

Time spent working and body weight in the elderly population: An analysis of the effects and mechanisms

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ABSTRACT

This paper evaluates the causal effects of working part-time and working full-time on body weight using data from the Health and Retirement Study. Additionally, we study these effects when we allow for heterogeneity across socio-economic status measured by income and education. Since retirement decision is a potential source of endogeneity, we follow an instrumental variable approach using retirement eligibility ages as instruments. We also investigate possible mechanisms which could explain the effects of working part-time and working full-time on body weight. To do this, we use data from the American Time Use Survey. We find that retirees have higher BMI than old workers. We also find that individuals with a higher socio-economic status usually have lower BMI. Furthermore, the allocation of time made by retirees and full-time workers on activities such as watching TV seems to favor sedentarism.

by
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To my family,

Acknowledgments

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1. Introduction

In developed countries, the population is aging fast. The fall in fertility rate and the increase in life expectancy are factors that promote the rise of aging populations. Consequently, dependency ratios present an increasing trend in industrialized nations. The exponential growth of the dependency ratio could only be diminished by the rise in the fertility rate of the native population or immigration composed by groups of young people. Besides, immigration of qualified and young individuals would enrich the country and help to promote future economic growth. Also, migration of low educated individuals who could occupy blue-collar positions which national workers are not willing to fill would have positive externalities for their economy. Additionally, the aging population has noticeable implications for the public budget since it increases the cost of public health care and public pensions. The labor force is then changing in developed countries, and there is an increase in labor participation of the elderly. Consequently, older people are retiring later. According to the report "Aging in the United States" published by the Population Reference Bureau (PRB) (Mather et al., 2015), by 2014, about 23% of men and 15% of women with ages 65 and above were in the labor force, and these levels are projected to rise further shortly. Longevity is a key factor that explains this behavior but is not the only one. There are other economic and social factors that might help to explain why the elderly are postponing their retirement (Szinovacz et al., 2013). The Great Recession (2008-2009) influenced late retirements for those individuals who were younger than 65 given the rising unemployment and the instability in the stock market (Pfeffer et al., 2013, Gustman et al., 2014). Furthermore, the households where the head of the family is an older person are more likely to retire later. Mostly, if they still have children (Rohwedder, 2009). Also, they are even more likely to postpone their retirement in those households where a close relative was affected by the consequences of the economic crisis such as the loss of her/his house, unemployment or decrease of net wealth due to the fall on the stock market (Pfeffer et al., 2013). Therefore, the elderly not only might work longer but also, they might reduce their own consumption to help sustain their families. The latter could translate into reducing their own health care expenditures (Hurd & Rohwedder, 2013). All of these could force old individuals to remain working longer. Hence, macroeconomic factors have an impact on an individual's participation in the labor force, whereas personal factors are crucial.

Retiring late, then might affect health problems for the elderly and worsen their health conditions. It is relevant to notice that in industrialized countries, the elderly often suffer from some diseases very related to obesity and overweight. In the U.S., obesity is one of the major health problems. The mentioned PRB report reveals that obesity has been increasing among the elderly, reaching about 40% of the population who are between 65 and 74 years old in 2009-2012. Since almost

half of the American population suffers from obesity and the U.S. leads the list of countries with a higher rate of obesity, this issue is an object of concern. Obesity has great implications on health care costs (Finkelstein et.al, 2003) and could bring a wide variety of illnesses such as hypertension, diabetes, cardiovascular diseases and physical disabilities (Van Itallie et al., 1985; Must et al., 1999; Zamboni et al., 2005; Sturm et al., 2004). Furthermore, the implications are not only limited to the field of health. It also influences socio-demographic and economic factors. Wang et al. (2005) predict that by 2030, about 86% of the adults will become obese or overweight. Besides, health-care costs due to obesity and overweight are forecasted to double every decade, and it will comprise between 16% and 18% of the total amount of the U.S. health-care costs. As a consequence, to the future dimension of this health problem, life expectancy in the U.S. will fall since current generations will follow the same or worse behavioral health pattern as their parents and so on and so for (Olshansky et al., 2005). The latter, jointly with the decreasing trend in fertility, does not ensure the rise of the dependency ratio. Therefore, education, health care, and pensions and all the types of public expenditures will need to adjust to this reality.

There is a growing interest in the relationship between income level and obesity. There is an inverse relationship between these two variables (Jeffrey et al., 1991). Low income earners usually buy lower quality nourishment because of their low price in comparison with healthier food. This type of nutriment is high on sugar and fats. It is to say, food with higher energy intake (Drewnowski & Specter, 2004). This fact combined with the sedentary behavior of American citizens is a key factor that cause obesity. Also, food portions in marketplaces are substantially higher than recommended, which contributes to the obesity epidemic. This trend has increased since the '70s and exceed federal standards for nutritional guidance and food labels. Firms have noticed that consumers feel more attracted to big size packages and low prices (Young et al., 2002), and the American Institute of Cancer Research claims in a recent survey that Americans usually do not pay attention to the size of portions and keeping a proper body weight. Therefore, education is an essential factor to address the obesity problem and the overall current dietary of Americans. Likewise, the link between education level and obesity is a focus of interest in the literature. Education is observed to be negatively correlated with obesity and positively correlated with income level. Promoting education might relieve income disparities and mortality due to obesity (Meara et al., 2008). Wealthier and higher educated individuals choose healthier food because they know it is better for them and they have a higher level of disposable income to do so. Higher education is associated with higher income, longer life expectancy and better health at old ages. Hence, the socio-economic status given by income and education is a very important factor of influence on overweight and obesity.

