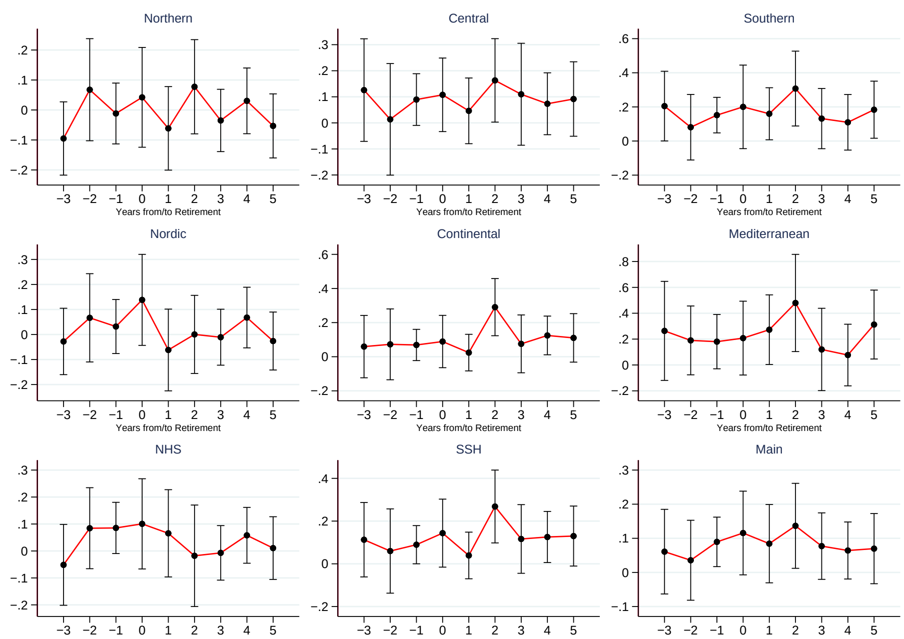
(b)

Notes: Graph (a) plots estimated coefficients associated with leads and lags in Life Satisfaction. Graph (b) plots estimated coefficients associated with leads and lags in CASP. The 0 reflects the year of the retirement; -3,-2,-1 denote up to three years before retirement; 1, 2, 3, 4, 5 up to more than 5 years after retirement. The entire sample referred to 12,774 individuals (36249 observations) aged between 50 and 75 that stayed in she survey from 2 up to 5 waves.

Figure 2.8 – The effect of retirement on SWB - Heterogeneity in Life Satisfaction and CASP



(a)



(b)

Notes: Graph (a) plots estimated coefficients associated with leads and lags in Life Satisfaction. Graph (b) plots estimated coefficients associated with leads and lags in CASP. The 0 reflects the year of the retirement; -3,-2,-1 denote up to three years before retirement; 1, 2, 3, 4, 5 up to more than 5 years after retirement. In the first rows, Northern, Central, and Southern refer to geographical area of residence. In the second rows, Nordic, Continental, and Mediterranean refer to social security systems. In the third row, NHS and SSH refer to different healthcare system, while Main reports the main estimation results of Table 2.5. The entire sample referred to 12,774 individuals (36249 observations) aged between 50 and 75 that stayed in she survey from 2 up to 5 waves.

Chapter 3

Evaluating the Impact of Energy Poverty in a Multidimensional Setting

[1]

Abstract

We study the relationship between energy poverty and subjective well-being by combining objective and subjective indicators in a multidimensional energy poverty index and showing how this information tool can be used in econometric analysis even when the available information takes the form of an ordinal variable. We show that information on subjective well-being and multidimensional energy poverty can be framed within a simultaneous bivariate ordered probit model while accounting for the endogeneity related to consideration of subjective indicators. Estimations show that, for any severity level, being energy poor significantly reduces the probability of being satisfied with life. By contrast, no effects are detected with standard affordability measures. This points to the capability of multidimensional energy poverty indicators in modelling the welfare losses perceived by individuals and identifying the most vulnerable households.

JEL Classification: C35, I31, I32

Keywords: multidimensional energy poverty, subjective well-being, limited dependent variable methods, welfare analysis

[1]This chapter has been supervised by professor Rinaldo Brau.

3.1 Introduction

Even in wealthy countries, there may be a portion of the population that is unable to purchase a basic set of goods and services based on energy use. According to the Building Performance Institute Europe (Atanasiu, Kontonasiou, and Mariottini, 2014), in 2012, about 10.8% of the European population was unable to maintain adequate warmth in their homes or were living in energy poverty(henceforth EP). The size of the problem has been increasing over the last 15 years. People subjected to EP usually spend a high share of their income on electricity, oil, and gas; live in inefficient and unhealthy dwellings; and are exposed to severe consequences concerning health, social exclusion, and overall household welfare.

In developed economies, the earliest policies to support vulnerable citizens took place in the United Kingdom in the early 1990s. In more recent times, other European countries have begun to recognize EP as a distinct phenomenon vis-à-vis income poverty and to implement specific supporting programs. Since 2006, the European Union has pushed for spreading policies supporting the energy poor across all European countries.[2] According to the latest projects (e.g. the European Energy Poverty Observatory) run by the European Commission, EP should be officially considered a distinct phenomenon from income poverty that should be separately analyzed.[3] This view embraces similar considerations made in several studies that reported EP as a complex phenomenon with its own peculiarities (Hills, 2011, 2012, Welsch and Biermann, 2017).

Considering EP as a distinct phenomenon with respect to income poverty entails that the identification and measurement of energy poor people should not be (exclusively) based on monetary indicators derived from variables such as energy prices and expenditures. In operative terms, the measurement of EP can be obtained starting from an information set that comprises a few deprivation indicators made available at the individual and/or household level in household surveys.

[2] See European Commission, EPEE 2006.

[3] See the European Energy Poverty Observatory and the previous EU Fuel Poverty Network. As witnessed by the name of this network, the expression “fuel poverty” is recurrently used. For the sake of simplicity, we are generally using the term “energy poverty” even when referring to studies or documents where the expression “fuel poverty” was actually used (and the focus slightly different).

Most of the existing literature points to a set of objective welfare EP indicators (e.g. Boardman, 1991,Hills, 2011,Moore, 2012,Legendre and Ricci, 2015). However, the scope for including subjective measures in the economic analysis is nowadays embedded in the economic debate on welfare evaluation, where the use of subjective well-being (henceforth SWB) approaches has become common practice (e.g., see OECD Better Life Index 2013). SWB approaches have been applied to different fields, e.g., health care (Ferrer-i-Carbonell and Praag, 2002), social science (Frey and Stutzer, 2002), evaluation of public goods (Luechinger, 2009b) and energy provision mix (Welsch and Biermann, 2014a,b). Accordingly, even in the analysis of EP, subjective indicators have been recently considered in a few studies. This is the case in the recent works by Welsch and Biermann (2017), who investigate the effects on life satisfaction of electricity, oil, and gas prices (standard objective measures) in different European countries; and by Biermann (2016), who finds that fuel poverty measures related to households' expenditure on energy are always associated with a significant negative effect on SWB that adds to that of income poverty. Other studies have adopted an SWB perspective by trying to define a subjective measure of EP (Papada and Kaliampakos (2016); Rehdanz, Welsch, Narita, and Okubo (2015); Lawson, Williams, and Wooliscroft (2015) and Waddams Price, Brazier, and Wang (2012)).

To the best of our knowledge, what is apparently missing in the extant literature is an analysis of individuals' well-being where the combined information from objective and subjective measures of EP, considered within a multidimensional approach, is exploited to econometrically assess the relationship between EP and SWB. With the aim to widening the set of the methodological tools that can be used in this field of economic analysis, we first show how to subsume a set of available indicators (pointing to both subjective and objective dimensions of households' energy deprivation), in a single multidimensional energy poverty index (henceforth MEPI) that provides information on EP even at the individual level. This is done by adapting to EP analysis (and the data at hand) the methodology that Alkire and Foster (2011) have proposed for standard multidimensional poverty measurement. Considering subjective indicators of EP makes these kinds of indices trivially endogenous in their relationship with SWB. Coupled to its ordinal nature, at least in our application, this endogeneity issue impacts on the detection of an appropriate econometric modeling strategy.We suggest estimating the individual-level relationship between SWB and the MEPI by employing a bivariate ordered probit model with exclusion restrictions. This allows us to account for the correlation between the two variables. Moreover, provided that an opportune set of instruments is available, this solution is adequate to face a general set of endogeneity problems related to unobservable factors. This approach is valid even in a cross-sectional environment and could be potentially applied when using alternative multidimensional indices partially based on subjective measures.[4]

We develop our MEPI and carry out the empirical analyses by using the Italian version of the European Union Survey on Income and Living Conditions (henceforth ITSILC). As for the information on SWB, we exploit a question about the degree of life satisfaction included in a specific module on social exclusion, which is asked to be evaluated on a 11-point scale.[5]

We first provide an explorative analysis that shows the potential from using the MEPI to identify EP while pointing at the same time to the discrepancies arising between subjective and objective measures of EP, and especially between multidimensional indices and traditional monetary indicators of fuel poverty. Subsequently, we econometrically assess the relationship between SWB and the MEPI by identifying the causal relationship between EP and life satisfaction by means of exclusion restrictions referred to the year of construction of the dwellings. The results not only confirm theoretical predictions, by detecting a significant negative relationship between subjective well-being and energy poverty (for any MEPI's severity level, being energy poor reduces the probability of being satisfied with life), but also point to the capability of multidimensional subjective indicators in explaining the impact of EP on SWB compared with traditional expenditure-related measures.

The paper is structured as follows. In Section 2, we sketch a background of the relevant literature. Section 3 describes the construction of multidimensional poverty indices and their application to the data at hand. Section 4 illustrates the conceptual model in which the empirical analysis is framed. Section 5 illustrates the results of the econometric analysis, and Section 6 contains a few concluding remarks.

[4]A very recent example is the composite fuel poverty index proposed by Charlier and Legendre (2019).

[5]In the following, the words life satisfaction, subjective well-being, and utility will be considered interchangeable.

3.2 Energy Poverty, its measurement and the Subjective Well-being approach

The two main topics in which our work is framed are the EP measurement methods and the relationship between SWB and EP.

3.2.1 Energy Poverty Measurement

Approaches to the analysis of EP measurement can be broadly categorized as either affordability or energy deprivation. The former is inherently unidimensional, being based on reference monetary thresholds that define the maximum level of income or expenditure share spent on energy (the term *fuel* is often used) that can be considered *affordable* by individuals or households. Boardman (1991) provides a starting point for this approach by simply stating that EP occurs when any household needs to spend more than 10% of its income on total fuel use (the so-called Ten Percent Rule). Variations of this elementary approach are the so-called 2M indicators, double mean, or double median, which count as energy poor those individuals whose energy expenditure share is greater than the double of the mean (or median).[6] More recent studies, e.g., Hills (2011, 2012) propose a Low-Income High Costs composite indicator, which counts individuals as energy poor if they spend more than 60% of the median of the disposable income distribution *and* they fall below a given income poverty line. Finally, affordability has been seen within a Minimum Income Standard framework that considers as energy poor those individuals lacking a minimum income required to satisfy primary needs after paying housing costs and energy costs (Moore, 2012). Close to Moore's indicator is the Residual Income Indicator (Miniaci, Scarpa, and Valbonesi, 2014), which is aimed at understanding how many (not energy-related) goods an individual can purchase apart from energy.

By taking a different perspective, the energy deprivation approach points to the importance of

[6] This approach has been also developed with multiple thresholds to improve its adaptability to differentiated energy demand, such as the dual threshold affordability measure by Faiella and Lavecchia, 2015), which we will use as a benchmark in our empirical analysis.

considering the different dimensions of EP, thereby paralleling the debate that characterizes the comparison between multidimensional approaches to poverty measurement and unidimensional poverty measures based on income (e.g. Bourguignon and Chakravarty, 2003; Atkinson, 2003; Alkire and Foster, 2011). The focus of the analysis is on how people are affected by living in energy-inefficient houses. In this respect, both the material manifestations of EP and subjective indicators of discomfort related to living in unhealthy dwellings should be considered. Several indices and indicators have been used: Healy (2003), Healy and Clinch (2004) and Thomson and Snell (2013) carry out cross-sectional and within-country analyses by considering information often included in household surveys, such as damp walls and/or floors, heating system, window frames, self-assessed judgments such as "cannot afford to heat home adequately", "unable to pay utility bills" and "lack of adequate heating facilities". A few recent studies have compared objective and subjective measures of EP. This is particularly the case of Waddams Price, Brazier, and Wang (2012), who point to the large differences emerging in the identification of the energy poor among UK citizens when using information arising from self-assessed EP instead of the Ten Percent Rule. They conclude that both sources of information should be used by policy makers to detect the actual occurrence of EP in the economy. Similar remarks have been raised by Lawson, Williams, and Wooliscroft (2015), with an application to New Zealand, and by Papada and Kaliampakos (2016) regarding Greece. Waddams Price, Brazier, and Wang (2012) also outline the need for a multidimensional objective and subjective indicator to give a more complete picture of EP incidence.

In fact, if we take advantage of the results from the income poverty literature, then multidimensional deprivation approaches can enable the analyst to assess even the intensity of EP problems experienced by the energy poor, thereby enriching the incidence information usually provided by affordability measures. As shown by a few recent contributions, this can be done also by combining affordability and energy deprivation approaches. This is the case of the work by Nussbaumer, Bazilian, and Modi (2012) who, by applying the methodology introduced in the poverty literature by Alkire and Foster (2011), were the first to develop an MEPI centered on the deprivation experienced by households in several African countries. Subsequent applications, where an MEPI *à la*

Alkire-Foster is explicitly proposed, are those by Nussbaumer, Nerini, Onyeji, and Howells (2013), in a global analysis of EP in developing countries, and Okushima (2017), in evaluating EP in Japan after the Fukushima accident. An alternative multidimensional index of fuel poverty, where both subjective and objective measures are considered, is proposed by Charlier and Legendre (2019).

3.2.2 Subjective Well-being and Energy Poverty

Individual satisfaction with living conditions is a subjective latent variable that can be reasonably assumed to range continuously between a lower bound of complete dissatisfaction and an upper bound of complete satisfaction. In practice, however, information on individual satisfaction is usually recovered from answers that use rankings, e.g., from excellent to very bad, or a numerical scale. Nonetheless, the viewpoint by the wider literature based on SWB approaches is that these kinds of self-assessed questions on satisfaction can elicit very important information on individual perceived losses caused by social exclusion, health deprivation, or more generally material deprivation, with the ultimate goal of better designing appropriate public policies for support.[7] A wide set of factors is expected to impact on individual well-being and be reflected in self-assessed indicators of SWB, e.g., income, health, leisure, job characteristics, accommodation, education, social exclusion, unemployment and status in employment, personal life shocks, and marital status (Frey and Stutzer, 2002; Blanchflower and Oswald, 2004; Ferrer-i-Carbonell, 2013; Bellani and D'Ambrosio, 2011 and Clark, Frijters, and Shields, 2008a). The latter two studies are of particular interest for the present study because they find that the use of deprivation indicators is more relevant than the use of traditional monetary indicators to capture the effect of poverty on SWB.

Concerning energy issues, a subjective perspective was adopted by Welsch and Biermann (2014a)in an assessment of electricity supply structures in Europe. In works by Welsch and Biermann (2014b) and Rehdanz, Welsch, Narita, and Okubo (2015) with a focus on the impact of the Fukushima nuclear accident, and a study by Welsch and Biermann (2016) on the nuclear power plant externalities in Switzerland, and in an analysis by Moellendorff and Welsch (2017) on the

[7] For a broader review of the SWB approach see Frey and Stutzer, 2002 and Ferrer-i-Carbonell, 2005.

perception of renewable power spreading in Germany. To our knowledge, the aforementioned study by Welsch and Biermann (2017) is the first where the SWB approach is applied in order to evaluate the welfare impact of EP.

Building on this recent stream of literature, in this paper, we exploit the multidimensional information provided by both the objective and subjective indicators of energy deprivation by proposing an empirical framework where the information on multidimensional deprivation can be exploited for econometric analyses once properly accounting for the ordinal nature of SWB indicators and MEPIs.

3.3 Identifying and Measuring Energy Poverty

We use data from the IT-SILC,[8] the Italian version of EU-SILC, which is the European survey that reports the statistics on income and living conditions and is released by Eurostat. It was launched in 2003 and has been implemented since 2010 in all EU-27 countries. It is mainly designed to study social exclusion and monitor poverty in the EU. The EU-SILC questionnaire is part of more extensive national level surveys, containing a richer set of questions about energy consumption, expenditure, and dwelling inefficiency than the European survey.

Information available in IT-SILC on potential energy deprivation (henceforth *ed*) is summarized in Table 3.1. We can note that *ed1* and *ed5* correspond to the standard deprivation indicators usually considered in the existing literature which has already exploited the EU-SILC survey (e.g. Thomson and Snell (2013); Atanasiu et al, 2014). The *ed2* and *ed3* represent a more detailed version of a similar single question of EU-SILC; *ed4* refers to the absence of any heating expenditure.[9] *ed1*, *ed2*, and *ed3*, (directly collected by the interviewers) can be considered objective indicators referring to inefficient dwelling's condition. By contrast, *ed5* is an indicator based on the subjective perception

[8] Version released in 2016 by the Italian National Institute of Statistics (ISTAT). The data refer to 2013.

[9] Unlike the national data release of the survey, EU-SILC does not provide information on the absence/presence of heating expenditure (*ed4*) and distinction between living in a damp home (*ed2*) or a house with damages on the roof, ceilings, windows, etc (*ed3*). The remaining two indicators are common to the national and European versions of SILC.

of being able to keep home adequately warm or not.

The original survey contains information on 44,622 individuals. However, we drop those observations for which the information year of dwelling construction (997), SWB (13,110), *eds*, and other controls were missing (940), along with discarding children aged less than 16 (6,279) given the fact that the questionnaire is submitted only for all household members aged over 16. We end up with 23,193 observations.[10] For these individuals, the most affecting deprivation is the presence of damp with 18%. The second more affecting deprivation is the presence of any problems with roofs and window fixtures, which regards 11% of the sample. The less recurrent deprivations are those referring to financial difficulties for utility bills and lacking heating facilities. The subjective indicator impacts 16% of the sample.

Table 3.1 – Energy Deprivation Questions and their incidence

Variable acronym	Question	Mean
ed1	Has the household been in arrears due to financial difficulties for utility bills for the main dwelling?	0.09
ed2	Has the dwelling any problems with the damp on walls, floors, ceilings or foundations?	0.18
ed3	Has the dwelling any problem with damaged roof, ceilings, doors, windows or floors?	0.11
ed4	Absence of any heating expenditure.	0.05
ed5	Can your household afford to keep its home adequately warm?	0.16

Notes: ITSILC data referring to 2013. The variables can be found into the dataset as hs021, umid, tetti, hh050, except for the ed4, which is recovered from the energy-specific expenditure analysis. The 'Mean column refers to the incidence of each deprivation in the sample. Sample size: 23,193.

3.3.1 Combining subjective and objective indicators in a Multidimensional Energy Poverty Index

To fully exploit the information provided by the previous set of *ed* indicators, we follow the

[10]While the number of missing records for the controls and the instrument can be considered as at random, the high amount of missing data in the dependent variable would limit the generalisation of the results. The missing values are partially caused by the fact that no proxy interview is allowed given the subjective nature of the variable, and that the Module on Well-being is a secondary module. The individuals who skipped these module might be on average more dissatisfied than others, and if it is the case, one would expect an under representation of lower levels in the distribution of the life satisfaction. However, on average, the representativeness of the original sample is guaranteed, given that the pre-sample selection summary statistics are similar to the ones post selection. In addition, the SWB distribution is still representative as follows the standard Western country average distribution. In any case, this issue should be further explored to validate the generalisation of the findings.

approach used by Alkire and Foster (2011) to build the multidimensional poverty index (MPI). This methodology allows us to analyze both the incidence and the intensity of EP across households and is particularly suited for analyses where energy deprivations are typically categorical or ordinal variables. Its key feature is the shaping of the procedure of identification of the energy poor individuals through the use of two thresholds. This makes it possible to set the analysis at an intermediate point between the union and the intersection rules of identification that are used in the poverty measurement literature.[11] The former classifies as poor each person presenting at least one deprivation. Conversely, the intersection rule identifies as poor the individual displaying all the deprivations under scrutiny. Alkire and Foster (2011)'s identification strategy stands in-between the two, conditional on the analyst's setting of the two thresholds.

In formal terms, let n be the sample size and d the number of *eds* presented in Table 3.1. For sake of completeness, let also introduce a vector $\mathbf{w}$ of dimension d of positive numbers summing to d, whose j-th value provides the weight associated with the j-th dimension. Given the choice of the deprivation indicators, the application of the A-F methodology formally requires the use of a first threshold, taking the form of a vector of "deprivation cut-off" ($\mathbf{z}$), which identifies how many *eds* associated with a given individual will contribute to the value of the multidimensional index. In this case, where all the *eds* are binary indicators taking value 0 or 1 (where 1 stands for "deprived"), we simply have $\mathbf{z} = [1, \dots, 1]$.

Applying the previous threshold to each observation and weighting the importance of the *eds* with the elements of $\mathbf{w}$, we obtain the weighted count of deprivations suffered by a single individual i, *i.e.*:

$$c_i^w = \sum_{j=1}^{d} (w_j \times I_j(\mathbf{z})), \tag{3.1}$$

where $I_j = 1$ if the person is deprived in indicator j, $I_j = 0$ otherwise.

The second threshold, which we can label by k, determines the maximum (weighted) number of the dimension for which an individual i can be deprived without being considered as energy poor: the extremes $k \leq \min w_j$ and $k = d$ will give the union and the intersection rules of identification. On

[11] See, for example, Atkinson (2003) or Bourguignon and Chakravarty (2003).

the basis the threshold k, we can compute a multidimensional index for individual i, corresponding to the weighted share of the possible deprivations identified for individual i:

$$MEPI_i^w = \frac{1}{d}\sum_{j=1}^{d}(c_i^w \times \vartheta_i(k)), \tag{3.2}$$

where $\vartheta_i = 1\ iff \quad c_i^w \geq k$, $\vartheta_i = 0$ otherwise. The previous index provides information about the intensity of EP that can be usefully inserted in the regression analysis, but with the caveat that it can take a limited number of ordered values.[12]

An aggregate index of EP, for a given weighting scheme w, is obtained by taking the average of individual deprivation shares over the whole population:

$$MEPI^w = \frac{1}{n}\sum_{i=1}^{n} a_i^w, \tag{3.3}$$

where $a_i^w = \frac{1}{d}\sum_{j=1}^{d}(c_i^w \times \vartheta_i)$. This aggregate MEPI provides a summary evaluation of the incidence and the intensity of EP in a given economy. Alkire and Foster (2011) point out that this kind of index can be seen even as an *adjusted headcount ratio*, given by the product of two simpler statistics: the average deprivation share across the energy poor ($A = \frac{a_i^w}{pd}$); and the share of energy poor in the population, i.e. the multidimensional headcount ratio $MHR = \frac{p}{n}$, where p is the number of the energy poor and n is the population dimension. Therefore, an alternative expression for the MEPI at the aggregate level will be:

$$MEPI^w = A \times MHR. \tag{3.4}$$

The previous expression clarifies that the average MEPI will always range between 0 and 1. As shown by Alkire and Foster (2011), the most important property of the index is given by the dimensional monotonicity, i.e. it increases whenever the individuals' deprivation count increases

[12] Namely, up to $d+1$ values in the case of equal weights and the threshold k is chosen sufficiently low so as to ensure that the union identification rule applies (d values related to the counts of energy deprivation of individuals identified as poor, plus a zero value related to not being energy poor). The expected number of levels of $MEPI_i^w$ will be a weakly decreasing function of the stringency of the multidimensional poverty cut-off k. In the extreme case of totally differentiated weights, the maximum possible number of values would be $d \times d$.

(and vice versa).[13]

The previous description points to the role of different weighting schemes and values for k that can be used for the computation of MHR and $MEPI^w$. In the case of the standard MPI used in the Human Development Reports by the United Nations Development Programme, Santos and Alkire (2011) remark that "intricate weighting systems create challenges in interpretation". One may think that all the deprivations point to the same category, and reasonably assume equal weights. Otherwise, situations where deprivation dimensions can be logically nested in separate groups naturally lead to more articulated weighting structures. The very simple rule usually adopted in this case is that of assigning the same aggregate weight to each nest and then equally sharing this aggregate weight within nests.[14] In our case - where we can distinguish between subjective and objective indicators - we will first adopt a baseline structure with equal weights; subsequently use the nested weighting structure scheme, where 50% of the overall weight is attached to the (single) subjective energy deprivation indicator and the remaining weight is equally shared among the objective eds; finally, carry out some robustness assessments.

3.3.2 Assessing Energy Poverty in Italy.

We appraise the potential of a multidimensional approach that aggregates the information available for the analysis of EP by computing a few simple statistics in terms of incidence (with the multidimensional headcount ratio MHR) and intensity (with the aggregate MEPI). These results are compared to the distribution and incidence of two affordability measures, namely the $10\%Rule$ and a Modified$10\%Rule$ (henceforth $10\%Rule_{modified}$).[15] The analysis is carried out both by con-

[13] Specifically, the index satisfies the properties of weak monotonicity, monotonicity, and dimension monotonicity, together with decomposability (which allows subgroup analysis), replication invariance (which ensures comparisons across differently sized populations), symmetry (which ensures equal emphasis is given to any person or group), nontriviality and normalization (which ensures that the minimum (0) and the maximum (1) are different values).

[14] In the case of the MPI, the three dimensions to which this scheme is applied are Education, Health and Living Standards. Each of them has a different number of deprivations. Likewise, Sadath and Acharya (2017) build their multidimensional energy poverty indicator by considering three equally important nests (Lighting, Cooking, Additional measures)

[15] With this label we are referring to dual-threshold indicator that has been applied to Italy by Faiella and Lavecchia (2015). More precisely, this indicator is computed as $10\%Rule_{modified} = \frac{\sum_i^N v_i}{N} \times 100$, where $v_i = 1 \quad iff$ at least one between electricity consumption $> 0.10\times$ income and fuel consumption $> 0.05\times$ income, while $10\%Rule = \frac{\sum_i^N v_i}{N} \times 100$, where $v_i = 1 \quad iff$ energy consumption $> 0.10\times$ income.

sidering equal weights for the various *eds* and the nested weighting structure defined above (where the subjective indicator takes half of the total weights).[16] As a baseline value, we set the poverty identification cutoff k equal to $d/3$, equivalent to one-third of the maximum weighted count of deprivations that an individual can achieve, which is the value typically used for the computation of the MPI.

The top Panel of Table 3.2 reports the different headcount ratios. According to the MHR, 22.14% of the sample is affected by EP. Conversely, the problem would only regard 3.70% of individuals when referring to the M.10%Rule indicator, and 7.49% according to 10% Rule. It is worth pointing out that only 1.45% of the sample is detected as energy poor by the three measures. It turns out that they are capturing different potential vulnerabilities. The affordability measure is likely to capture mainly people suffering from income poverty, whereas the multidimensional measure is considering all the individuals who are living in inefficient dwellings, including those who cannot even afford to reach the threshold and, therefore, cannot be considered by the affordability measure. These findings support the claim by Waddams Price, Brazier, and Wang (2012) when stressing the need to use subjective and objective indicators other than affordability measures when measuring EP.

The overlapping degree between our multidimensional indices and affordability measures can be assessed by means of the additional content of Table 3.2. The central panel reports the average MEPIs. The overall mean intensities are about 0.08 according to $MEPI$ and 0.10 to $MEPI_n$, whereas the average severities among the energy poor are respectively 0.49 and 0.60. The right bottom Panels display the distributions of the individual MEPIs across their different levels, then the percentage of overlapping between the two affordability measures and the different levels of the MEPIs. Looking at the $MEPI$ 0 level, 84.59% of the sample is not experiencing EP. When looking at the distribution of the $10\%Rule_{modified}$ and $10\%Rule$ energy poor, it is quite surprising to see that no energy poor people according to the indices are detected at the highest level of $MEPI$. Conversely, 77.33% of $10\%Rule$ and 72.59% of $10\%Rule_{modified}$ of energy poor would not be targeted by the MEPI. It seems quite reasonable to think of these individuals as *false positive* because they are not reporting any of the five deprivations that comprise the MEPI, including

[16] Henceforth, subscripts with the expression "$_n$" will always refer to some form of nesting structure.

the self-assessment about whether the family can afford to keep its home warm or not, nor the indicator of having been in arrears due to financial difficulties for utility bills. The same evidence emerges when referring to $MEPI_n$ distribution.

Table 3.2 – Multidimensional Energy Poverty: Summary Statistics and Overlapping Degree between Affordability Measures

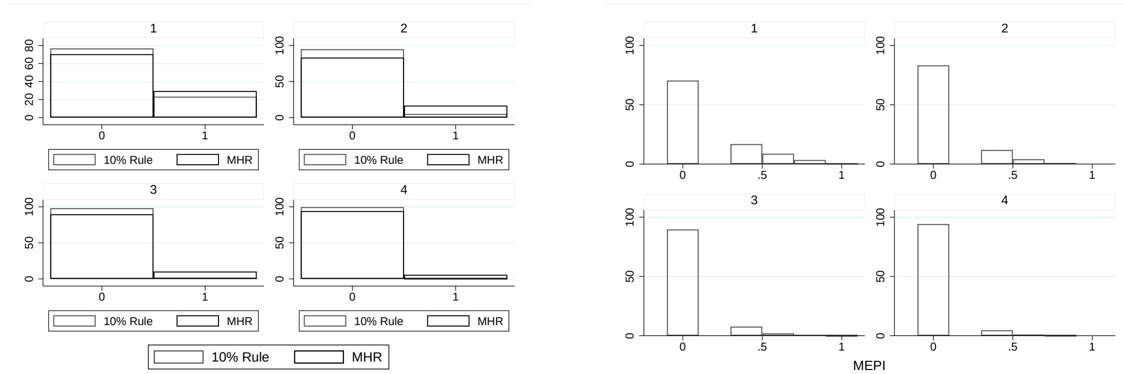
		Average EP			
		MHR	15.49%	MHR_n	16.83%
		10% Rule	7.49%	$10\%Rule_{modified}$	3.6 %
		Average Intensity			
		Equal weights		Nested Weights	
		Overall MEPI	0.0754	Overall MEPI_n	0.1013
		MEPI among poor	0.4867	MEPI_n among poor	0.6020
Overlapping of affordability measures across MEPI levels (%)					
Scenario		Energy Poor		Non-Energy Poor	
$MEPI$		$10\%Rule$	$10\%Rule_{modified}$	$10\%Rule$	$10\%Rule_{modified}$
Level 0	84.50	77.33	72.59	85.09	84.96
Level 1	10.23	13.58	14.82	9.96	10.05
Level 2	3.94	7.25	9.76	3.67	3.72
Level 3	1.21	1.84	2.82	1.16	1.15
Level 4	0.12	0	0	0.13	0.13
$MEPI_n$					
Level 0	83.16	74.05	66.00	83.90	83.82
Level 1	1.01	1.55	2.00	0.97	0.98
Level 2	6.69	9.78	12.24	6.44	6.48
Level 3	4.92	7.08	9.18	4.74	4.75
Level 4	2.93	5.70	7.76	2.70	2.74
Level 5	1.17	1.84	2.82	1.11	1.11
Level 6	0.12	0	0	0.13	0.13

Notes: The 10% rule considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. The $10\%Rule_{modified}$ is a dual threshold affordability measure, which considers an individual as energy poor if at least one condition holds between the electricity consumption equal or greater than the 10% of household disposable income and the fuel consumption equal or greater than the 5% of household disposable income. $MEPI$ refers to the intensity measure of EP with equal weights. $MEPI_n$ refers to the intensity measure of EP with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations. ITSILC data referring to 2013; Sample size:23,193.

Figure 3.1 provides another view of the analysis by displaying both the incidence (MHR and 10%Rule) and the intensity (MEPI) of EP by equivalized household income quartiles, showing a decreasing relationship.[17] The richer the household, the less is affected by EP according to both measures. The decomposition is especially helpful for targeting the individuals that the affordability measure is not considering, given that only 23.25% of the first income quartile is energy poor according to the 10%Rule index, whereas the MHR counts 41.18%. This confirms the apparent limitations of measures that mainly capture the income–poverty dimension.

[17] Eurostat equivalence scale has been used.

Figure 3.1 – Percentage distribution of 10% Rule, MHR, and MEPI by equivalized income quartiles



(a) (b)

Notes: The 10% rule considers an individual as poor if energy consumption $> 0.10\times$ income. MHR is the multidimensional headcount ratio; MEPI is the multidimensional index of energy poverty. ITSILC data referring to 2013; Sample size: 23,193.

3.4 Modeling the Relationship between Subjective Well-being and Multidimensional Energy Poverty

We now show how the use of the individual-level MEPI, as defined in the previous Section, may facilitate the inclusion of EP as a determinant of individual welfare in empirical analyses adopting an SWB approach.

Following Decancq, Fleurbaey, and Schokkaert (2015), we consider a 'general satisfaction function' $SWB^*(l_i, R_i, s_i)$ for individual i and defined by a vector l_i of m different aspects of life that provide satisfaction, the associated R_i preference orderings on l_i and individual scaling factors s_i (related to those personal characteristics and situations that may influence the level (but not the order) of well-being evaluations). For our empirical assessment, we can summarize all the observable scaling factors and relevant aspects of life in a vector $\mathbf{x}_i$, *except* the EP aspect, which yields:

$$SWB_i^* = S(\mathbf{x}_i, EP_i^*, \mu_{iSWB}) \tag{3.5}$$

where μ_{iSWB} represents the unobservable individual heterogeneity that affects the perception of satisfaction.

When using data from SILC surveys, information on the latent SWB is recovered from a question (in the form of an ordered variable with ten levels) expressing life satisfaction. Likewise, also the empirical counterpart of EP_i^*, $MEPI_i$, is an ordered variable (with eight levels, including the absence of EP). For the econometric analysis, this entails the use of models for ordered variables such as the ordered probit model.