After all these arguments, we suspect that there is a clear relationship between labor participation of older people in industrialized countries and obesity. There has been a rising trend to sedentary jobs. Automatism of productions and

digital transformation might be two of the most remarkable reasons why this is becoming the fashion among all types of jobs, such as blue and white-collar jobs. Hence, this type of labor market configuration favors overweight and obesity, which increases the importance of the latter cited issues. Therefore, it is quite relevant to study the effect of the number of work hours on a worker's weight.

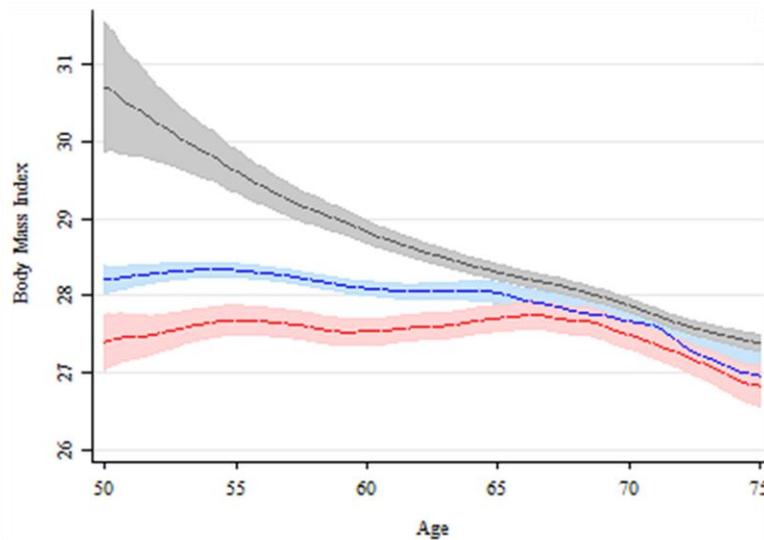


Figure 1: BMI by age and labor market status

Figure 1 shows that retired American individuals have on average higher Body Mass Index (BMI) than old full-time workers and old part-time workers. We also observe that full-time workers present a higher BMI than part-time workers. Therefore, retiring partially or fully seems to be correlated with higher body weight. On the one hand, we could expect that, in general, retirees spent more time in sedentary activities such as watching TV than exercising since it is very likely that they suffer from some impairment condition or cardiovascular disease. Overall, old Americans occupy most of their day in sedentary activities (Matthews et al., 2008). Also, retirees have more time to cook and have a healthier diet. On the other hand, retirement also brings isolation and depression for some people who transitioned from a very demanding job to have a great disposable amount of time (Wenger et al., 1996) and leads them to an unhealthy lifestyle concerning activities and eating behavior.

However, identifying the causal effect of retirement on health outcomes is difficult since retirement decision is usually a source of endogeneity. De Vaus et al. (2007) find that the diminishing responsibilities of individuals who gradually transition from work to retirement lead them to have better overall health in comparison to those who directly transition directly to retirement. This study does not account for endogeneity. Dave et al. (2008) find that American individuals who are partly retired have better health outcomes than people who enjoy full retirement, and both groups are worse in comparison with those who are working full-time. Neuman (2008) observes that retirement and a decrease in the number of work hours sustain physical health in the United States. He considers that

individuals are retired if they work less than 1,200 hours per year. He then assumes that partially retired and fully retired individuals are the same. He uses retirement eligibility ages of the respondent as instrumental variables for the number of hours worked.

We already cited some reasons why the effect of retirement hours usually implies weight gain. It is necessary to go deeper into the mechanisms that might motivate this relation. The literature on this topic is rather scarce. Eibich (2015) finds that retirement could improve health considerably since individuals could destine more time to sleep or exercise. However, there are studies about how time spent on different activities link to higher better health outcomes. Sleeping less than 7 hours a day is considered harmful for health and leads to higher BMI (Knutson et al., 2007; Watson et al., 2010). Ham et al. (2009) provide empirical evidence that additional time exercising is usually negatively correlated with low BMI. Overall, eating at restaurants in the U.S. and prepared food entails weight gain and obesity (Lin et al., 1999). Satia et al. (2004) observe that individuals who spend additional time eating in a fast-food restaurant on average have higher BMI than those who do not.

On the contrary, Kolodinsky and Goldstein (2011) find that this type of activity does not cause overweight or obese, but it does in those cases when an individual has a BMI higher than 25. Also, eating and drinking while doing other activities such as watching TV entails weight gain. The type of food and drinks that individuals consume while watching a film are usually high on sugar and fat. Consequently, there is a positive relationship between eating while watching TV and overweight (Liang et al., 2009). Abramowitz (2016) investigates the relationship between working time, time spent on health-related activities and BMI.

In this study we investigate a number of issues which have not been addressed previously in the literature. First, we study the effect of working on physical health. In particular, we address separately the effect of working full-time and working part-time to understand how it varies with respect to retirement. We use as a measure of physical health body fat, particularly, we use BMI. We follow an instrumental variable approach, using retirement eligibility ages of respondent and spouse as instruments for working part-time and working full-time.