We can control for several covariates that are well discussed as determinants of SWB in the life satisfaction literature. They include social–economic conditions, demographic determinants, job conditions, household income relative position, dwelling typology and characteristics, the region of residence, and urbanization level. Nonetheless, we cannot rule out that residual unobserved subjective factors may affect both SWB_i^* and EP_i^*, the latter being based in part on subjective perceptions. This entails typical endogeneity problems, which are well known in the SWB literature (e.g. Ferrer-i-Carbonell, 2005, Blanchflower and Oswald, 2004, Frey and Stutzer, 2002). For instance, it has been pointed out that optimism affects individuals' life satisfaction as well as the perception of being energy deprived or not. The potential endogeneity of EP_i^* can be modeled by means of a two-equation system, which we estimate by a *bivariate* ordered probit model, given the ordered nature of the SWB indicator and of $MEPI_i$, which is our empirical measure of EP. In this model, we can achieve identification by using an instrumental variable approach, which takes the form of an exclusion restriction on the vector of explanatory variables that model SWB, while considered in the (auxiliary) equation for $MEPI_i$. The exclusion restriction has to be a variable correlated with our EP but not directly correlated with the individual utility. Finding an exogenous instruments is not effortless, given that out dependent variable is a subjective evaluation of the life. Surely factors such as dwelling quality indicators or climate zone correlate with EP, but by definition depend on personality traits and individual preferences, which it is not possible control for, thus violating the main assumption of instrument validity. Looking at the several determinants of EP detected, for example, by Legendre and Ricci (2015), it is reasonable to say that there are objective and technical factors that describe dwellings directly influence the probability of being energy poor but do not directly affect the statement of SWB. The energy performance of the buildings subsumes several factors, - i.e. the building history or innovation in the construction sector. As remarked, for example, by Fabbri (2015), a good predictor of the inefficiency of a dwelling is the year of construction of the building. The more recent is a dwelling, the less likely to have energy inefficiency problems (e.g. more efficient power systems). Accordingly, we set the year classes of the building construction as our instrumental variables, relevant for the $MEPI_i$ and uncorrelated to our main dependent variable SWB_i^*. A possible objection to this identification strategy is that the choice of dwelling could be affected by self-selection. This problem may arise due to individual characteristics such as the health status, the income level, and more generally personality traits and preferences. For instance, having poor health may induce to prefer newer buildings (e.g. more salubrious) or less central renewed dwellings (e.g. avoiding high level of air pollution and the renewing constraints of the city centers); similarly, high income individuals would prefer either older buildings (living in historical city centers that are quite common in Italy) or larger and more expensive dwellings (e.g. living in detached houses in less urban areas). As a consequence, in the absence of adequate conditioning on a wide set of controls, SWB_i^* might eventually be correlated to the oldness of the building. That is why we consider a wide set of explanatory variables: individual health status, job position, income relative position with respect to their reference group, material deprivation and value of the house. Conditional on all these controls, we claim that the SWB_i^* equation is purged from any remaining direct effect of the year of construction on life satisfaction. As a note of caution, it must be recognized that the buildings' history often includes property renovations (or lack of), this way making the age an imperfect indicator of energy inefficiency. It turns out that the strength of this set of dummy instrumental variables must be empirically tested.

3.4.1 A bivariate ordered probit model

Define the empirical counterpart of our latent variable equation system as:

$$\begin{aligned} SWB_i &= MEPI_i\beta_1 + \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1} + e_i \\ MEPI_i &= \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} + \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2} + u_i \end{aligned} \tag{3.6}$$

where SWB_i is the observed level of overall satisfaction; $MEPI_i$ is the individual EP intensity; $\mathbf{x}_{1i}$ is the vector of observable characteristics that may affect both the life satisfaction and EP; $\mathbf{x}_{2i}$ refers to the set of instruments; u_i and e_i are the unobservable components.

The two ordered dependent variables are defined as follows:

$$SWB_i = \begin{cases} 0 \quad if \quad SWB_i^* \leq t_1 \\ \vdots \\ j \quad if \quad t_j > SWB_i^* \geq t_{j-1} \\ \vdots \\ J \quad if \quad SWB_i^* > t_J \end{cases} \quad MEPI_i = \begin{cases} 0 \quad if \quad EP_i^* \leq \alpha_1 \\ \vdots \\ w_k \quad if \quad \alpha_k > EP_i^* \geq \alpha_{k-1} \\ \vdots \\ 1 \quad if \quad EP_i^* > \alpha_K \end{cases} \tag{3.7}$$

We also impose the standard assumption on the cutoff points that are monotonically increasing so that $t_0 = \alpha_0 = -\infty$ and $t_J = \alpha_K = +\infty$. Following Calhoun (1989), Greene and Hensher (2010), and Sajaia (2008), the conditional joint probability distribution is expressed by:

$$\begin{aligned} Pr(SWB_i = j, & MEPI_i = k \mid MEPI_i, \mathbf{x}_{1i}, \mathbf{x}_{2i}) = \\ & \Phi_2(\alpha_k - \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}, (t_j - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \\ & - \Phi_2(\alpha_{k-1} - \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\theta_2, (t_j - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \\ & - \Phi_2(\alpha_k - \mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}, (t_{j-1} - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \\ & + \Phi_2(\alpha_{k-1} - \mathbf{x}_{1i}^{'}\{\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}, (t_{j-1} - \beta(\mathbf{x}_{1i}^{'}\boldsymbol{\theta_1} - \mathbf{x}_{2i}^{'}\boldsymbol{\theta_2}) - \mathbf{x}_{1i}^{'}\boldsymbol{\delta_1})\xi, \tilde{\rho}) \end{aligned} \tag{3.8}$$

where Φ_2 is the bivariate standard normal distribution, $\xi = \frac{1}{\sqrt{(1+2\beta\rho+\beta^2)}}$ and $\tilde{\rho} = \xi(\beta + \rho)$. The error terms are normally distributed: $(e_i, u_i) \sim N(0, \Sigma)$, where $\Sigma = [\tilde{\rho}_{jk}]$ is the variance-covariance matrix. Sajaia (2008) develops this particular specification and refers to it as the simultaneous bivariate ordered probit. When β equal zero the model refer to a SUR. The β is the parameter associated to the endogenous latent variable, that is the model consider the endogeneity of the latent variable only whether β is different from zero. This particularly fit with our framework where we are interested in assessing the effect of the observed EP severity while addressing the endogeneity of the latent counterpart. Applications of this model can be found in health economics (Bünnings and Tauchmann, 2015); education economics (Kalb and Van Ours, 2014) and economic psychology studies (Farrell, Fry, and Risse, 2016).

3.5 Econometric analysis

3.5.1 Variables and sample definition.

We consider a broad set of potential determinants of SWB, taking advantage of the literature cited in Section 2.2. Namely, we control for individual-level characteristics (sex, age and age square, marital status, general health conditions, education level, working conditions); dwelling typology and characteristics; region of residence and urbanization level.

The SWB variable is an individual question that ranks the degree of satisfaction within a range of 11 levels, from 0 (not at all satisfied) to 10 (completely satisfied).[18] Figure 3.2 (a) displays the distribution of SWB across individuals in the sample. As expected, it follows the typical Western European trend and is left-skewed.[19] Figure 3.2 (b) reports the distribution of SWB across the levels of our EP index. In general, the higher the index, the less satisfied the individuals.

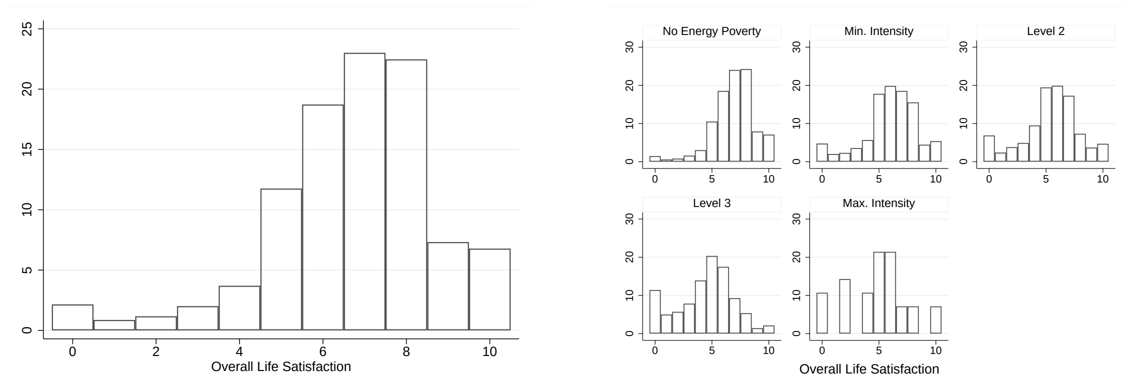
As extensively explained in Section 3, the aggregate intensity of EP experienced by individuals is measured by our individual EP intensity index, MEPI. While its value indicates the average intensity experienced in the sample, the individual value of the index can be seen as the degree of EP suffered by each individual targeted as poor. Therefore, we exploit this individual contribution to the aggregate measure as an individual proxy of the degree of EP experienced to assess its effect on subjective utility (SWB).

The main descriptive statistics are reported in Table 3.3. Our final sample comprises 46% men,

[18]The variable in ITSILC is *PW010*

[19]Layard and Sachs (2017)

Figure 3.2 – Percentage distribution of overall life satisfaction.



(a) (b)

Notes: Graph (a) shows the distribution of the overall satisfaction across the whole sample. Graph (b) reports the distribution of the overall individual satisfaction for the different MEPI levels.
ITSILC data referring to 2013; Sample size: 23,193.

with an average age of about 55 years. Around 32% of the sample declared itself as an employee and 29% as retired, and the median level of education is upper-secondary was 36%, with only 13% of individuals having tertiary education. Equivalized household income is about 19450 euros. Following Clark, Frijters, and Shields (2008a), we do not use this variable directly. We consider, instead, the household relative position with respect to a reference group defined by having the same class age, education level, and region of residence. An individual is defined richer than the reference group when her household equivalized income is statistically larger than the average income of the group. Around 41% of the individuals are richer than the reference group. Moreover, an indicator for multidimensional material deprivation (henceforth, MMDI) is built by applying the Alkire-Foster methodology to subsume in a single index a series of social-material deprivation.[20] Regarding the dwelling characteristics, around 78% of individuals are homeowners and 62% of dwellings are located in non-urban areas. Around 29% of the respondents live in semi-detached houses and 26% in buildings with more than 10 flats. Dwelling's quality is measured by the monthly paid or imputed rent (for those who are the homeowners): the average is around 550 Euros.

Table 3.3 – Respondents Related Characteristics: Summary Statistics

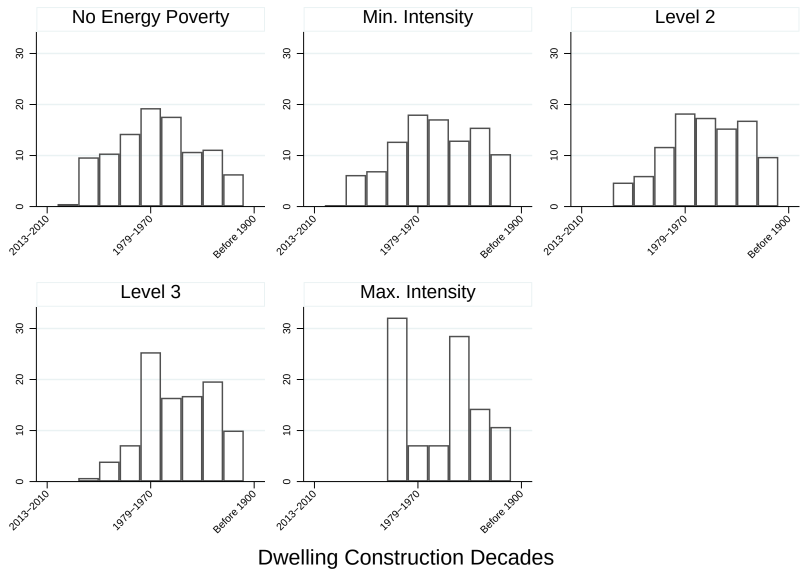
[20] In details, the financial deprivation dimension is computed from the variables *hs120, hs060, hs011, hs031, pd070* ; the primary needs dimension from *hh081, hh091, pd080, pd030, frigo, hs100, hs090, hs080, hs070, hs050*; the secondary needs from *hs040, stovigli, videocam, parab* ; the cultural needs dimension from *pd060, pd050*; and finally the medical needs from *ph040, ph050*.

Variable	Label	Mean	Std. Dev.
Equivalised Income	equivalised household income	19,444	14,701
Richer than reference group	1 if richer than reference group	0.41	-
MMDI	multidimensional index of material deprivation	0.14	-
Male	1 if male	0.46	-
Age	age at the date of the interview	54.73	16.49
Employee	1 if employed	0.32	-
Unemployed	1 if unemployed	0.07	-
Self-employed	1 if self-employed - full and part time	0.11	-
Retired	1 if retired	0.29	-
Pre-Primary	1 if ISCED level = 0	0.03	-
Primary	1 if ISCED level = 1	0.19	-
Low-secondary	1 if ISCED level = 2	0.26	-
Upper-secondary	1 if ISCED level = 3	0.36	-
Post-secondary	1 if ISCED level = 4	0.03	-
First-tertiary	1 if ISCED level = 5	0.13	-
Married	1 if married	0.61	-
Separated	1 if separated	0.04	-
Divorced	1 if divorced	0.03	-
Never married	1 if never married	0.20	-
Widowed	1 if widowed	0.12	-
Children	1 if they have children	0.23	-
Self-assessed health1	very good health	0.10	-
Self-assessed health2	good	0.53	-
Self-assessed health3	fair	0.25	-
Self-assessed health4	poor	0.10	-
Self-assessed health5	very bad health	0.02	-
Owner	1 if dwelling owner	0.78	-
Detached	1 if living in detached house	0.22	-
Semi-detached	1 if living in a semi detached house	0.29	-
Flat-less10	1 if living in a building with less than 10 flat	0.23	-
Flat-more10	1 if living in a building with more than 10 flat	0.26	-
N. of rooms	number of rooms available to the household	3.41	1.10
No-urban area	1 if living in a no urban area	0.62	-
Proxy for dwelling quality	paid or imputed rent (in Euros)	551	286
Dwelling's construction 2013-2010	1 if constructed between 2013 and 2010	0.00	-
Dwelling's construction 2000-2009	1 if constructed between 2000 and 2009	0.09	-
Dwelling's construction 1990-1999	1 if constructed between 1990 and 1999	0.10	-
Dwelling's construction 1980-1989	1 if constructed between 1980 and 1989	0.14	-
Dwelling's construction 1970-1979	1 if constructed between 1970 and1979	0.19	-
Dwelling's construction 1960-1969	1 if constructed between 1960 and 1969	0.18	-
Dwelling's construction 1950-1959	1 if constructed between 1950 and 1959	0.11	-
Dwelling's construction 1900-1949	1 if constructed between 1900 and 1949	0.12	-
Dwelling's construction before 1900	1 if constructed between before 1900	0.07	-

Notes: ITSILC data referring to 2013; Sample size: 23,193.

The bottom part of Table 3.3 reports the summary information on the set of dummies indicating the dwelling's construction age by means of which we deal with the endogeneity of the EP variable. The original variable available in ITSILC contains nine classes, defined from 1 to 9, where 1 refers to the more recent dwelling (after 2010 up to 2013) and 9 the oldest (before 1900). Classes 2–7

Figure 3.3 – Percentage distribution of dwelling construction decades among MEPI levels (2013–before 1900)



Notes: ITSILC data referring to 2013; Sample size: 23,193.

(from 2000-2009 to 1950-1959) account for 10 years each, class 8 accounts for 1900–1949, and class 9 accounts for any year before 1900. Figure 3.3 summarizes the distribution across MEPI levels, which is entirely left skewed for those who experience the more intense EP.

3.5.2 Estimation Results

Table 3.4 reports the main results related to the estimation of equation (6). In parallel to Section 3.2, a baseline model where the components of the MEPI at the individual level are assigned equal weights is compared to a nested weighting scheme and a model based on the 10%*rule* affordability measure. First, note that the Wald test of independent equations associated with the correlation coefficient ρ confirms the scope for considering a joint probability model. The relationship between EP and the wide set of socio-economic factors for which we are controlling for follows the economic intuition whether an equal weights or a nested weighting structure is adopted. With respect to the reference individual (employee, single, with tertiary education, in very good health and living in a detached house) the MEPI is positively associated with unemployment and material deprivation, becomes lower for richer individuals, whether in absolute terms or with respect to their reference group, augments as the level of education and self-assessed health decreases. A decreasing relationship with age is detected for most individuals, as the estimated turning point with the coefficients of the quadratic specification is about 19 years old (value referred to Model 1).[21]. The three negative estimated coefficients of the dwelling types show that, *ceteris paribus*, living in each of the three different dwelling types reduces EP compared with living in a detached house and, as expected, a higher dwelling quality implies lower EP. Finally, our exclusion restriction based on the dummy set of dwelling's construction age (reference class is 2010–2013) has statistical support and all the coefficients are positive as expected. The older the dwelling, the higher the probability of staying in a more severe energy poverty level.[22]

In the SWB equation, given we are interested in assessing the effect of the observed EP severity, we include a full set of dummies referring to the individual MEPI levels (no EP is the reference group).[23] As expected, the estimated coefficients are negative and statistically significant and show an increasing impact, apart from the highest intensity level, which actually refers to a very limited number of individuals (28). The same nonlinear pattern is found in the case of Model 2, with the difference that the higher number of EP levels originated by the nested weighting structure detect a clearly steep gradient only for the above-median levels.[24]

To better assess the performance of the MEPIs at the individual level, we can compare the previous results with those arising from the estimation of the simultaneous system using the $10\%Rule$ affordability measure. Model 3 in Table 3.4 shows that this indicator is not significant in the SWB equation.[25] Looking at the $10\%Rule$ equation, none of the dummy instruments are statistically significant. In strictly economic terms, affordability of energy expenditures do not depend on the oldness of the building.[26]

[21]Looking at the single eds, we have noted that older people are less likely to state that they can not heat home adequately. A similar finding has been found for the UK (Deller and Waddams Price, 2018)

[22]Results, available on request, are strongly robust when considering a single dummy that takes value 1 when construction of the building was begun before 1970.

[23]For a similar specification in the case of a bivariate probit model, see Kalb and Van Ours, 2014.

[24]In this case, some of the instrument dummies for the oldest dwellings are not statistically significant, but a joint Wald test strongly supports the identification.

[25]It is worth remembering that $10\%Rule$ is a binary variable (0 not energy poor, 1 when energy poor). This yields a 'semi-ordered bivariate probit model' that does not involve modifications to the formal structure described in Section 4.1 (e.g., see Greene and Hensher, 2009: 225).

[26]Other sharp differences arise. For example, the effects of the income variables, whether in absolute or relative terms, appear much stronger in their effect on $10\%Rule$ *vis-à-vis* MEPI, as a trivial consequence of the fact that

Coming back to the SWB equation in the specifications based on the MEPI, we can appraise that the estimates related to the other covariates are mostly consistent with the economic intuition. Namely, a progressive reduction of SWB as health conditions deteriorate and material deprivation increases, a lower life satisfaction when the individual is unemployed, as compared to the baseline status of employed. The opposite applies to retired people. Related to that, the coefficients of Age and Age2 detect a positive relationship between SWB and age for over fifty-year-old people (the turning point is at about 54 years old), whereas decreasing for younger cohorts. Married people appear more satisfied with life than singles. So are individuals with children.[27] We finally highlight that the weighting structure for the MEPI indicator impacts on the statistical significance of income variables and education level dummies. Namely, a positive effect is found for both only in the case of Model (1).

affordability indicators are based on income.

[27]Without specific identification strategies designed for these socio-demographic characteristics, we do not assign any causal relationship to these findings. For example, several studies report empirical evidence of a negative or non-significant effect of children on SWB. For a discussion of the effects of divorce, widowhood, first child, and marriage see Clark, Frijters, and Shields (2008a).

Table 3.4 – Main Estimation Results

	(1) $MEPI$ equation	(1) SWB equation	(2) $MEPI_n$ equation	(2) SWB equation	(3) $10\%Rule$ equation	(3) SWB equation
	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE
MEPI Level2		-0.240 (0.039)***		-0.288 (0.079)***		
MEPI Level3		-0.391 (0.055)***		-0.236 (0.039)***		
MEPI Level4		-0.668 (0.081)***		-0.294 (0.047)***		
MEPI Level5		-0.214 (0.215)		-0.371 (0.058)***		
MEPI Level6				-0.611 (0.083)***		
MEPI Level7				-0.181 (0.203)		
10% Rule						0.056 (0.049)
Log Equivalized Income	-0.057 (0.008)***	0.045 (0.009)***	-0.070 (0.008)***	0.020 (0.012)	-0.517 (0.056)***	-0.449 (0.112)***
Richer than reference group	-0.217 (0.024)***	0.058 (0.019)***	-0.272 (0.024)***	-0.027 (0.035)	-0.763 (0.059)***	-0.669 (0.146)***
MMDI	1.874 (0.110)***	-0.907 (0.112)***	1.337 (0.103)***	-0.578 (0.195)***	0.493 (0.148)***	-0.090 (0.478)
Male	0.008 (0.023)	-0.046 (0.014)***	-0.003 (0.022)	-0.047 (0.016)***	-0.123 (0.033)***	-0.137 (0.031)***
Age	0.008 (0.005)*	-0.027 (0.003)***	0.008 (0.004)*	-0.023 (0.004)***	0.007 (0.007)	-0.007 (0.012)
Age2	-0.021 (0.004)***	0.025 (0.003)***	-0.019 (0.004)***	0.019 (0.004)***	0.001 (0.006)	0.014 (0.011)
Unemployed	0.181 (0.037)***	-0.377 (0.032)***	0.241 (0.036)***	-0.279 (0.050)***	0.228 (0.062)***	0.021 (0.180)
Self-employed	-0.068 (0.037)*	-0.079 (0.023)***	-0.107 (0.039)***	-0.109 (0.026)***	0.305 (0.049)***	0.251 (0.081)***
Retired	-0.026 (0.033)	0.014 (0.022)	-0.033 (0.032)	0.001 (0.024)	0.078 (0.042)*	0.081 (0.040)**
Pre-Primary	0.509 (0.074)***	-0.177 (0.060)***	0.682 (0.073)***	0.046 (0.096)	0.330 (0.114)***	0.192 (0.169)
Primary	0.449 (0.050)***	-0.125 (0.037)***	0.643 (0.052)***	0.084 (0.079)	0.343 (0.074)***	0.231 (0.130)*
Low-Secondary	0.349 (0.043)***	-0.135 (0.028)***	0.511 (0.045)***	0.033 (0.063)	0.183 (0.067)***	0.087 (0.105)
Upper-Secondary	0.140 (0.041)***	-0.082 (0.021)***	0.271 (0.044)***	0.012 (0.038)	0.143 (0.062)**	0.089 (0.077)
Post-Secondary	0.154 (0.072)**	0.032 (0.040)	0.179 (0.078)	0.082 (0.049)*	0.253 (0.099)**	0.243 (0.099)**
Married	-0.055 (0.033)*	0.191 (0.022)***	-0.070 (0.033)**	0.156 (0.029)***	-0.277 (0.050)***	-0.166 (0.119)
Separeted	0.025 (0.057)	-0.153 (0.040)***	0.097 (0.055)*	-0.108 (0.045)**	0.103 (0.088)	0.024 (0.107)
Divorced	0.068 (0.064)	-0.084 (0.043)**	0.182 (0.061)***	-0.015 (0.048)	0.166 (0.081)**	0.108 (0.093)
Widowed	0.054 (0.047)	-0.055 (0.032)*	0.051 (0.046)	-0.039 (0.034)	0.184 (0.061)***	0.140 (0.074)*
Children	0.012 (0.030)	0.149 (0.019)***	-0.089 (0.030)	0.099 (0.026)***	-0.134 (0.046)***	-0.057 (0.082)
Good Health	0.113 (0.039)***	-0.216 (0.026)***	0.185 (0.040)***	-0.141 (0.039)***	-0.072 (0.063)	-0.174 (0.092)*
Fair Health	0.432 (0.044)***	-0.483 (0.037)***	0.470 (0.044)***	-0.321 (0.076)***	-0.093 (0.068)	-0.339 (0.186)*
Poor	0.646 (0.051)***	-0.808 (0.051)***	0.633 (0.051)***	-0.592 (0.107)***	0.016 (0.075)	-0.406 (0.319)
Very Bad Health	0.889 (0.071)***	-1.102 (0.078)***	0.870 (0.070)***	-0.809 (0.149)***	-0.068 (0.109)	-0.642 (0.425)
Dwelling Quality	-0.031 (0.006)***	0.018 (0.003)***	-0.044 (0.007)***	0.004 (0.007)	0.025 (0.007)***	0.033 (0.008)***
Owner	-0.323 (0.025)***	0.066 (0.025)***	-0.332 (0.025)***	-0.031 (0.044)	-0.067 (0.039)*	-0.006 (0.064)
No urban area	0.035 (0.027)	0.082 (0.017)***	0.050 (0.026)*	0.091 (0.018)***	0.239 (0.039)***	0.254 (0.037)***
N. Rooms	-0.004 (0.011)	0.029 (0.007)***	0.026 (0.011)***	0.040 (0.008)***	0.034 (0.016)**	0.046 (0.016)***
Semi-detached	-0.132 (0.029)***	0.033 (0.020)	-0.121 (0.028)***	-0.000 (0.025)	-0.107 (0.038)***	-0.074 (0.048)
Flat-less10	-0.155 (0.031)***	-0.003 (0.023)	-0.128 (0.030)***	-0.033 (0.027)	-0.299 (0.045)***	-0.266 (0.069)***
Flat-more10	-0.142 (0.035)***	-0.038 (0.024)	-0.143 (0.034)***	-0.074 (0.029)***	-0.559 (0.052)	-0.523 (0.094)***
2010-2013	-0.938 (0.234)***		-0.491 (0.181)***		-0.074 (0.087)	
2000-2009	-0.577 (0.056)***		-0.206 (0.067)***		-0.021 (0.038)	
1990-1999	-0.549 (0.057)***		-0.190 (0.071)***		-0.000 (0.018)	
1980-1989	-0.464 (0.051)***		-0.131 (0.063)**		0.010 (0.015)	
1970-1979	-0.360 (0.047)***		-0.053 (0.053)		0.020 (0.017)	
1960-1969	-0.326 (0.045)***		-0.110 (0.054)**		-0.001 (0.019)	
1950-1959	-0.158 (0.051)***		0.074 (0.052)		0.055 (0.039)	
1900-1949	-0.085 (0.048)*		0.034 (0.055)		0.049 (0.032)	
ρ	0.114***		0.356***		0.891*	
Regional residence	Yes		Yes		Yes	
AIC	110345.147		115349.368		96471.849	
BIC	111118.101		116154.529		97196.494	
Log-Likelihood	-55076.573		-57574.684		-48145.924	
Observation	23193		23193		23193	

Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the significance level of ρ is referred to a Wald test of independent equations. The 10%$rule$ considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. $MEPI$ refers to the intensity measure of EP with equal weights. $MEPI_n$ refers to the intensity measure of EP with nested weights (half of the weight to the subjective ed, half to the objective eds). The poverty cut-off is set to d/3, where d is the number of the deprivations. MMDI is the multidimensional material deprivation index. ITSILC data referring to 2013; Sample size: 23,193.

We have tested the robustness of our main analysis according to several dimensions. We have first verified whether the expected negative relationship between EP and SWB could be detected by a different affordability measure ($10\%Rule_{modified}$). The related estimation results are reported in the left-hand-side of Table C1 in the Appendix: the very small estimated coefficient, considering it actually different from zero by considering a level of statistical significance at 10%, would point to a counter-intuitive positive effect on SWB. A second possible challenge to robustness of the results in Table 3.4 could be related to the presence of historical buildings (quite common in Italy) characterized by important restoration works, for which the positive relationship between ancientness and energy inefficiency could not hold. Because of that, we have considered a restricted sample that excludes the dwellings built before 1900. The results reported in the middle part of Table C1 not only confirm that the effect of the MEPI levels is stable in magnitude, but also that the results for the other covariates are in line with the main estimation results. The same applies (right-hand-side of the table) to the lack of explanatory power of $10\%Rule$.[28]

Given the bivariate ordered probit estimation, the magnitude of the coefficients is not informative about the size of the effects. To assess the magnitude of the impact of our MEPI on different levels of SWB, we compute the average partial effects (APEs) of an increase of EP intensity and the correspondent average percentage variation. We have subsumed this exercise with the Tables C2 and C3. Table C2 displays the APEs comparison between $MEPI$ and $MEPI_n$. The Levels refer to the severity of EP, that is Level 1 represents the change in probability from a condition of no EP to the first level of MEPIs. The first rows illustrate how the increase in EP severity turns into a higher probability of being completely dissatisfied (SWB=0) up to the penultimate levels MEPIs level. The APEs at the highest EP level reflect the lack of statistical significance of the related coefficient. The second and the third rows report respectively the probability of being satisfied at the median (SWB=7) and at the highest level (SWB=10). At the latter case, symmetrically to the complete dissatisfaction level, very strong reduction in the predicted probabilities can be possible. At the median SWB level, the APEs are smaller - for example, a change from level 5

[28] For the sake of brevity, we omit to report additional robustness checks carried out by using other specifications of the MEPI - obtained by excluding some *eds*, or adding the 10% Rule indicator as sixth *ed*, which all confirm the negative and significant estimates for MEPI levels.

to level 6 in MEPI_n implies a reduction of about 12% - because the predicted class probability arises from the combination of "exits" to lower life satisfaction levels with "entries" from higher levels. Table C3 illustrate a similar exercise but carried out by considering different reference individuals, namely being richer than the reference group, unmarried, having very bad health, and being retired. Only APEs from Model (1) are shown. As can be seen from the APEs reported in the bottom panel, retirees follow the sample average displayed in Table C2 at any level of SWB and for any severity level of EP. Individuals richer than their reference group are less sensitive at the lowest level of SWB, but strongly affected at the highest level of SWB. The opposite applies to unmarried individuals. Individuals in very bad health are, instead, highly sensitive at the lowest level of satisfaction (SWB=0) for any level of EP. Contrarily, at the highest level of satisfaction the APEs are extremely small.

As a final input, especially to have a "touchstone" for the discussion of the policy implications of our analysis, in Table C4 we have reported the APEs (in absolute terms and as percentage variations) arising from the two baseline specifications of the individual MEPI and those related to a few covariates that are commonly expected to affect life satisfaction. For sake of simplicity, a change from no EP to an intermediate intensity level is considered. In addition to the usual big percentage variations at the extremes of the SWB distribution, we can appraise that the impact of EP is broadly comparable to that of being unemployed can be seen and much stronger than that associated with the condition of being richer than the reference group. As expected, the partial effects of having very bad health are the strongest.

Overall, our results are in line with previous work on EP and SWB (e.g., Welsch and Biermann (2017)). Nonetheless, exploiting a multidimensional measure of EP instead of energy prices to proxy energy affordability seems to provide a complementary framework for investigating the effect and the size of EP intensity on SWB.

3.6 Discussion and Conclusion

Measuring the extent to which EP impacts on households or individuals helps policymakers to develop strategies to improve the welfare of energy poor people. Our analysis has shown that multidimensional EP measures can be used to subsume the explanatory power of subjective and objective indicators used previously in economic analyses. This turns out to be useful in identifying the energy poor as well as improving the analysis of the effect of EP on household and individual welfare.

In particular, we have defined our MEPI as a combination of subjective and objective deprivations referred to inadequacies of dwellings. We found that, when assessing the EP in a deprivation framework, the condition of being energy poor is not only more common than when evaluated in a mere affordability framework, but also still occurring for high income percentiles, though, as expected, the severity decreases when income increases. Moreover, the degree of overlapping with affordability indicators is generally low.

Our MEPI has been subsequently exploited to model the welfare losses due to EP in an SWB framework. We have shown that the ordinal nature of both SWB indicators and MEPI measures can be adequately modeled employing a bivariate ordered probit model, where endogeneity due to unobserved factors related to the (common) subjective nature of well-being and EP indicators has been tackled by means of theoretically reasonable and statistically valid exclusion restrictions. Our results detected relevant negative effects of EP on individual utility that appear robust to changes in the sample considered or the way single deprivations are included in the MEPI. Looking at specific characteristics, the retirees broadly follow the sample average effects, richer than their reference group are less sensitive to EP for the lowest level of SWB. Contrarily, unemployed people are less sensitive for the highest level of satisfaction. Likewise, people in very bad health seems to become less sensitive to EP while increasing their satisfaction, even at the highest significant level of EP severity. This apparently couterintuitive pattern could be related to the fact that the health status is a primary determinant of low SWB. The relative weight is somehow displayed by comparing the effect of intermediate intensity of EP to the effect of having very bad health, which is extremely stronger. However, the intermediate intensity of EP is found to cause changes in the probability of being in a given level of stated life satisfaction comparable to those associated with the unemployment status.

We believe that improving analyses based on subjective perception is of particular relevance when dealing with developed countries, in which the basic material needs are usually ensured. Concerning the planning of policies supporting energy poor people, the aforementioned findings first point to the importance of the method adopted to identify energy poor households to avoid the exclusion of an important share of vulnerable individuals not detected by affordability measures. It is an open question whether collecting information on buildings' energy efficiency and individuals' subjective evaluation would represent a manageable task for public bodies in terms of monetary costs and privacy issues.

Second, although recognizing that the use of an SWB approach may represent an important tool for detecting social and economic hardship and avoiding the exclusion of frail individuals, some doubts might be cast on a plain reliance on mere subjective welfare indicators. For very high levels of stated life satisfaction, we have found evidence of decreasing sensitivity to high severity of EP, despite the actual occurrence of energy poor conditions in dwellings, which represent an *objective* potentially harmful situation that could negatively impact on the health and economic productivity of the household. Coupled with the empirical evidence of the presence of EP independently of the household's wealth, this may, in principle, legitimate public intervention to implement policies for promoting responsible behavior both in terms of energy consumption and care of dwellings even though self-assessments do not consider it a real problem.