We already motivated the importance of income and education respect to health outcomes. This leads to the second question which is related to the heterogeneity effects of income and education on the impact of working part-time and working full-time on BMI. We intend to study the impact of socio-economic status on the relationship of retirement decision on BMI. The reasoning behind this motivation is that, under the assumption that individuals are rational, people with a higher socioeconomic level will buy higher-quality food and healthier food which is usually more expensive in the US. Level of income and level of education are two variables which inform about an individual's socio-economic status and allow to differentiate across socioeconomic groups. The effect of labor force participation

on BMI across these two socio-economic factors might differ. Therefore, we would like to study whether having higher income has a lower impact on retiring has on BMI, since we expect that these individuals eat healthier than individuals with low income level. Moreover, we would like to analyze whether old workers with high education are healthier since we expect that they are more aware of the effect that certain type of food has on health. To answer these questions, we use panel data from the Health and Retirement Study (HRS). This dataset includes detailed information on demographic features, labor market force characteristics and health-related characteristics of the elderly population in the U.S.

The third research question is related to the study of the mechanisms which might drive the effect of labor market participation on BMI. Here we also consider differentials in income and education since mechanisms might differ among these groups. We consider time use data to answer our second question. The American Time Use Survey (ATUS) provides information about daily time spent on several activities, demographic characteristics, and health features.

This paper is structured as follows. In Section 2, we answer the first two research questions. Section 2.1 contains the data description and the summary statistics and description of the main variables which are used to investigate the effect of working part-time and working full-time on BMI. In Section 2.2, we provide a detailed explanation of the followed methodology and description of the main assumptions. Section 2.3 provides an exploratory graphical analysis. Section 2.4 discusses the results. Section 2.5 describes robustness checks performed to the results. Section 3 includes the analysis of the mechanisms that drive the effect of working part-time and full-time on physical health along with the study of the heterogeneous effects of income and education for the impact of labor market participation on BMI. Section 3.1 describes the ATUS, includes descriptive statistics on the main variables and time use activities. Section 3.2 describes the methodology. Section 3.3 presents the main results. Section 3.4 describes robustness checks of the results. Finally, Section 4 contains the conclusions of the study and issues for further research.

2. Effects of working part-time and full-time on BMI

2.1 Data description

2.1.1 General description of the survey data

To study the effects of working part-time and working full-time on BMI for the elderly, we use data from the Health and Retirement Study (HRS). The HRS is a longitudinal biennial survey launched since 1992, which collects representative information on retirement and health of more than 20,000 American respondents who are older than 50, it is to say, of the elderly. The HRS is carried out by phone (usually for those respondents who are 80 or older) or face to face (main procedure for those younger than 80). This study is performed in even years by the Survey Research Center at the University of Michigan and supported by the National Institute of Aging (NIA) and the Social Security Administration (SSA). This survey collects information on several aspects such as demographic features, health indices, health care expenditures, wages, work, and pension plans. We make use of 8 waves which comprehend the period 2000-2014 and count with most of the data for our dependent variables.

We impose the following sample restrictions. First, we only consider individuals between 50 and 75 years old. Second, we exclude respondents who never worked, who are unemployed or disabled; and we also, do not consider those whose last worked age was 50 or if information on last worked age is missing in all survey years nor if information on last worked age was complete but data on last worked year is missing in all other survey years. Third, we dropped respondents who reported their last job ended before the age of 50 in all survey years, or who reported this in given survey years and this information was missing in other survey years, or if this information was missing in all survey years. These sample restrictions lead to an unbalanced panel dataset with a sample size of 21,127 respondents and 213,162 observations.

2.1.2 Measuring hours worked

One of the aims of this research is to study how time use of people spending different working hours affect their physical health, measured by BMI. The definition we use for labor market status is based on the total number of hours worked in all jobs. In the HRS, information about a worker's main job and secondary job (if he/she has more than one job). The questions are "*Are you doing any work for pay at the present time?*" and "*Are you currently doing any other work for pay such as another business of your own, a second job or the military reserves?*", respectively. Thus, we take as the total number of hours worked, the average number of hours worked in the main job and the secondary job. We consider the

number of hours worked per week and the number of weeks worked per year as the main criteria to distinguish between different categories for labor status. We define full-time workers as those individuals who work 35 or more hours of work per week and 36 or more weeks per year. As part-time workers, we consider those individuals who work less than 35 hours per week and less than 36 or more weeks per year. Finally, fully retired individuals are those who do not work any hour per week.

It is important to mention that HRS offers two definitions of labor statuses for those who work less than 35 hours per week: "working part-time" and "partly retired." An individual can report working part-time but also being retired. In this case, we assign this kind of respondent the labor force status "partly retired," which we include in the part-time working category.