Bibliography

Alessie, Rob, Lusardi, Annamaria, and Aldershof, Trea (1997). "Income and wealth over the life cycle evidence from panel data". *Review of Income and Wealth* 43.1, 1–32.

Alkire, S. and Foster, J. (2011). "Counting and multidimensional poverty measurement". *Journal of Public Economics* 95.7-8, 476–487.

Allin, Sara, Masseria, Cristina, and Mossialos, Elias (2009). "Measuring socioeconomic differences in use of health care services by wealth versus by income". *American journal of public health* 99.10, 1849–1855.

Angelini, V., Brugiavini, A., and Weber, G. (2009). "Ageing and unused capacity in Europe: is there an early retirement trap?" *Economic Policy* 24.59, 463–508.

Apouey, B. H., Guven, C., and Senik, C. (2017). "Retirement and Unexpected Health Shocks".

Atalay, K., Barrett, G. F, and Staneva, A. (2019). "The effect of retirement on elderly cognitive functioning". *Journal of health economics* 66, 37–53.

Atanasiu, B., Kontonasiou, E., and Mariottini, F. (2014). "Alleviating fuel poverty in the EU. Investing in home renovation, a sustainable and inclusive solution". *Buildings Performance Institute Europe (BPIE), Brussels.*

Atchley, Robert C (1982). "Retirement as a social institution". *Annual review of sociology* 8.1, 263–287.

Atkinson, A. B. (2003). "Multidimensional deprivation: contrasting social welfare and counting approaches". *Journal of Economic Inequality* 1.1, 51–65.

Auerbach, A.J. and Lee, R. (2011). "Welfare and generational equity in sustainable unfunded pension systems". *Journal of public economics* 95.1-2, 16–27.

Balia, S. and Jones, A. M. (2008). “Mortality, lifestyle and socio-economic status”. *Journal of health economics* 27.1, 1–26.

Banks, James, Bassoli, Elena, and Mammi, Irene (2019). “Changing attitudes to risk at older ages: The role of health and other life events”. *Journal of Economic Psychology*, 102208.

Barnay, T. and Defebvre, É. (2018). “Retired, at last? The short-term impact of retirement on health status in France”.

Battistin, E. et al. (2009). “The retirement consumption puzzle: evidence from a regression discontinuity approach”. *American Economic Review* 99.5, 2209–26.

Behncke, S. (2012). “Does retirement trigger ill health?” *Health economics* 21.3, 282–300.

Bellani, L. and D’Ambrosio, C. (2011). “Deprivation, Social Exclusion and Subjective Well-Being”. *Social Indicators Research* 104.1, 67–86.

Belloni, M., Meschi, E., and Pasini, G. (2016). “The effect on mental health of retiring during the economic crisis”. *Health economics* 25, 126–140.

Bertoni, M. (2015). “Hungry today, unhappy tomorrow? Childhood hunger and subjective wellbeing later in life”. *Journal of health economics* 40, 40–53.

Bertoni, M., Brunello, G., and Mazzarella, G. (2018). “Does postponing minimum retirement age improve healthy behaviors before retirement? Evidence from middle-aged Italian workers”. *Journal of health economics* 58, 215–227.

Bertoni, M., Maggi, S., and Weber, G. (2018). “Work, retirement, and muscle strength loss in old age”. *Health economics* 27.1, 115–128.

Biermann, P. (2016). *How fuel poverty affects subjective well-being: Panel evidence from Germany*. eng. Oldenburg Discussion Papers in Economics V-395-16. Oldenburg.

Bingley, P. and Martinello, A. (2013). “Mental retirement and schooling”. *European Economic Review* 63, 292–298.

Blanchflower, D. G. and Oswald, A. J. (2004). “Well-being over time in Britain and the USA”. *Journal of Public Economics* 88.7-8, 1359–1386.

Blazer, D. G. (2002). “Epidemiology of depression: prevalence and incidence”. *Principles and practice of geriatric psychiatry*, 389–392.

Boardman, B. (1991). *Fuel poverty: from cold homes to affordable warmth*. Pinter Pub Limited.

Bonsang, E., Adam, S., and Perelman, S. (2012). "Does retirement affect cognitive functioning?" *Journal of health economics* 31.3, 490–501.

Bonsang, E. and Klein, T. J. (2012). "Retirement and subjective well-being". *Journal of Economic Behavior & Organization* 83.3, 311–329.

Börsch-Supan, A., Brandt, M., et al. (2013). "Data resource profile: the Survey of Health, Ageing and Retirement in Europe (SHARE)". *International journal of epidemiology* 42.4, 992–1001.

Börsch-Supan, A. and Jürges, H. (2006). *Early retirement, social security and well-being in Germany*. Tech. rep. National Bureau of Economic Research.

Bound, J. et al. (1999). "The dynamic effects of health on the labor force transitions of older workers". *Labour Economics* 6.2, 179–202.

Bourguignon, F. and Chakravarty, S. R. (2003). "The measurement of multidimensional poverty". *The Journal of Economic Inequality* 1.1, 25–49.

Brickman, P. and Campbell, D. (1971). "1971. Hedonic Relativism and Planning the Good Society". *Adaptation Level Theory: A Symposium (Academic Press, New York)*.

Brunello, G. et al. (2016). "The causal effect of education on health: What is the role of health behaviors?" *Health economics* 25.3, 314–336.

Bünnings, C. and Tauchmann, H. (2015). "Who opts out of the statutory health insurance? A discrete time hazard model for Germany". *Health economics* 24.10, 1331–1347.

Calhoun, C. A. (1989). "BIVOPROB : A Computer Program for Maximum-Likelihood Estimation of Bivariate Ordered-Probit Models for Censored Data". *IIASA Working Paper* June.

Card, D. et al. (2012). "Inequality at work: The effect of peer salaries on job satisfaction". *American Economic Review* 102.6, 2981–3003.

Cawley, J., Heckman, J., and Vytlacil, E. (2001). "Three observations on wages and measured cognitive ability". *Labour economics* 8.4, 419–442.

Celidoni, M., Dal Bianco, C., and Weber, G. (2017). "Retirement and cognitive decline. A longitudinal analysis using SHARE data". *Journal of health economics* 56, 113–125.

Celidoni, M. and Rebba, V. (2017). “Healthier lifestyles after retirement in Europe? Evidence from SHARE”. *The European Journal of Health Economics* 18.7, 805–830.

Charlier, D. and Legendre, B. (2019). “A Multidimensional Approach to Measuring Fuel Poverty.” *The Energy Journal* 40.2, 27–53.

Clark, A. E., D’Ambrosio, C., and Ghislandi, S. (2016). “Adaptation to poverty in long-run panel data”. *Review of Economics and Statistics* 98.3, 591–600.

Clark, A. E., Diener, E., et al. (2008). “Lags and leads in life satisfaction: A test of the baseline hypothesis”. *The Economic Journal* 118.529, F222–F243.

Clark, A. E., Etilé, F., et al. (2005). “Heterogeneity in reported well-being: evidence from twelve European countries”. *The Economic Journal* 115.502, C118–C132.

Clark, A. E., Frijters, P., and Shields, M. A. (2008a). “Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles”. *Journal of Economic Literature* 46.1, 95–144.

– (2008b). “Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles”. *Journal of Economic literature* 46.1, 95–144.

Clark, A. E. and Georgellis, Y. (2013). “Back to baseline in Britain: adaptation in the British household panel survey”. *Economica* 80.319, 496–512.

Clark, A. E., Knabe, A., and Rätzel, S. (2010). “Boon or bane? Others’ unemployment, well-being and job insecurity”. *Labour Economics* 17.1, 52–61.

Clark, A. E. and Oswald, A. J. (1994). “Unhappiness and unemployment”. *The Economic Journal* 104.424, 648–659.

Coe, N.B., Gaudecker, HM. von, et al. (2012). “The effect of retirement on cognitive functioning”. *Health economics* 21.8, 913–927.

Coe, N.B. and Lindeboom, M. (2008). “Does Retirement Kill You? Evidence from Early Retirement Windows”. *CentER Discussion Paper* 93.

Coe, N.B. and Zamarro, G. (2011). “Retirement effects on health in Europe”. *Journal of health economics* 30.1, 77–86.

Cottini, E. and Ghinetti, P. (2017). "Is it the way you live or the job you have? Health effects of lifestyles and working conditions". *The BE Journal of Economic Analysis & Policy* 17.3.

Cottini, E. and Lucifora, C. (2013). "Mental health and working conditions in Europe". *ILR Review* 66.4, 958–988.

Cubı-Mollá, P., Jofre-Bonet, M., and Serra-Sastre, V. (2017). "Adaptation to health states: Sick yet better off?" *Health economics* 26.12, 1826–1843.

Dave, D., Rashad, I., and Spasojevic, J. (2008). "The effects of retirement on physical and mental health outcomes". *Southern Economic Journal* 75.2, 497–524.

Decancq, K., Fleurbaey, M., and Schokkaert, E. (2015). "Happiness, Equivalent Incomes and Respect for Individual Preferences". *Economica* 82, 1082–1106.

Deci, E. L and Ryan, R. M. (2008). "Hedonia, eudaimonia, and well-being: An introduction". *Journal of happiness studies* 9.1, 1–11.

Deller, D. and Waddams Price, C. (2018). "UKERC-funded Project:Energy Affordability and Old Age: Expenditure versus self-reported perceptions". *CCP Research Bullettin* 35, 14.

Di Tella, R., MacCulloch, R. J., and Oswald, A. J. (2001). "Preferences over inflation and unemployment: Evidence from surveys of happiness". *American economic review* 91.1, 335–341.

– (2003). "The macroeconomics of happiness". *Review of Economics and Statistics* 85.4, 809–827.

Diener, E., Lucas, R. E, and Scollon, C. N. (2009). "Beyond the hedonic treadmill: Revising the adaptation theory of well-being". *The science of well-being*. Springer, pp. 103–118.

Dippel, C. et al. (2019). "Mediation Analysis in IV Settings With a Single Instrument".

Disney, R., Emmerson, C., and Wakefield, M. (2006). "Ill health and retirement in Britain: A panel data-based analysis". *Journal of health economics* 25.4, 621–649.

Dolan, P., Peasgood, T., and White, M. (2008). "Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being". *Journal of economic psychology* 29.1, 94–122.

DuGoff, E. H. et al. (2014). "Multiple chronic conditions and life expectancy: a life table analysis". *Medical care* 52.8, 688–694.

Easterlin, R. A. (1974). "Does economic growth improve the human lot? Some empirical evidence". *Nations and households in economic growth*. Elsevier, pp. 89–125.

Eibich, P. (2015). "Understanding the effect of retirement on health: Mechanisms and heterogeneity". *Journal of health economics* 43, 1–12.

Espinosa, J. and Evans, W. N. (2008). "Heightened mortality after the death of a spouse: Marriage protection or marriage selection?" *Journal of health economics* 27.5, 1326–1342.

Fabbri, K. (2015). "Building and fuel poverty, an index to measure fuel poverty: An Italian case study". *Energy* 89, 244–258.

Faiella, I. and Lavecchia, L. (2015). "La povertà energetica in Italia energy poverty in Italy". *Politica Economica* 31.1, 27–76.

Farrell, L., Fry, T. R. L., and Risse, L. (2016). "The significance of financial self-efficacy in explaining women's personal finance behaviour". *Journal of Economic Psychology* 54, 85–99.

Fastame, Maria Chiara, Penna, Maria Pietronilla, and Hitchcott, Paul Kenneth (2015). "Life satisfaction and social desirability across the late life span: What relationship?" *Quality of Life Research* 24.1, 241–244.

Ferrer-i-Carbonell, A. (2005). "Income and well-being: An empirical analysis of the comparison income effect". *Journal of Public Economics* 89.5-6, 997–1019.

– (2013). "Happiness economics". *SERIEs* 4.1, 35–60.

Ferrer-i-Carbonell, A. and Frijters, P. (2004). "How important is methodology for the estimates of the determinants of happiness?" *The Economic Journal* 114.497, 641–659.

Ferrer-i-Carbonell, A. and Praag, B. M. S. van (2002). "The subjective costs of health losses due to chronic diseases. An alternative model for monetary appraisal". *Health Economics* 11.8, 709–722.

FitzRoy, F. R. and Nolan, Michael A. (2018). "Education, income and happiness: panel evidence for the UK". *Empirical Economics*, 1–20.

Fonseca, R., Kapteyn, A., Lee, J., et al. (2014). "A longitudinal study of well-being of older Europeans: does retirement matter?" *Journal of population ageing* 7.1, 21–41.

Fonseca, R., Kapteyn, A., and Zamarro, G. (2017). "Retirement and Cognitive Functioning: International Evidence". *Financial Decision Making and Retirement Security in an Aging World*, 46.

Frey, B. S. and Stutzer, A. (2002). "What can economists learn from happiness research?" *Journal of Economic literature* 40.2, 402–435.

Frijters, P. and Beatton, T. (2012). "The mystery of the U-shaped relationship between happiness and age". *Journal of Economic Behavior & Organization* 82.2-3, 525–542.

Frölich, M. and Huber, M. (2017). "Direct and indirect treatment effects–causal chains and mediation analysis with instrumental variables". *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 79.5, 1645–1666.

Giustinelli, P. and Shapiro, M. D. (2019). *SeaTE: Subjective ex ante Treatment Effect of Health on Retirement*. Tech. rep. National Bureau of Economic Research.

Gorry, A., Gorry, D., and Slavov, S. N. (2018). "Does retirement improve health and life satisfaction?" *Health economics* 27.12, 2067–2086.

Greene, W. H. and Hensher, D. A. (2010). *Modeling ordered choices: A primer*. Cambridge University Press.

Greenwald, Herbert J and Satow, Yoichi (1970). "A short social desirability scale". *Psychological Reports* 27.1, 131–135.

Groot, W. (2000). "Adaptation and scale of reference bias in self-assessments of quality of life". *Journal of health economics* 19.3, 403–420.

Grossman, M. (1972). "On the concept of health capital and the demand for health". *Journal of Political economy* 80.2, 223–255.

Gruber, J. and Wise, D. (1998). "Social security and retirement: An international comparison". *The American Economic Review* 88.2, 158–163.

Healy, J. D. (2003). *Fuel Poverty and Policy in Ireland Studies in Public Policy*.

Healy, J. D. and Clinch, J. P. (2004). "Quantifying the severity of fuel poverty, its relationship with poor housing and reasons for non-investment in energy-saving measures in Ireland". *Energy Policy* 32.2, 207–220.

Hills, J. (2011). “Fuel poverty: the problem and its measurement”.

– (2012). “Getting the measure of fuel poverty: Final Report of the Fuel Poverty Review”.

Horner, E. M. (2014). “Subjective well-being and retirement: analysis and policy recommendations”. *Journal of Happiness Studies* 15.1, 125–144.

Hyde, M. et al. (2003). “A measure of quality of life in early old age: the theory, development and properties of a needs satisfaction model (CASP-19)”. *Aging & mental health* 7.3, 186–194.

Jones, A. M., Rice, N., and Roberts, J. (2010). “Sick of work or too sick to work? Evidence on self-reported health shocks and early retirement from the BHPS”. *Economic Modelling* 27.4, 866–880.

Kalb, G. and Van Ours, J. C. (2014). “Reading to young children: A head-start in life?” *Economics of Education Review* 40, 1–24.

Kapteyn, A., Smith, J. P., and Soest, A. van (2007). “Vignettes and self-reports of work disability in the United States and the Netherlands”. *American Economic Review* 97.1, 461–473.

Kesavayuth, D., Rosenman, R. E., and Zikos, V. (2018). “Retirement and health behaviour”. *Applied Economics* 50.54, 5859–5876.

Kesavayuth, D., Rosenman, R. E., Zikos, V., et al. (2016). “The dynamic effects of retirement on well-being.” *Working Paper Series-School of Economic Sciences, Washington State University* 2016-15.

Kozma, Albert and Stones, MJ (1988). “Social desirability in measures of subjective well-being: Age comparisons”. *Social Indicators Research* 20.1, 1–14.

Kuhn, P. et al. (2011). “The effects of lottery prizes on winners and their neighbors: Evidence from the Dutch postcode lottery”. *American Economic Review* 101.5, 2226–47.

Larraga, L. et al. (2006). “Validation of the Spanish version of the EURO-D scale: an instrument for detecting depression in older people”. *International Journal of Geriatric Psychiatry: A journal of the psychiatry of late life and allied sciences* 21.12, 1199–1205.

Lawson, R., Williams, J., and Wooliscroft, B. (2015). “Contrasting approaches to fuel poverty in New Zealand”. *Energy Policy* 81, 38–42.

Layard, R. and Sachs, J. (2017). *World Happiness Report 2017*.

Lazear, E. P. (1986). “Retirement from the labor force”. *Handbook of labor economics* 1, 305–355.

Legendre, B. and Ricci, O. (2015). “Measuring fuel poverty in France: Which households are the most fuel vulnerable?” *Energy Economics* 49, 620–628.

Leimer, B. (2017). “No’Honeymoon Phase’-Whose Health Benefits from Retirement and When”. *Gutenberg School of Management and Economics & Research Unit “Interdisciplinary Public Policy” Discussion Paper Series* 1718.