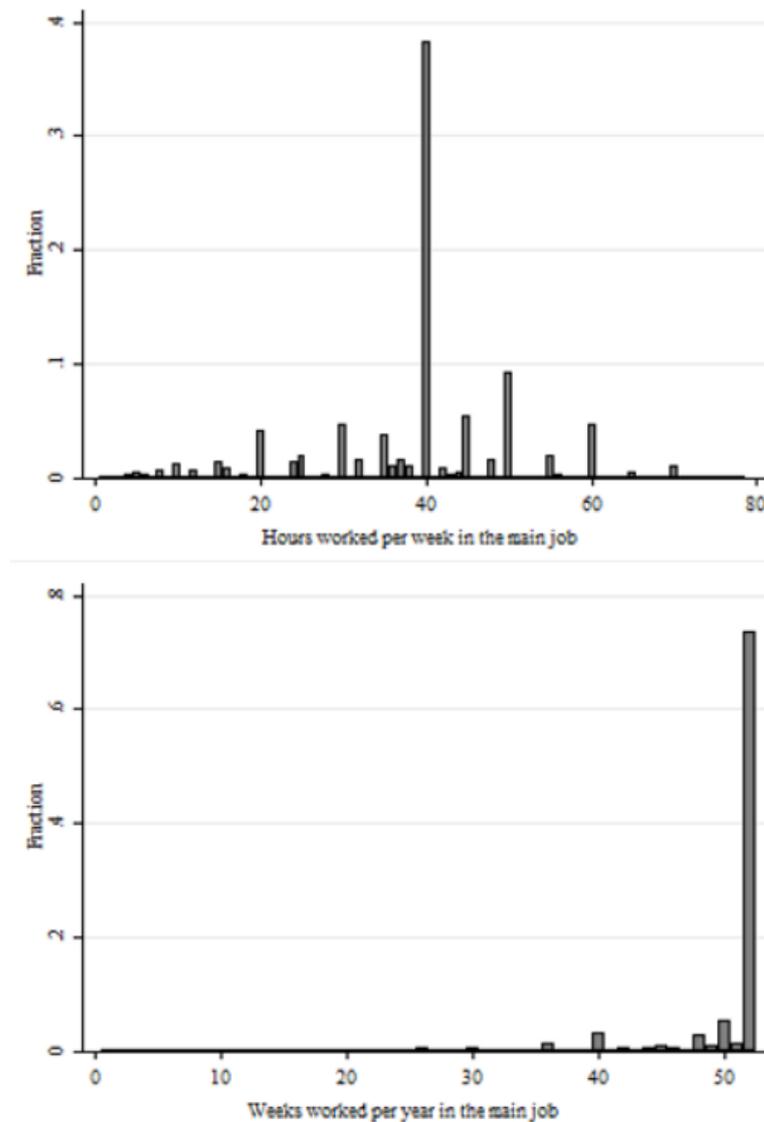


Figure 2: Distribution of hours worked per week and weeks worked per year (after sample restrictions)

Figure 2 depicts the distributions of the number of hours worked per week in all the survey years comprehend in the period of study (2000-2014). The graph displays that most of the respondents work more 35 or more hours per week and

more than 36 weeks per year. Among these individuals, 74% work 35 hours or more while and among those respondents who work less than 35 hours per week, 21% of individuals work less than 20 hours per week.

2.1.3 Measuring health

We use Body Mass Index (BMI) as a measure of physical health. BMI is defined as the ratio between the respondent's weight in kilograms and the squared of their height in meters. Additionally, we also consider other indices such as being obese and overweight. According to the existing literature, obesity is defined as a BMI higher than 30, and overweight greater than 25 and lower or equal to 30.

2.1.4 Measuring income

The HRS provides broad information about the respondent's income. We expect that individuals with higher income level are healthier, in the sense that they shall have lower BMI. There are several reasons why this might occur such as the fact that American people with higher income level will buy healthier and more expensive food (Young et al., 2002) or will take care of their own health since they can afford it (Meara et al., 2008).

To study the impact that working time has across different socio-economic groups, we focus first on the level of income to study the heterogeneous impact that working time might have on individuals with different income level within our sample and to extrapolate the resulting finding to the population we consider several measures of income. That way, we explore whether using different definitions of income lead to different results. We expect that results are similar for all the considered income measures, and thus obtaining more robust results.

First, we make use of the total household income which is defined as the total of income that a household accumulates per year. That way, it also includes individual earnings and the pension of the respondent and partner. Second, we consider separately individual earnings. The latter measure is defined as the total of respondent's yearly salary (including several types of earnings such as bonuses, extra pay, salary from a second job, military reserve earnings, professional practice, and trade income. Third, we consider the net total household income which we define as the difference of total household income and individual earnings (yearly). Fourth, we use total wealth, including secondary housing, and we define it as the total of wealth components excluding debt components. Furthermore, the weekly wage rate is also considered and defined as the weekly wage for respondent's who are currently employed and the imputed weekly wage for those who are unemployed. Lastly, we consider the total weekly wage rate as the sum of both respondent and partner's weekly wage. These six income measures are used as dummy indicators to group our sample into two categories: low income and high income. Some of these variables, such as weekly wage rate, total weekly wage rate, and individual earning, show a high number of missing

observations. These measures are conditioned on being employed or being part of the labor force after retirement. In Figure 3, we present the distribution of each income measure after applying sample restrictions. We observe that the distributions are skewed right so our data for these variables are lower bounded. If we set the two categories for these variables, we may find a problem of bias since we would have many missing observations and values of zero after setting the retirement eligibility ages. To ease this issue, we make use of the average income for each income measure as the best representative of the center of the distributions. As a threshold, we consider the median, and we will use in a later stage of the paper average as a robustness check. Hence for each income measure, the category "low income" comprehends the mean values which are lower than the median, and "high income" those above or equal to the median.

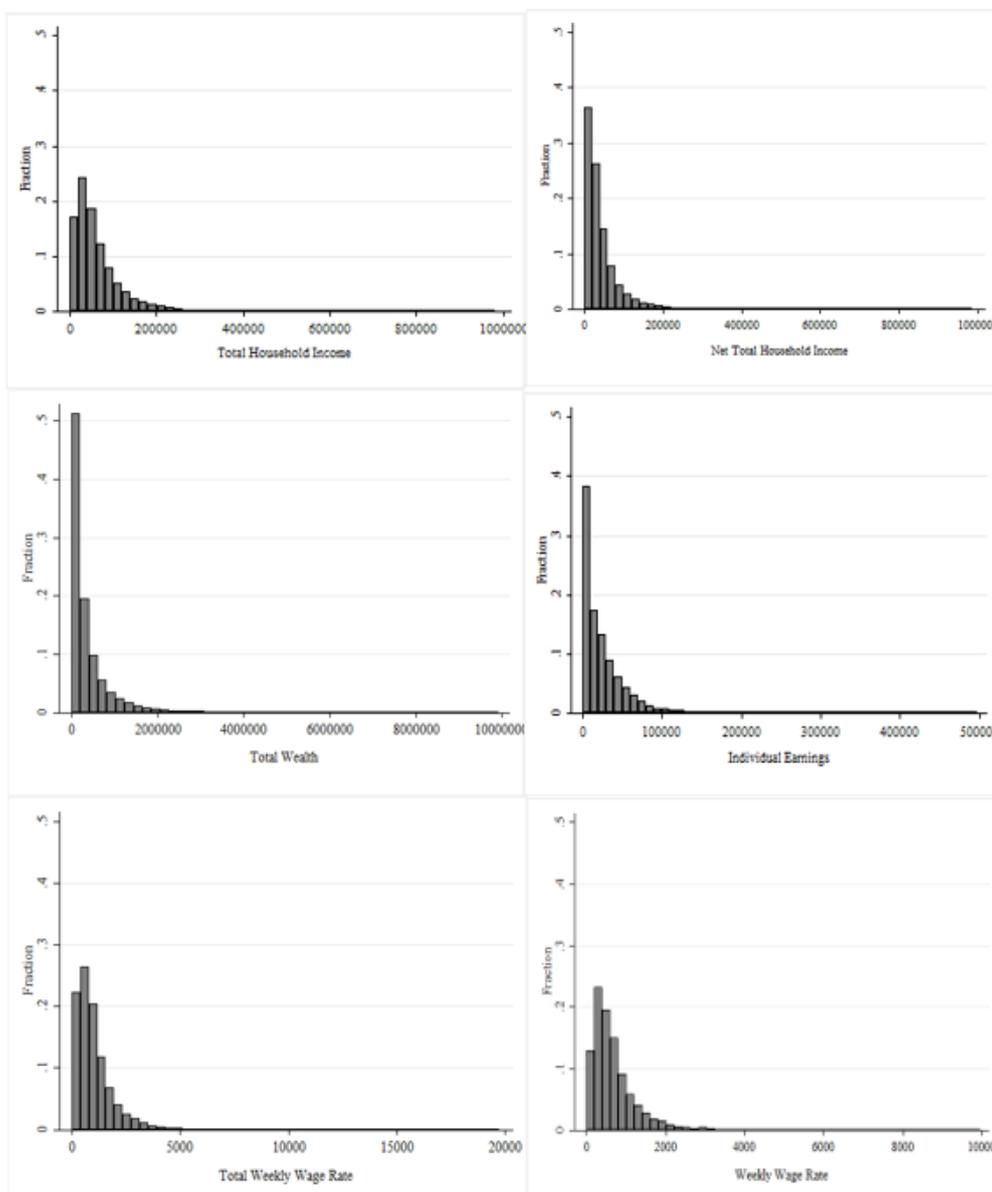


Figure 3: Distributions of the income measures (after sample restrictions)

2.1.5 Measuring education

As we pointed out in the Introduction section, one of the targets of this paper is to explore the impact that working time has on BMI across different socio-economic groups for old individuals. We expect that the effect differs across them since they might have different behaviors with respect to their own health care.

We already mentioned in the previous section why we focus on income level groups since it is a measure of an individual's socio-economic status. Another important indicator of the socio-economic status is the level of education, which is highly correlated with income level according to previous research (Meara et al., 2008). We hold the hypothesis that higher educated individuals are expected to be healthier since they might be more conscious of the impact on certain behaviors have on their weight. Individuals with high income level and highly educated might choose healthier food since they are more likely to know what is better to consume for them and they have more disposable income to do so. HRS provides detailed information about the educational attainment reached by the respondent. We make use of this information to explore the impact that working part-time and working full-time has on BMI across differentials in education level.

In the U.S., education is mandatory by law for the range of age 5 to 18. This range varies according to the state government. The education levels that fall within that age span are organized as follows: elementary school, middle school, and high school. For those who do not finish high school for any reason, they can still obtain a similar diploma called GED certification¹ Apart from the compulsory education, individuals could have a higher education which can be classified as follows: junior college, bachelor, graduate and post-graduate. In Figure 4, we can explore the distribution of our sample across different education levels. We observe that most of the individuals have at least the high school diploma.

¹ The General Educational Development test (GED) is addressed to those individuals who did not graduate in high school, but they completed at least 40% of the credits of the last high school year (this percentage also may depend on the State), and its certification is equivalent to the high school diploma.