Lucifora, C. and Vigani, D. (2018). “Health care utilization at retirement: The role of the opportunity cost of time”. *Health economics* 27.12, 2030–2050.

Luechinger, S. (2009a). “Valuing air quality using the life satisfaction approach”. *The Economic Journal* 119.536, 482–515.

– (2009b). “Valuing air quality using the life satisfaction approach”. *Economic Journal* 119.536, 482–515.

MacKinnon, D. (2012). *Introduction to statistical mediation analysis*. Routledge.

Mazzonna, F. and Peracchi, F. (2012). “Ageing, cognitive abilities and retirement”. *European Economic Review* 56.4, 691–710.

– (2017). “Unhealthy retirement?” *Journal of Human Resources* 52.1, 128–151.

McMahan, E. A and Estes, D. (2011). “Hedonic versus eudaimonic conceptions of well-being: Evidence of differential associations with self-reported well-being”. *Social Indicators Research* 103.1, 93–108.

Miniaci, R., Scarpa, C., and Valbonesi, P. (Dec. 2014). “Energy affordability and the benefits system in Italy”. *Energy Policy* 75, 289–300.

Moellendorff, C. von and Welsch, H. (2017). “Measuring Renewable Energy Externalities: Evidence from Subjective Well-being Data”. *Land Economics* 93.1, 109–126.

Moore, R. (2012). “Definitions of fuel poverty: Implications for policy”. *Energy Policy* 49, 19–26.

Motegi, H., Nishimura, Y., and Oikawa, M. (2017). “Retirement and Cognitive Decline: Evidence from Global Aging Data”.

Nussbaumer, P., Bazilian, M., and Modi, V. (2012). “Measuring energy poverty: Focusing on what matters”. *Renewable and Sustainable Energy Reviews* 16.1, 231–243.

Nussbaumer, P., Nerini, F. F., et al. (2013). "Global insights based on the multidimensional energy poverty index (MEPI)". *Sustainability* 5.5, 2060–2076.

OECD (2005). "Pensions at a glance 2005: public policies across OECD countries". *OECD Publishing.*

– (2007). "Pensions at a Glance 2007: Public policies across OECD countries". *OECD Publishing.*

– (2009). "Pensions at a Glance 2009:Retirement-Income Systems in OECD Countries." *OECD Publishing.*

– (2013). "Pensions at a Glance 2013. OECD and G20 Indicators". *OECD Publishing.*

– (2016). "Pensions at a Glance 2015: OECD and G20 Indicators". *OECD Publishing.*

– (2017a). *How's Life?2017:Measuring Well-being.* OECD Publishing, p. 340.

– (2017b). "Pensions at a Glance 2017. OECD and G20 Indicators". *OECD Publishing.*

OECD/EU (2016). *Health at a Glance: Europe 2016: State of Health in the EU Cycle.*

Okushima, S. (2017). "Gauging energy poverty: A multidimensional approach". *Energy* 137, 1159–1166.

Oswald, A. J. and Powdthavee, N. (2008). "Does happiness adapt? A longitudinal study of disability with implications for economists and judges". *Journal of public economics* 92.5-6, 1061–1077.

Oswald, A. J., Proto, E., and Sgroi, D. (2015). "Happiness and productivity". *Journal of Labor Economics* 33.4, 789–822.

Papada, L. and Kaliampakos, D. (2016). "Measuring energy poverty in Greece". *Energy Policy* 94, 157–165.

Powdthavee, N. (2009). "Ill-health as a household norm: Evidence from other people's health problems". *Social Science & Medicine* 68.2, 251–259.

Prince, M. J. et al. (1999). "Development of the EURO–D scale–a European Union initiative to compare symptoms of depression in 14 European centres". *The British Journal of Psychiatry* 174.4, 330–338.

Qari, S. (2014). "Marriage, adaptation and happiness: Are there long-lasting gains to marriage?" *Journal of Behavioral and Experimental Economics* 50, 29–39.

Rehdanz, K. et al. (2015). “Well-being effects of a major natural disaster: The case of Fukushima”. *Journal of Economic Behavior and Organization* 116, 500–517.

Roberts, J., Rice, N., and Jones, A. M. (2010). “Early retirement among men in Britain and Germany: How important is health?” *The Geneva Papers on Risk and Insurance-Issues and Practice* 35.4, 644–667.

Robone, S., Jones, A. M., and Rice, N. (2011). “Contractual conditions, working conditions and their impact on health and well-being”. *The European Journal of Health Economics* 12.5, 429–444.

Rohwedder, S. and Willis, R. J. (2010). “Mental retirement”. *Journal of Economic Perspectives* 24.1, 119–38.

Sadath, Anver C and Acharya, Rajesh H (2017). “Assessing the extent and intensity of energy poverty using Multidimensional Energy Poverty Index: Empirical evidence from households in India”. *Energy Policy* 102, 540–550.

Sajaia, Z. (2008). “Maximum likelihood estimation of a bivariate ordered probit model: Implementation and Montecarlo simulations”. *Stata Journal* 4.ii, 1–18.

Salthouse, T. A. (2006). “Mental Exercise and Mental Aging: Evaluating the Validity of the “Use It or Lose It” Hypothesis”. *Perspectives on Psychological Science* 1.1, 68–87.

Santos, M. E. and Alkire, S. (2011). “Training material for producing national human development reports: The Multidimensional Poverty Index (MPI)”. *MPI: Construction and analysis. Oxford: Oxford Poverty and Human Development Initiative.*

Schaap, R. et al. (2018). “The effects of exit from work on health across different socioeconomic groups: A systematic literature review”. *Social Science & Medicine* 198, 36–45.

Social Protection (MISSOC), Mutual Information System on (January 1, 2018 version). *Database of the European Commission: Directorate-General for Employment, Social Affairs and Equal Opportunities*. Comparative tables Retirement Ages conditions.

Staubli, S. and Zweimüller, J. (2013). “Does raising the early retirement age increase employment of older workers?” *Journal of public economics* 108, 17–32.

Steptoe, A., Deaton, A., and Stone, A. A. (2015). “Subjective wellbeing, health, and ageing”. *The Lancet* 385.9968, 640–648.

Thomson, H. and Snell, C. (2013). “Quantifying the prevalence of fuel poverty across the European Union”. *Energy Policy* 52, 563–572.

Tubeuf, S., Jusot, F., and Bricard, D. (2012). “Mediating Role of Education and Lifestyles in the Relationship Between Early-Life Conditions and Health: Evidence from the 1958 British Cohort”. *Health economics* 21, 129–150.

Van Ourti, Tom (2003). “Socio-economic inequality in ill-health amongst the elderly: should one use current or permanent income?” *Journal of Health Economics* 22.2, 219–241.

Van Praag, B. M. S., Ferrer-i-Carbonell, A., et al. (2004). *Happiness quantified: A satisfaction calculus approach*. Oxford University Press.

– (2011). “Happiness economics: A new road to measuring and comparing happiness”. *Foundations and Trends® in Microeconomics* 6.1, 1–97.

Waddams Price, C., Brazier, K., and Wang, W. (2012). “Objective and subjective measures of fuel poverty”. *Energy Policy* 49, 33–39.

Welsch, H. and Biermann, P. (2014a). “Electricity supply preferences in Europe: Evidence from subjective well-being data”. *Resource and Energy Economics* 38, 38–60.

– (2014b). “Fukushima and the preference for nuclear power in Europe: Evidence from subjective well-being data”. *Ecological Economics* 108, 171–179.

– (2016). “Measuring nuclear power plant externalities using life satisfaction data: A spatial analysis for Switzerland”. *Ecological Economics* 126, 98–111.

– (2017). “Energy affordability and subjective well-being: Evidence for European Countries”. *The Energy Journal* 38.3, 159–176.

Zantinge, E. M. et al. (2013). “Retirement and a healthy lifestyle: opportunity or pitfall? A narrative review of the literature”. *The European Journal of Public Health* 24.3, 433–439.

Zhu, R. and He, X. (2015). “How does women’s life satisfaction respond to retirement? A two-stage analysis”. *Economics Letters* 137, 118–122.

Ziebarth, N. R. and Grabka, M. M. (2009). "In vino pecunia? The association between beverage-specific drinking behavior and wages". *Journal of Labor Research* 30.3, 219–244.

Appendices

A

Retirement Rules

Overall, the SRA and the ERA have been reconstructed by means of Angelini, Brugiavini, and Weber (2009), OECD reports (Pensions at Glance 2005, 2007, 2011, 2014, 2015), MISSOC Tables (Update January 2018) and country-specific social security systems.

Austria

- **Statutory Retirement Age** is fixed at 65 for men and 60 for women, as long the individual has 15 insurance years in the last 30 years or 15 years of contribution (AlterPension). (Staubli and Zweimüller, 2013; PensionsVersicherungsanstalt, updated on February 2018)
- **Early Retirement Ages** are regulated by different retirement schemes. One of them is the "Vorzeitige Alterspension wegen langer Versicherungsdauer", and it concerns early retirement due to long contributions. This pension fixed at 60 for men and 55 for women until the 31st September 2000. Then, it has been reformed in 2000 and in 2003. Specifically, for men born from the fourth quarter in 1940 until the second quarter in 1942, ERA increased by 2 months for every birth quarter (2000-reform) and it was followed by an increase of 1 month for each quarter until the last quarter of 1952 cohort (2003-reform). The same increase was applied for women born between 1945 and 1948 during the 2000-reform, and, until the 1957 cohort during the 2003-reform (See Staubli and Zweimüller, 2013 for details on this reforms). However, other pensions exist. In 2000-reform they also introduced a new pension, named "Langzeitversicherungspension" long insurance pension. This ERA starts from 60 and 55 respectively for men and women who reach 45 and 40 years of contributions until they reach 62 for both of them, according to birth cohort. It can be seen as an exception of the reforms. Nevertheless, Austrian government provides for other two type of pension. One dedicated to heavy jobs and and other one, Korridorpension. Since we do not have enough information to

model these last two, we only pick the Vorzeitige Alterspension before and after the reforms and its exceptions.

Belgium

- **Statutory Retirement Ages** from 1961 to 1998 were fixed at 65 for men and 60 for women, and, for men it has actually never changed. Instead, women age have increased until reaching 65 since 2009. The increases were 61 until 2001; 62 until 2003; 63 until 2005, 64 until 2009. (Social Protection (MISSOC), January 1, 2018 version;OECD, 2005, 2007, 2009, 2013, 2016, 2017b)
- **Early Retirement Ages** were introduced in 1966. Then, ERA are set to 60 for men and 55 for women until 1986; 60 for both after 1986 until 1997, without any contribution constraints. From 1998 until 2012, it is fixed at 60 with 35 years of contribution. Since then, it has been gradually increased both the age and the years of contribution[29] to 62. (Angelini, Brugiavini, and Weber, 2009 + the other references)

Denmark

- **Statutory Retirement Age** was fixed at 67 before 2003. From 2004, it is set to 65.
- **Early Retirement Age** was not provide until 1976. Indeed, from 1976 to 1978, it was 60 for both men and women. Then, it became 60 with 30 years of contributions until 2007. For individuals born after 1954 the ERA increases by 6 months for each 6-month cohort, until it reaches 62.5 for whom is born before the 30th of June 1965. Moreover, it increases to 63 years for individuals born between July 1956 and December 1958; to 63.5 for individuals born in the first semester of 1959 and to 64 for those born after July 1959. (Social Protection (MISSOC), January 1, 2018 version OECD(2005, 2007, 2011, 2013, 2015); Social Security Program-SSA.gov)

[29] The years of contribution vary between 32-36 years depending on the birth cohorts.

France

- **Statutory Retirement Age** was 65 years old until 1994. Then, from 1995 to 2012, it was 60. Since 2012, it has started a gradual increase.
- **Early retirement Ages** are linked to long careers and heavy jobs. Before 1994, it was 60 for every individuals. Then, it becomes 56. For individuals who worked in heavy sectors(transport and energy) is set to 55 years old. (Social Protection (MISSOC), January 1, 2018 version; Angelini, Brugiavini, and Weber, 2009; Leimer, 2017)

Germany

- **Statutory Retirement Age** was fixed at 65 until 2007. From 2008 it is 67.
- **Early retirement Ages** was not feasible for men until 1973 while it was 60 with 15 years of contributions for women. Then, from 1973 to 2007, 63 with 35 years of contributions for men and 60 with 15 years of contributions for women. Now, ERA are 63 for men and 60 for women with 35 years of contribution. (Börsch-Supan, Brandt, Hunkler, Kneip, Korbmacher, Malter, Schaan, Stuck, and Zuber, 2013 Social Protection (MISSOC), January 1, 2018 version; Angelini, Brugiavini, and Weber, 2009)

Spain

- **Statutory Retirement Age** was fixed at 65 until 2011, and from 2012 it was added the contribution constraint of 38.6. Otherwise, it is 67.
- **Early Retirement Age** is considered only for voluntary retirement. Before 2011, it was 60. Between 2011 and 2013, it was set to 61. At the moment, it is possible with 36 years of contribution from 2 years before the NRA. (Social Protection (MISSOC), January 1, 2018 version; Angelini, Brugiavini, and Weber, 2009; Seguridad Social Española)

Sweden

- **Statutory Retirement Age** was 67 from 1961 to 1994. Then, it decreased to 65, both for men and women.
- **Early Retirement Age** was 60 both for men and women until 1997; from 1998 to 2007, 61 both for men and women.Social Protection (MISSOC), January 1, 2018 version; OECD; Angelini, Brugiavini, and Weber, 2009)

The Netherlands

- **Statutory Retirement Age** was 65 years both for men and women until 2013. It has started increasing by 1 months each year.
- **Early Retirement Age** is 60 for people born before 1950. In the period between 1975 and 1995 was 60 with minimum 10 years of contribution. Then, it has been set to 62 with at least 35 years of contribution.

Switzerland

- **Statutory Retirement Ages** were until 1974 65 and 63 respectively for men and women. For men, it never changed. For women, it shrinks at 62 between 1974 and 2003, then it increased again to 63 in 2004 and 64 from 2005.
- **Early Retirement Ages** did not exist before 1990. Then, for men, were fixed at 62 until 2006 and to 63 from 2007. For women, it was 59 until 1997; 60 until 2004; 61 until 2006 and 62 since 2007.

Italy

- **Statutory Retirement Ages** have been changing quite often since 1961. The differences are based on job sector(public or private), gender and type of job (employees or self-employed). From 1961 to 1993, NRA were for men working in private (public) 60 (65) and 55 (60) for women; in 1994, 61 for men and 56 for women; in 1995, 61.5 for men and 56.5 for women; in

1996, 62 for men and 57 for women; in 1997, 63 for men and 58 for women; in 1998, 63.5 for men and 58.5 for women; in 1999, 64 for men and 59 for women; from 2000 to 2007, 65 for men and 60 for women (both private and public sector); in 2012, 66 for men with at least 20 years of contribution, both for employees and self-employed; 62 for women employees, 63.5 for self-employed and 66 for both man and women in public sector; from 2013, all the previous ages for 2012 have been increased by 3 months. (INPS; Angelini et al. 2009; Brugiavini et al; Belloni et al.)