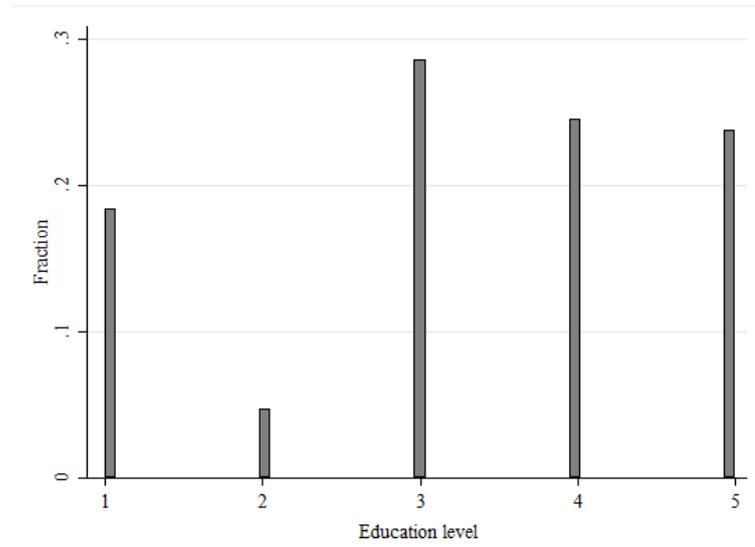


Figure 4: Distribution of the variable education level (after sample restrictions).²

Taking all this information into consideration, we construct a binary indicator for "low education" and "high education" using information based on the HRS question about the highest education level completed. We group then those respondents who have at least obtain high school graduate in the former category, and we encompass those with higher qualifications than high school level in the latter category. Then, our indicator takes the value of one if the respondent belongs to the category "high education" and zero if she/he belongs to the "low education" group.

2.1.6 Instrumental variables

The variable retirement is considered to be endogenous. To deal with this source of bias, we follow the instrumental variable approach. We choose as instruments retirement eligibility ages. We make use of six instruments which consist of the retirement eligibility ages for respondent and spouse. Three of this set of instruments are dummy variables which are indicators to whether the respondent is between early and the normal retirement age, between the normal retirement age and the age of 70, and above the age of 70. The same indicators are presented for the spouse. It is necessary that these variables affect retirement decision separately by itself, so they are good predictors of the effects of labor market choice. That is, the instruments should be strongly correlated with the endogenous variable and orthogonal to the error term. Then, the instrumental variables provide independent sources of exogenous variation for each endogenous variable, so that they alone allow to identify the causal effect on BMI.

² The category "1" refers to the number of individuals who attained education until high school, "2" refers to those who did not attained high school level but obtained the GED diploma, "3" refers to those with high school diploma, "4" refers to those with some college, and "5" to those with a college diploma and/or a higher education level.

According to the United States Social Security Administration, the early retirement age is 62 while individuals' normal retirement occurs within 65 and 67, and late retirement beyond 67. In the US, individuals are allowed to delay their retirement until they are 70 and even beyond their 70's. Most of the individuals who are above their 70's are not likely to be part of the earnings scheme, that is they are not working anymore since they are retired. The former, allows them to obtain higher retirement benefits from Social Security because of the actuarial adjustment. This is the reason why some individuals prefer to postpone their retirement to that age since future benefits are higher even though current benefits are lower. Therefore, we expect that retirement eligibility ages are good predictors of labor market participation as it has been already discussed in the literature. Coile and Gruber (2000), Bonsang et al. (2012), Mazzona and Peracchi (2012, 2017), Kantarci (2017, 2018) show in their studies that retirement eligibility ages are significant predictors of retirement decisions and labor market participation. Furthermore, Neuman (2008) also considers retirement eligibility ages of the partner since it makes sense that the respondent's retirement choice depends on whether the companion is eligible for social security benefits. The latter behavioral finding is supported by several studies which conclude that individuals tend to coordinate their retirement with spouse's retirement since they value it more (Gustman and Steinmeier, 2000, 2004, 2014).

As robustness checks, we explore the use of other instrumental variables. We consider being ever able to reduce work hours as an instrument. It is based on a question from HRS which asks the respondent whether she/he could reduce work paid hours in the regular schedule. We construct a dummy indicator which takes the value of one if the respondent can reduce work paid hours and zero otherwise. This variable is an instrument for working part-time given that reducing work time increases the likelihood of working full-time rather than full-time.

Additionally, we consider being self-employed as an instrumental variable. To construct a binary indicator, we use information from HRS based on the question of whether the respondent is or has ever been self-employed in her/his current or past main job. However, in the survey, we do not have information about this question for retirees and for those who skipped the question for being out of the labor force. Hence, we use a dummy variable that takes a value of one if the respondent has been self-employed in one or more survey years and zero otherwise. It is expected that this instrument is a good predictor of the effects of working part-time and full-time on BMI since these individuals have more flexibility to choose their way to participate in the labor force, that is, between working part-time, full-time or being partly retired.

Finally, we also consider firm size as an instrument. This variable is relevant for our analysis since depending on the firm-size, old individuals could choose to work more or fewer hours. Small-size firms usually offer higher flexibility to their employees allowing them to work part-time for several reasons. For instance, the

relationship between employer and employee is closer than it could be in a large-size firm, so it is more likely that the former consent the latter's requests. Some of these firms are even formed by family members. There are also economic-based reasons that can explain this fact. One of these motives is the fact that it is costly for this type of firms to hire and fire individuals, so they are more likely to hold agreements that satisfy both the employer and worker. However, large-size firms are usually less flexible and old workers are less likely to ask for working fewer hours since the firm can replace them more easily, and also the cost of it would probably not affect much their activity. It is based on the HRS question about the number of employees working in at the respondent's place of work. As it occurred with the latter instrument, there is missing information for those who are retired or skip the question. We construct a fictitious variable which takes the value of one if the respondent has ever worked in a large firm for one or more survey years. We use the definition given in the Affordable Act from the U.S. House of Representatives (2010) which agrees that a firm could be considered large if it has 50 or more employees.

2.1.7 Descriptive statistics

In table 1, we present the sample statistics. We distinguish between the averages for the full-time survey period and for the waves 1992, 2002 and 2014, to explore how the average values change over time for certain variables. Hence, we can observe that during the period 2000-2014 the average age is 62.30, where 48.24% are women, 51.33% are under early retirement eligibility age, 14.74% are between early and normal retirement eligibility ages, 16.17% are between normal retirement eligibility ages and age of 70, 17.17% are over the age of 70, 49.34% of the sample has high education, the average BMI is 28.05, 40.59% have overweight and 29.20% are obese, 74.65% has a spouse or partner. With regards to labor market information, 16.06% work part-time, 46.49% work full-time, 37.42% are retired, 24.79% have been self-employed, 59.09% have ever been able to reduce work hours, and 47.66% have ever worked in a large firm.

The most remarkable difference between the survey waves is observed for the variables overweight and obese. The percentage of respondents who are overweight decreases noticeably, while the percentage of respondents who are obese decreases and increases noticeably from 1992 wave to 2014 wave. Also, we observe that the percentage of respondents who work full-time and are retired increase from the 1992 wave to 2002 and the 2014 wave.

Table 1: Descriptive statistics (HRS)

	All waves	1992 wave	2002 wave	2014 wave
<i>Demographics</i>				
Age (50-75) (average)	62.30	57.04	64.20	63.01
Female (%)	48.24	39.75	48.03	53.64
Under early ret. age (%)	51.33	87.68	37.18	47.62
Bet. early and nor. ret. age (%)	14.74	6.66	16.99	21.12
Bet. nor. ret. age and age 70 (%)	16.17	4.57	24.68	13.61
Over age 70 (%)	17.17	1.10	21.16	17.65
High education (%)	49.34	41.31	46.69	57.70
BMI	28.05	26.94	27.80	29.27
Overweight (%)	40.59	43.04	41.24	37.55
Obese (%)	29.20	20.40	27.51	37.91
Married or partnership (%)	74.65	74.86	81.02	69.82
<i>Labour market information</i>				
Part-time worker (%)	16.06	15.50	16.26	16.05
Full-time worker (%)	46.49	69.08	38.53	42.95
Retired (%)	37.42	15.42	45.20	41.00
Ever been self-employed (%)	24.79	25.53	26.25	22.42
Ever been able to reduce work hours (%)	59.09	56.94	62.12	55.41
Ever worked in a large firm (%)	47.66	44.42	47.25	50.19
N.Obs.	91,379	5,844	6,929	8017
N.Ind.	21,127			

Notes: 1. Those values presented in percentages might not add up to 100% due to rounding. 2. The percentages (are averages) and averages are calculated with out considering missing values. 3. The number of observations and individuals are based on employment status.

2.2 Empirical approach

This section aims to explain the methodology that we follow to disentangle the effects of working part-time and working full-time on BMI for older people with differentials in income level and education. To do so, we use panel data from HRS for the period (2000-2014) and follow an instrumental variable approach to obtain causal effects of labor market participation on BMI across income level and education groups. In the literature, retirement eligibility ages have been used as valid instruments of retirement. We follow the approaches of Neuman (2008) and Kantarci (2017, 2018) who investigate the effect of the number of hours worked on different health outcomes. We distinguish between two estimation models, fixed effects model and random effects model, depending on the assumption we make about the unobserved time-invariant characteristics. In order to choose which model results more efficient for the purpose of the study, we make use of the Hausman test. Hereby, we provide a detailed explanation of the implementation of the empirical methodology.

2.2.1 Panel data

In this subsection, we base our explanations on Verbeek (2008). One of the aims of the study is to investigate the effect of working part-time and working full-time on physical health measured by BMI for older people, accounting for differentials in income and education. We then use panel data from the HRS for the period 2000-2014. The use of panel data allows us to exploit the within-individual variation to identify the causal effect of labor market participation on BMI since it allows to analyze changes at individual level outcomes. That way, we could get more efficient estimators and solve endogeneity bias problems. A first attempt to estimate this causal relationship could be to estimate the parameter of the variable of interest using Ordinary Least Squares (OLS), given by the following equation:

$$y_{it} = \alpha + f(\text{Age}_{it}) + x'_{it}\beta + u_{it}, \quad (2.2.1)$$

where i refers to the respondent ($i= 0, 1, 2, \dots, I$) and t to the time period ($t= 0, 1, 2, \dots, T$), y_{it} is BMI of respondent i in period t , $f(\text{Age}_{it})$ is defined as a continuous polynomial in age for individual i in period t to capture the non-linear relationship between age and body weight. x'_{it} is defined as the variance covariance matrix which includes dummy variables for working part-time and working full-time for respondent i in period t . The variable retirement is left as category of reference to avoid perfect multicollinearity. The parameter of interest is β . This vector measures the effects of working part-time and working full-time on BMI.

$$u_{it} = \alpha_i + \varepsilon_{it} \quad (2.2.2)$$

The error term u_{it} is defined as the idiosyncratic error term and includes the component α_i which accounts for unobserved heterogeneity that is constant for each i . In other words, α_i refers to all individual effects on BMI which are constant and unobservable. This term then identifies potential correlation overtime. It is a random component. ε_{it} is defined as the remaining idiosyncratic error term, which is assumed to be random, and independently and identically distributed (i.i.d.).

$$y_{it} = \alpha_i + \lambda_t + f(\text{Age}_{it}) + x'_{it}\beta + \varepsilon_{it} \quad (2.2.3)$$