- **Early Retirement Ages** have been provide since 1965. Until 1995, 35 years of contributions (25 in the public sector) both for men and women, without age constraints; from 1996 to 1997 in the private and public sector 52 with 35 years of contribution (or 36 years of contribution independently of age), for self-employed 56 with 35 years of contribution both for men and women; in 1998 the age is 53 for the public sector, 54 for the private sector and 57 for self-employed; in 1999 the age is 53 for the public sector, 55 for the private sector and 57 for self-employed; in 2000, 54 for the public sector, 55 for the private sector, 57 for self-employed; in 2001, 55 for the public sector, 56 for the private sector, 58 for self-employed; in 2002, 55 for the public sector, 57 for the private sector, 58 for self-employed; in 2003, 56 for the public sector, 57 for the private sector, 58 for self-employed; from 2004 to 2007, 57 for both the private and public sector, 58 for self-employed; from 2008 to 2009, 58 (59) for employees (self-employed) with 35 years of contribution; in 2010, 59 (60) for employees (self-employed) with 36 years of contribution; in 2011, 60 (61) for employees (self-employed) with 35 years of contribution. Moreover, since 2008, with 40 years of contribution, there is no age constraint. In 2012, the years of contribution are 42.1 (41.1) for men (women) and is increasing every year (+4 months in 2013, +1 month from 2014 to 2016) [Angelini, Brugiavini, and Weber, 2009; INPS]

Table A1 – Estimation results: Mediating Model

	(1) No Activities	(2) BMI	(3) Smoker	(4) Ex-Smoker	(5) Alcohol Abuse
Retired	-0.0755***	0.0033	0.0059	-0.0273	0.0758***
	(0.019)	(0.027)	(0.030)	(0.029)	(0.029)
TimeR	0.0059***	-0.0051*	0.0028	-0.0019	-0.0092***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.1163***	-0.0124	-0.1661***	0.1548***	-0.0018
	(0.043)	(0.052)	(0.056)	(0.054)	(0.060)
Log-Income	-0.0013	-0.0012	0.0025	-0.0019	0.0041**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Married	0.0303**	0.0345**	-0.0013	0.0037	0.0048
	(0.014)	(0.017)	(0.017)	(0.016)	(0.017)
Live Alone	0.0205**	-0.0021	0.0281**	-0.0218**	0.0097
	(0.009)	(0.011)	(0.011)	(0.011)	(0.010)
N.Children	0.0002	0.0013	0.0012	0.0019	0.0031
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
N.Grandchildren	-0.0033**	0.0006	-0.0016	0.0018	-0.0007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Interview date	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.2049	0.3099	0.1419	0.0191	0.8076
Individuals	11167	11167	11167	11167	11167
Obs.	30048	30048	30048	30048	30048

Notes: Interview date includes month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2 – Estimation results: First Stage of Health Equations

	DE Models		TE Models	
	Retired	TimeR	Retired	TimeR
Above ERA	0.1082***	-1.5831***	0.1081***	-1.5898***
	(0.009)	(0.052)	(0.009)	(0.051)
Above SRA	0.1913***	0.7084***	0.1914***	0.7058***
	(0.009)	(0.054)	(0.009)	(0.053)
Distance ERA	-0.0037*	-0.1246***	-0.0036**	-0.1247***
	(0.002)	(0.015)	(0.002)	(0.015)
Distance SRA	-0.0008	0.5594***	-0.0011	0.5642***
	(0.005)	(0.032)	(0.005)	(0.032)
Age	0.0000	0.4134	0.0008	0.4124
	(0.059)	(0.379)	(0.060)	(0.372)
Log-Income	0.0024	-0.0318***	0.0024	-0.0329***
	(0.001)	(0.010)	(0.001)	(0.010)
Married	-0.0129	-0.6972***	-0.0124	-0.6964***
	(0.018)	(0.132)	(0.018)	(0.131)
Live Alone	-0.0332***	-0.3549***	-0.0332***	-0.3509***
	(0.012)	(0.090)	(0.012)	(0.091)
Children	-0.0058	0.0451	-0.0057	0.0435
	(0.004)	(0.028)	(0.004)	(0.027)
Grandchildren	0.0032	-0.0788***	0.0032	-0.0801***
	(0.002)	(0.015)	(0.002)	(0.016)
No Activities	0.0022	0.2160***		
	(0.010)	(0.066)		
BMI	0.0083	-0.0325		
	(0.009)	(0.057)		
Smoker	0.0095	-0.2850		
	(0.028)	(0.199)		
Ex-Smoker	0.0124	-0.4655**		
	(0.029)	(0.210)		
Abuse Alcohol	0.0023	-0.2179***		
	(0.008)	(0.046)		
Resid No Activities			0.2106***	-0.2569**
			(0.017)	(0.102)
Resid BMI			0.0091	0.3260***
			(0.013)	(0.096)
Resid Smoker			0.2877***	-0.9019***
			(0.048)	(0.312)
Resid Ex-Smoker			0.3382***	-1.0358***
			(0.052)	(0.331)
Resid Abuse Alcohol			-0.1060***	0.1668**
			(0.012)	(0.075)
Interview Date	Yes	Yes	Yes	Yes
F-test for excluded instruments	332.84	638.71	339.75	643.97
Individuals	11167	11167	11167	11167
Observation	30048	30048	30048	30048

Notes: Interview date includes month and year of interview fixed effect. The Resid terms refer to the generated residuals from the mediating models. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 – Estimation Results: Robustness Checks I

	SAH			Depression			Cognitive		
	Balanced Panel	Age×Country	Wealth	Balanced Panel	Age×Country	Wealth	Balanced Panel	Age×Country	Wealth
Retired	0.1281***	0.1496***	0.1731***	-0.0111	-0.0142	-0.0249	-0.0036	0.0077	0.0038
	(0.043)	(0.039)	(0.045)	(0.035)	(0.030)	(0.033)	(0.007)	(0.006)	(0.008)
TimeR	-0.0169***	-0.0133***	-0.0126***	0.0080**	0.0101***	0.0095***	-0.0024**	-0.0021***	-0.0025***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Resid NoActiv.	-0.2404***	-0.1950***	-0.2093***	0.1277***	0.1052***	0.1129***	-0.0072	-0.0129***	-0.0131***
	(0.046)	(0.028)	(0.028)	(0.039)	(0.024)	(0.026)	(0.008)	(0.004)	(0.005)
Resid BMI	-0.0448	-0.0428**	-0.0468**	-0.0482**	-0.0311**	-0.0353**	0.0037	0.0016	0.0010
	(0.030)	(0.020)	(0.021)	(0.022)	(0.015)	(0.016)	(0.005)	(0.003)	(0.003)
Resid Smoker	-0.0252	-0.0371	-0.0197	-0.0181	-0.0280	-0.0311	-0.0031	0.0070	0.0043
	(0.079)	(0.058)	(0.060)	(0.052)	(0.044)	(0.045)	(0.011)	(0.009)	(0.010)
Resid ExSmoker	-0.0177	-0.0937	-0.0774	0.0220	0.0116	0.0148	0.0003	0.0061	0.0047
	(0.083)	(0.061)	(0.066)	(0.055)	(0.047)	(0.047)	(0.012)	(0.010)	(0.011)
Resid Alcohol	0.0150	0.0110	0.0151	0.0015	-0.0049	-0.0030	-0.0050	-0.0007	0.0011
	(0.025)	(0.018)	(0.018)	(0.019)	(0.015)	(0.016)	(0.004)	(0.003)	(0.003)
Log-Income	0.0024	0.0001		-0.0015	-0.0025		0.0007	0.0006*	
	(0.003)	(0.002)		(0.002)	(0.002)		(0.000)	(0.000)	
Q Wealth 1			-0.0275**			0.0147			-0.0018
			(0.013)			(0.010)			(0.002)
Q Wealth 2			-0.0140			0.0112			-0.0014
			(0.010)			(0.008)			(0.002)
Q Wealth 3			-0.0099			0.0054			-0.0005
			(0.008)			(0.006)			(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.7848	0.2682	0.3945	0.3363	0.4055	0.5051	0.9107	0.7422	0.3876
Individuals	2874	11167	10098	2874	11167	10098	2874	11167	10098
Obs.	11496	30048	27146	11496	30048	27146	11496	30048	27146

Notes: Controls includes age, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4 – Estimation Results: TE Robustness Check (II)

	(1) Health Index	(2) Euro-D Scale	(3) Memory	(4) Fluency	(5) Numeracy	(6) Low Grip Strenght
Retired	0.0433***	-0.1538	0.6307**	-0.7825	-0.0096	-0.0741***
	(0.014)	(0.179)	(0.292)	(0.570)	(0.061)	(0.024)
TimeR	-0.0056***	0.0573***	-0.1461***	-0.0737	0.0077	0.0050**
	(0.002)	(0.020)	(0.035)	(0.066)	(0.007)	(0.003)
Resid No Activities	-0.1168***	0.8165***	-0.5785***	-0.1288	-0.0523	0.0803***
	(0.014)	(0.131)	(0.182)	(0.429)	(0.039)	(0.021)
Resid BMI	0.0122	-0.1077	0.0671	0.0223	0.0125	0.0044
	(0.009)	(0.077)	(0.127)	(0.279)	(0.028)	(0.012)
Resid Smoker	0.0083	0.2587	-0.7845*	1.1408	0.2144**	0.0381
	(0.019)	(0.242)	(0.405)	(0.863)	(0.084)	(0.033)
Resid Ex-Smoker	-0.0043	0.5020*	-1.0039**	1.6259*	0.2028**	0.0417
	(0.021)	(0.261)	(0.429)	(0.913)	(0.089)	(0.035)
Resid Abuse Alcohol	0.0091	0.0698	0.0004	-0.0245	-0.0322	-0.0006
	(0.006)	(0.073)	(0.125)	(0.232)	(0.031)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.5039	0.6160	0.6854	0.2611	0.6941	0.1804
Individuals	11167	11167	11167	11167	11167	11167
Obs.	30048	30048	30048	30048	30048	30048

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 – Estimation Results: TE Education Heterogeneity

	SAH		Depression		Cognitive	
	Low Skilled	High Skilled	Low Skilled	High Skilled	Low Skilled	High Skilled
Retired	0.0973	0.1340**	0.1106*	-0.0690	-0.0078	0.0009
	(0.080)	(0.060)	(0.059)	(0.050)	(0.012)	(0.012)
TimeR	-0.0084	-0.0253***	0.0059	0.0169***	-0.0049***	-0.0015
	(0.010)	(0.007)	(0.008)	(0.006)	(0.002)	(0.002)
Resid No Activities	-0.1875***	-0.2172***	0.1200***	0.0767*	-0.0145**	-0.0139
	(0.043)	(0.056)	(0.037)	(0.046)	(0.006)	(0.010)
Resid BMI	-0.0489	0.0078	-0.0673***	-0.0246	0.0029	-0.0015
	(0.033)	(0.042)	(0.026)	(0.031)	(0.005)	(0.007)
Resid Smoker	0.0941	-0.0731	-0.0854	-0.0189	0.0070	0.0150
	(0.117)	(0.107)	(0.083)	(0.079)	(0.017)	(0.018)
Resid Ex-Smoker	0.0609	-0.1361	-0.0130	0.0221	0.0022	0.0148
	(0.120)	(0.114)	(0.083)	(0.086)	(0.017)	(0.019)
Resid Abuse Alcohol	-0.0183	0.0178	0.0074	-0.0187	0.0012	0.0007
	(0.030)	(0.029)	(0.024)	(0.021)	(0.005)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.0427	0.3429	0.9009	0.0387	0.3091	0.8779
Individuals	4063	3359	4063	3359	4063	3359
Obs.	10812	9366	10812	9366	10812	9366

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6 – Estimation Results: Job SAH Heterogeneity II

	SAH					
	White Collar	WC-LS	WC-HS	Blue Collar	BC-LS	BC-HS
Retired	0.1567***	0.2214**	0.1174**	0.1262	0.0631	0.1568
	(0.043)	(0.097)	(0.049)	(0.101)	(0.144)	(0.151)
TimeR	-0.0145***	0.0133	-0.0277***	-0.0063	-0.0046	-0.0101
	(0.005)	(0.010)	(0.007)	(0.013)	(0.019)	(0.018)
Resid No Activities	-0.1914***	-0.2328***	-0.1654***	-0.2063***	-0.0872	-0.3434***
	(0.037)	(0.059)	(0.048)	(0.049)	(0.064)	(0.079)
Resid BMI	-0.0376	-0.0824**	0.0046	-0.0599	-0.0628	-0.0708
	(0.025)	(0.039)	(0.035)	(0.039)	(0.058)	(0.066)
Resid Smoker	-0.0448	-0.2073*	0.0363	-0.0636	0.0180	-0.0931
	(0.071)	(0.114)	(0.105)	(0.152)	(0.245)	(0.211)
Resid Ex-Smoker	-0.0909	-0.1823	-0.0327	-0.1617	-0.0517	-0.2106
	(0.077)	(0.117)	(0.109)	(0.159)	(0.254)	(0.223)
Resid Abuse Alcohol	0.0396*	0.0859*	0.0334	-0.0146	0.0133	-0.0613
	(0.021)	(0.044)	(0.024)	(0.035)	(0.049)	(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.5653	0.9401	0.3800	0.2391	0.4022	0.3140
Individuals	6971	2580	4269	3003	1542	1435
Obs.	19030	6906	12124	7933	4106	3827

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7 – Estimation Results: Job Depression Heterogeneity II

	Depression					
	White Collar	WC-LS	WC-HS	Blue Collar	BC-LS	BC-HS
Retired	-0.0560	0.0264	-0.0882**	0.0429	0.0735	0.0544
	(0.036)	(0.081)	(0.037)	(0.077)	(0.111)	(0.098)
TimeR	0.0102**	0.0064	0.0135**	0.0068	0.0121	0.0051
	(0.004)	(0.009)	(0.006)	(0.009)	(0.012)	(0.015)
Resid No Activities	0.0942***	0.1285**	0.0784**	0.1197***	0.0832	0.1747**
	(0.031)	(0.053)	(0.040)	(0.042)	(0.053)	(0.071)
Resid BMI	-0.0421**	-0.0837**	-0.0143	-0.0296	-0.0544	0.0059
	(0.021)	(0.039)	(0.025)	(0.029)	(0.047)	(0.048)
Resid Smoker	-0.0451	-0.1886*	0.0574	-0.0528	-0.0870	-0.0580
	(0.051)	(0.098)	(0.065)	(0.066)	(0.133)	(0.105)
Resid Ex-Smoker	0.0004	-0.1527	0.1035	-0.0037	-0.0495	-0.0027
	(0.055)	(0.103)	(0.068)	(0.069)	(0.141)	(0.114)
Resid Abuse Alcohol	0.0023	-0.0097	0.0031	-0.0340	0.0211	-0.0788**
	(0.017)	(0.041)	(0.020)	(0.026)	(0.037)	(0.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.3260	0.4244	0.6099	0.6986	0.9466	0.7233
Individuals	6971	2580	4269	3003	1542	1435
Obs.	19030	6906	12124	7933	4106	3827

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8 – Estimation Results: Job Cognitive Heterogeneity II

	Cognitive					
	White Collar	WC-LS	WC-HS	Blue Collar	BC-LS	BC-HS
Retired	0.0096	0.0142	0.0050	-0.0141	-0.0007	-0.0350
	(0.008)	(0.016)	(0.009)	(0.016)	(0.022)	(0.023)
TimeR	-0.0014	-0.0006	-0.0017	-0.0042**	-0.0040	-0.0055*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)
Resid No Activities	-0.0117*	-0.0054	-0.0151**	-0.0115	-0.0099	-0.0178
	(0.006)	(0.011)	(0.008)	(0.008)	(0.010)	(0.013)
Resid BMI	-0.0034	0.0005	-0.0060	0.0081	0.0033	0.0203**
	(0.004)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)
Resid Smoker	0.0016	-0.0077	0.0107	0.0079	0.0495	-0.0304
	(0.011)	(0.021)	(0.015)	(0.025)	(0.052)	(0.031)
Resid Ex-Smoker	-0.0013	-0.0021	0.0034	0.0057	0.0451	-0.0314
	(0.012)	(0.022)	(0.016)	(0.026)	(0.053)	(0.033)
Resid Abuse Alcohol	-0.0012	-0.0023	-0.0017	0.0006	0.0089	-0.0059
	(0.004)	(0.007)	(0.005)	(0.006)	(0.007)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.7166	0.8651	0.5908	0.4517	0.0186	0.1994
Individuals	6971	2580	4269	3003	1542	1435
Obs.	19030	6906	12124	7933	4106	3827

Notes: controls includes age, logarithm of household disposable income, being married, living alone, having children and grandchildren, month and year of interview fixed effect. Estimations use individual fixed effects. Standard errors in parentheses are bootstrapped and robust to clustering at the individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B

CASP composition

The list of the relevant question, all evaluated in a 4-scale, is the following:

- Control
  - *How often do you think your age prevents you from doing the things you would like to do?*
  - *How often do you feel that what happens to you is out of your control?*
  - *How often do you feel left out of things?*
- Autonomy
  - *How often do you think that you can do the things that you want to do?*
  - *How often do you think that family responsibilities prevent you from doing what you want to do?*
  - *How often do you think that shortage of money stops you from doing the things you want to do?*
- Pleasure
  - *How often do you look forward to each day?*
  - *How often do you feel that your life has meaning?*
  - *How often, on balance, do you look back on your life with a sense of happiness?*
- Self-realization
  - *How often do you feel full of energy these days?*
  - *How often do you feel that life is full of opportunities?*
  - *How often do you feel that the future looks good for you?*

Table B1 – The effect of retirement on SWB - Geographical Heterogeneity in Life Satisfaction and CASP

	Life Satisfaction						CASP					
	Northern		Central		Southern		Northern		Central		Southern	
Retired	-0.268**		0.003		-0.004		-0.285***		0.048		0.105**	
	(0.116)		(0.053)		(0.042)		(0.103)		(0.053)		(0.043)	
3 years before		0.012		0.140		-0.028		-0.095		0.126		0.205*
		(0.086)		(0.128)		(0.124)		(0.074)		(0.120)		(0.124)
2 years before		0.189		-0.223		-0.042		0.068		0.014		0.081
		(0.115)		(0.159)		(0.115)		(0.103)		(0.130)		(0.117)
Within 1 year		0.035		0.063		-0.040		-0.012		0.089		0.152**
		(0.071)		(0.066)		(0.063)		(0.062)		(0.060)		(0.063)
0-1 year		0.028		-0.008		-0.143		0.042		0.108		0.200
		(0.110)		(0.096)		(0.142)		(0.101)		(0.086)		(0.149)
1-2 years		0.096		-0.010		-0.025		-0.061		0.046		0.160*
		(0.093)		(0.085)		(0.097)		(0.085)		(0.077)		(0.093)
2-3 years		0.043		0.079		-0.043		0.077		0.163*		0.308**
		(0.110)		(0.114)		(0.135)		(0.095)		(0.097)		(0.133)
3-4 years		0.011		0.007		-0.083		-0.035		0.110		0.131
		(0.072)		(0.128)		(0.113)		(0.063)		(0.119)		(0.107)
4-5 years		0.088		-0.025		-0.098		0.030		0.073		0.110
		(0.075)		(0.084)		(0.099)		(0.067)		(0.072)		(0.099)
More than 5 years		0.008		-0.007		-0.147		-0.053		0.092		0.184*
		(0.073)		(0.094)		(0.106)		(0.065)		(0.087)		(0.102)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.713	0.236	0.438	0.456	0.140	0.704	0.114	0.621	0.000	0.079	0.758	0.113
Individuals	3256	3256	6086	6086	3432	3432	3256	3256	6086	6086	3432	3432
Obs.	9644	9644	16687	16687	9918	9918	9644	9644	16687	16687	9918	9918

Notes: Controls includes age, age2, log-income, difference with the reference group, a set of dummies on marital status, household size, homeowner, tenant, number of children and grandchildren, physical health, and the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2 – The effect of retirement on SWB - Heterogeneity in Life Satisfaction II

	(1)		(2)		(3)		(4)		(5)	
	Nordic		Continental		Mediterranenan		NHS		SSH	
Retired	-0.411		0.010		0.008		0.123		0.024	
	(0.292)		(0.059)		(0.042)		(0.144)		(0.063)	
3 years before		0.052		0.162		-0.090		0.005		0.139
		(0.087)		(0.120)		(0.245)		(0.104)		(0.114)
2 years before		0.173		-0.221		0.110		0.122		-0.231*
		(0.116)		(0.153)		(0.174)		(0.109)		(0.138)
Within 1 year		0.079		0.069		0.025		0.026		0.055
		(0.072)		(0.061)		(0.126)		(0.069)		(0.059)
0-1 year		0.034		0.072		-0.226		-0.108		0.027
		(0.116)		(0.100)		(0.172)		(0.121)		(0.104)
1-2 years		0.143		-0.002		0.110		0.162		-0.002
		(0.105)		(0.072)		(0.172)		(0.119)		(0.072)
2-3 years		0.038		0.120		0.211		0.135		0.035
		(0.103)		(0.115)		(0.251)		(0.135)		(0.113)
3-4 years		0.049		0.067		-0.157		-0.033		0.049
		(0.071)		(0.111)		(0.193)		(0.077)		(0.106)
4-5 years		0.103		-0.013		-0.083		0.013		-0.055
		(0.080)		(0.077)		(0.143)		(0.075)		(0.079)
More than 5 years		0.057		0.019		-0.056		-0.029		-0.008
		(0.076)		(0.095)		(0.169)		(0.085)		(0.094)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.745	0.226	0.298	0.637	0.145	0.755	0.007	0.666	0.609	0.632
Individuals	3991	3991	6690	6690	2093	2093	5349	5349	7425	7425
Obs.	11454	11454	19071	19071	5724	5724	15368	15368	20881	20881

Notes: Controls includes age, age2, log-income, difference with the reference group, a set of dummies on marital status, household size, homeowner, tenant, number of children and grandchildren, physical health, and the wave fixed effects. Estimation use individual fixed effect. Standard errors in parentheses () are clustered at individual level. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3 – The effect of retirement on SWB - Heterogeneity in CASP II

	(1)		(2)		(3)		(4)		(5)	
	Nordic		Continental		Mediterranenan		NHS		SSH	
Retired	-0.652*		0.046		0.054		0.395*		0.128*	
	(0.388)		(0.058)		(0.042)		(0.224)		(0.066)	
3 years before		-0.028		0.059		0.264		-0.052		0.113
		(0.081)		(0.111)		(0.233)		(0.091)		(0.106)
2 years before		0.067		0.073		0.190		0.084		0.060
		(0.107)		(0.126)		(0.162)		(0.091)		(0.120)
Within 1 year		0.032		0.069		0.180		0.085		0.089*
		(0.066)		(0.056)		(0.128)		(0.058)		(0.054)
0-1 year		0.138		0.089		0.208		0.101		0.144
		(0.111)		(0.093)		(0.173)		(0.102)		(0.097)
1-2 years		-0.062		0.024		0.273*		0.066		0.039
		(0.099)		(0.065)		(0.164)		(0.098)		(0.066)
2-3 years		0.000		0.291***		0.479**		-0.018		0.268***
		(0.095)		(0.102)		(0.228)		(0.114)		(0.104)
3-4 years		-0.011		0.075		0.120		-0.007		0.116
		(0.068)		(0.103)		(0.193)		(0.062)		(0.098)
4-5 years		0.068		0.125*		0.077		0.058		0.126*
		(0.074)		(0.069)		(0.145)		(0.063)		(0.073)
More than 5 years		-0.026		0.110		0.313*		0.011		0.130
		(0.070)		(0.086)		(0.162)		(0.071)		(0.085)
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SH J p-value	0.500	0.532	0.000	0.014	0.618	0.264	0.039	0.811	0.000	0.085
Individuals	3991	3991	6690	6690	2093	2093	5349	5349	7425	7425
Obs.	11454	11454	19071	19071	5724	5724	15368	15368	20881	20881

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard error are clustered at individual level

C

Table C1 – Estimation Results: Robustness checks (I)

	(1) $10\%Rule_{modified}$ equation	(1) SWB equation	(2) $MEPI$ equation	(2) SWB equation	(3) $10\%Rule$ equation	(3) SWB equation
	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE
$10\%Rule_{modified}$		0.152 (0.092)*				
MEPI Level2				-0.256 (0.040)***		
MEPI Level3				-0.370 (0.056)***		
MEPI Level4				-0.627 (0.084)***		
MEPI Level5				-0.185 (0.232)		
10% Rule						0.057 (0.045)
Log Equivalized Income	-0.480 (0.050)***	-0.333 (0.154)**	-0.054 (0.008)***	0.038 (0.009)***	-0.492 (0.054)***	-0.390 (0.111)***
Richer than reference group	-0.906 (0.089)***	-0.674 (0.262)**	-0.217 (0.025)***	0.033 (0.020)	-0.769 (0.060)***	-0.619 (0.155)***
MMDI	0.437 (0.198)**	-0.470 (0.495)	1.904 (0.115)***	-0.659 (0.125)***	0.556 (0.155)***	-0.194 (0.417)
Male	-0.139 (0.043)***	-0.146 (0.042)***	0.002 (0.024)	-0.048 (0.015)***	-0.118 (0.035)***	-0.132 (0.032)***
Age	0.001 (0.009)	-0.019 (0.012)	0.007 (0.005)	-0.026 (0.003)***	0.005 (0.007)	-0.012 (0.010)
Age2	-0.001 (0.008)	0.019 (0.011)*	-0.020 (0.005)***	0.023 (0.003)***	0.002 (0.007)	0.019 (0.009)**
Unemployed	0.258 (0.071)***	-0.079 (0.205)	0.188 (0.038)***	-0.349 (0.034)***	0.232 (0.064)***	-0.037 (0.159)
Self-employed	0.373 (0.058)***	0.251 (0.126)**	-0.067 (0.039)*	-0.096 (0.024)***	0.321 (0.051***)	0.232 (0.087)***
Retired	-0.029 (0.057)	-0.012 (0.050)	-0.022 (0.035)	0.002 (0.023)	0.086 (0.044)*	0.078 (0.042)*
Pre-Primary	0.241 (0.165)	0.027 (0.192)	0.543 (0.078)***	-0.105 (0.065)	0.354 (0.119) ***	0.163 (0.164)
Primary	0.272 (0.099)***	0.093 (0.149)	0.456 (0.053)***	-0.082 (0.040)**	0.369 (0.078)***	0.204 (0.131)
Low-Secondary	0.192 (0.086)**	0.033 (0.122)	0.352 (0.045)***	-0.102 (0.031)***	0.207 (0.070)***	0.068 (0.103)
Upper-Secondary	0.170 (0.081)**	0.072 (0.096)	0.135 (0.043)***	-0.074 (0.023)***	0.146 (0.065)**	0.066 (0.076)
Post-Secondary	0.237 (0.129)*	0.204* (0.119)	0.140 (0.077)*	0.046 (0.044)	0.223 (0.106)**	0.203 (0.102)**
Married	-0.125 (0.065)*	0.036 (0.114)	-0.044 (0.035)	0.187 (0.023)***	-0.273 (0.053)***	-0.120 (0.113)
Separeted	0.279 (0.104)***	0.115 (0.146)	0.019 (0.059)	-0.132 (0.042)***	0.099 (0.094)	0.007 (0.100)
Divorced	0.190 (0.103)*	0.084 (0.114)	0.090 (0.068)	-0.071 (0.046)	0.191 (0.086)**	0.110 (0.094)
Widowed	0.299 (0.081)***	0.195 (0.113)*	0.038 (0.050)	-0.062 (0.034)*	0.183 (0.066)***	0.116 (0.075)
Children	-0.109 (0.057)*	0.013 (0.090)	0.008 (0.031)	0.144 (0.020)***	-0.100 (0.048)**	-0.004 (0.071)
Good Health	0.028 (0.081)	-0.139 (0.107)	0.098 (0.041)**	-0.193 (0.027)***	-0.083 (0.065)	-0.202 (0.076)***
Fair Health	0.047 (0.087)	-0.342* (0.201)	0.407 (0.046)***	-0.427(0.041)***	-0.117 (0.071)*	-0.416 (0.145)***
Poor	0.086 (0.098)	-0.562* (0.322)	0.608 (0.053)***	-0.714 (0.056)***	0.018 (0.078)	-0.502 (0.256)**
Very Bad Health	0.095 (0.140)	-0.793* (0.439)	0.850 (0.074)***	-1.008 (0.085)***	-0.046 (0.114)	-0.771 (0.350)**
Dwelling Quality	0.040 (0.009)***	0.047 (0.008)***	-0.029 (0.007)***	0.015 (0.004)***	0.018 (0.007)**	0.028 (0.008)***
Owner	-0.099 (0.049)**	0.005 (0.079)	-0.320 (0.026)***	0.036 (0.026)	-0.071 (0.041)*	0.014 (0.061)
No urban area	0.241 (0.052)***	0.242 (0.056)***	0.028 (0.028)	0.067 (0.018)***	0.228 (0.040)***	0.233 (0.040)***
N. Rooms	-0.001 (0.022)	0.020 (0.021)	-0.007 (0.011)	0.026 (0.008)***	0.040 (0.017)**	0.052 (0.015)***
Semi-detached	-0.031 (0.052)	0.013 (0.049)	-0.143 (0.031)***	0.018 (0.022)	-0.119 (0.040)***	-0.070 (0.050)
Flat-less10	-0.184 (0.060)***	-0.132 (0.078)*	-0.152 (0.032)***	-0.013 (0.024)	-0.313 (0.047)***	-0.253 (0.075)***
Flat-more10	-0.315 (0.066)***	-0.261 (0.099)***	-0.148 (0.036)***	-0.053 (0.025)**	-0.560 (0.054)***	-0.492 (0.105)***
2010-2013	-0.144 (0.159)		-0.841 (0.210)***		-0.167 (0.114)	
2000-2009	-0.042 (0.064)		-0.489 (0.048)***		-0.094 (0.062)	
1990-1999	0.002 (0.029)		-0.455 (0.048)***		-0.063 (0.033)*	
1980-1989	0.015 (0.026)		-0.371 (0.041)***		-0.051 (0.028)*	
1970-1979	0.031 (0.025)		-0.270 (0.036)***		-0.037 (0.021)*	
1960-1969	-0.001 (0.031)		-0.248 (0.036)***		-0.065 (0.040)*	
1950-1959	0.088 (0.046) *		-0.067 (0.038)*		0.010 (0.020)	
1900-1949	0.089 (0.055)					
ρ	0.733		0.224***		0.822**	
Regional residence	Yes		Yes		Yes	
AIC	92513.653		102003.130		89375.364	
BIC	93238.297		102761.206		90085.562	
Log-Likelihood	-46166.826		-50906.565		-44598.682	
Observation	23193		21585		21585	

Notes: Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the significance level of ρ refers to a Wald test of independent equations. The 10% rule considers an individual as energy poor if energy consumption equals or exceeds 10% of household disposable income. The $10\%Rule_{modified}$ is a dual-threshold affordability measure, which considers an individual as poor if at least one condition holds between electricity consumption equal or greater than 10% of household disposable income and the fuel consumption equal or greater than 5% of household disposable income. MEPI refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations. MMDI is the multidimensional material deprivation index. ITSILC data referring to 2013; Sample size: 23,193.

Table C2 – Average Partial Effects of MEPIs: absolute and percentage variations

	APE					
	MEPI					
	Level 1	Level 2	Level 3	Level 4		
SWB=0	0.011	0.010	0.026	-0.037		
	(67.1)	(35.4)	(67.4)	(-58.2)		
SWB=7	-0.006	-0.009	-0.026	0.036		
	(-2.5)	(-4.0)	(-11.6)	(18.4)		
SWB=10	-0.026	-0.012	-0.016	0.030		
	(-36.0)	(-26.2)	(-45.3)	(160.5)		
	MEPI_n					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
SWB=0	0.015	-0.003	0.004	0.006	0.023	-0.035
	(92.2)	(-10.7)	(13.5)	(17.7)	(61.2)	(-59.0)
SWB=7	-0.009	0.003	-0.003	-0.005	-0.023	0.035
	(-3.9)	(1.3)	(-1.5)	(-2.4)	(-10.5)	(17.4)
SWB=10	-0.032	0.005	-0.005	-0.006	-0.015	0.032
	(-43.9)	(11.7)	(-11.6)	(-15.4)	(-42.4)	(160.3)

Notes: $MEPI$ refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations. APE yields the change in the probability that SWB equals 0, 7, and 10 when a covariate changes *ceteris paribus*. APEs are calculated using the finite difference method. The average variation in predicted probabilities in parenthesis () reflects the percentage variation in the total probability of belonging to the level 0, 7, and 10 of SWB, with respect to the baseline (before the variable change). Level 1 reflects a change from not being energy poor to the first level of severity. Level# reflects a change from the Level#-1 to the Level# of MEPI. ITSILC data referring to 2013; Sample size: 23,193.

Table C3 – Average Partial Effects of MEPI at some specific characteristics: absolute and percentage variations

	APE				Average Variation in Predicted Probabilities (%)			
	Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	Level 4
	Richer than reference group							
SWB=0	0.010	0.009	0.024	-0.034	68.9	36.3	69.3	-59.0
SWB=7	-0.004	-0.008	-0.024	0.033	-1.6	-3.4	-10.7	16.4
SWB=10	-0.028	-0.013	-0.017	0.032	-35.6	-25.9	-44.9	157.4
	Unmarried							
SWB=0	0.014	0.012	0.030	-0.044	65.2	34.4	64.9	-57.2
SWB=7	-0.012	-0.012	-0.030	0.044	-4.9	-5.5	-14.2	24.3
SWB=10	-0.022	-0.010	-0.012	0.024	-37.7	-27.4	-47.0	174.4
	Very bad health							
SWB=0	0.055	0.040	0.085	-0.132	39.3	20.8	36.2	-41.3
SWB=7	-0.031	-0.018	-0.028	0.049	-23.0	-17.3	-32.9	86.0
SWB=10	-0.003	-0.001	-0.001	0.002	-49.0	-36.1	-58.2	303.8
	Retirees							
SWB=0	0.011	0.010	0.025	-0.036	67.4	35.6	67.7	-58.3
SWB=7	-0.005	-0.009	-0.025	0.035	-2.3	-3.8	-11.3	17.8
SWB=10	-0.027	-0.012	-0.016	0.031	-35.8	-26.1	-45.1	159.3

Notes: $MEPI$ refers to the intensity measure of EP with equal weights. The poverty cut-off is set to d/3, where d is the number of the deprivations. APE yields the change in the probability that SWB equals 0, 7, and 10 when a covariate changes *ceteris paribus*. APEs are calculated using the finite difference method. Level 1 reflects a change from not being energy poor to the first level of severity. Level# reflects a change from the Level#-1 to the Level# of MEPI. ITSILC data referring to 2013; Sample size: 23,193.

Table C4 – Average Partial Effects of a few SWB determinants: absolute and percentage variations

	APE			Average Variation in Predicted Probabilities (%)		
	p0	p7	p10	p0	p7	p10
Median Level $MEPI$	0.021	-0.015	-0.039	126.2	-6.4	-52.8
Median Level $MEPI_n$	0.016	-0.010	-0.033	94.7	-4.1	-44.6
Richer	-0.003	0.001	0.010	-15.2	0.2	15.2
Unemployed	0.023	-0.016	-0.038	119.8	-6.8	-53.1
Very bad health	0.134	-0.106	-0.070	703.1	-45.3	-93.0

Notes: APE yields the change in the probability that SWB equals 0, 7, and 10 when a covariate changes *ceteris paribus*. APEs are calculated using the finite difference method. Median Level MEPI reflects a change from the pre-median to the median level of MEPI. Median Level $MEPI_n$ reflects a change from the pre-median to the median level of $MEPI_n$. For the other covariates the switch is from 0 to 1. Richer indicates being richer than reference group; very bad health indicates the lowest level of Self-Assess Health; unemployed indicates the current job situation when in unemployment. The average variation in predicted probabilities reflects the percentage variation in the total probability of belonging to the level 0, 7, and 10 of SWB, with respect to the baseline (before the variable change). ITSILC data referring to 2013; Sample size: 23,193.