Since we deal with several time periods, there is also the chance that specific periods are correlated with our variables. Hence, we could include the parameter λ_t which captures the correlation over individuals i within one period in time T . The error composite error term u_{it} is assumed to be as follows:

$$u_{it} = \alpha_i + \lambda_t + \varepsilon_{it} \quad (2.2.4)$$

To obtain consistent estimates of β , the OLS estimation method requires to assume that $E(x_{it}u_{it}) = 0$, it is to say, that the residuals are uncorrelated with the explanatory variables. This assumption is difficult to hold since there could be unobserved variables included in u_{it} that are correlated with both the BMI and variables in x_{it} such as working part-time and working full-time (also with age) mentioned, there are two advantages of using panel data. The first advantage is related to the efficiency argument. This improvement of efficiency in our estimations is made from the comparison between the use of cross-sectional data and panel-data. Since panel data presents variation over two dimensions, time and individuals, it results in a lower variance of the estimates. On the contrary, cross-section data only offers information about the time dimension. We assume a panel data sample and the following econometric model:

$$y_{it} = \alpha_i + \mu_t + \varepsilon_{it}, \quad (2.2.5)$$

where μ_t is the constant term, that is, the average of the population in period t : $y_{it} = \sum_{i=1}^I y_{it}$ and $t= 0, 1, 2, \dots, T$. If we estimate the change in the average over time $\mu_t - \mu_r$ t to s ($t \neq r$), the variance calculation shows a positive covariance over time for each individual i :

$$V(\hat{\mu}_t - \hat{\mu}_r) = V(\hat{\mu}_t) + V(\hat{\mu}_r) - 2cov(\hat{\mu}_t - \hat{\mu}_r) \quad (2.2.6)$$

This yields to a lower variance overall than in the case of cross-section data with two independent random samples since the positive covariance reduces the sum of the two variances. The second advantage is related to the identification argument. The structure of panel data allows controlling for omitted variable bias solving identification problems. If we use cross-section dataset as a pooled panel dataset would lead to biased estimates through α_i . However, if we transform panel data by

taking the first difference or by demeaning the data, all time-invariant and unobserved individual characteristics will drop. Running an OLS afterward with the transformed data will lead to unbiased estimates. To check whether we need to include unobserved individual effects and unobserved time effects we could run an OLS estimation and store the residuals as our best guess for the error term. We then run an OLS estimation, allowing for lags of u_{it} . Statistically significant results are evidence to include time-invariant individual effects. To decide on the inclusion of time effects, we could introduce time dummies on the latter model and seek significant results for these parameter estimates.

2.2.2 Fixed effects model

The present subsection uses explanations from Verbeek (2008). The fixed effects model results from augmenting equation (2.2.1) to the following model through equation (2.2.2). It can be expressed as follows:

$$y_{it} = \alpha + f(\text{Age}_{it}) + x'_{it}\beta + \alpha_i + \varepsilon_{it}, \quad (2.2.7)$$

where ε_{it} is assumed to be random and identically and independently distributed (i.i.d.) with mean zero and variance σ_ε^2 . We assume zero correlation. As we already mentioned in the former subsection, this assumption is not likely to hold for the reasons we explained. Here we also assume that α_i as N fixed unknown parameters. We can rewrite equation (2.2.7) by introducing a dummy variable for each respondent i in the model.

$$y_{it} = \sum_{j=1}^N \alpha_j d_{ij} + f(\text{Age}_{it}) + x'_{it}\beta + \varepsilon_{it}, \quad (2.2.8)$$

where $d_{ij} = 1$ if $i = j$ and 0 otherwise. Therefore, we have a set of N dummy variables in model (2.2.8). We then can estimate the set of parameters $\alpha_1, \alpha_2, \dots, \alpha_N$ and the vector β by OLS. The estimator for β is known as the least squares dummy variable (LSDV) estimator. The main disadvantage of using this estimation procedure is that as N gets larger, the number of parameters to estimate increases. Then, to avoid overfitting the model and increase artificially the variance of the estimated parameters, we can transform the data to estimate β and eliminate the time invariant individual effects α_i . To simplify expressions, we include the age variable into x_{it} . If we apply the sample average of y_{it} across time we obtain the following expression:

$$\bar{y}_{it} = \alpha_i + \bar{x}_{it}\beta + \bar{\varepsilon}_{it}, \quad (2.2.9)$$

where $\bar{y}_{it} = T^{-1} \sum_{i=1}^T y_{it}$, $\bar{x}_{it} = T^{-1} \sum_{i=1}^T x_{it}$ and $\bar{\varepsilon}_{it} = T^{-1} \sum_{i=1}^T \varepsilon_{it}$. If we compute $\bar{y}_{it} - y_{it}$ we get the following expression:

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)' \beta + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (2.2.10)$$

Here the set of parameters α_i vanish and we obtain the same estimate for β as in the LSDV estimator. This is referred as the within transformation and the OLS estimator for β is denominated the fixed effect estimator or the within estimator, which is equivalent to the LSDV estimator. The expression for the OLS fixed effects estimator for β is the following:

$$\hat{\beta}_{FE} = ((\sum_{i=1}^I \sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)')^{-1}) \sum_{i=1}^I \sum_{t=1}^T (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i), \quad (2.2.11)$$

if we assume normality of the error term ε_{it} , the fixed effects estimator also presents a normal distribution. For consistency we need that $E[(x_{it} - \bar{x}_i)\varepsilon_{it}] = 0$. This is the assumption of strict exogeneity and implies that x_{it} are uncorrelated with the error term and \bar{x}_i is also orthogonal to the error term. If these assumptions hold, the N intercepts can be estimated as the following expression:

$$\hat{\alpha}_i = \bar{y}_i + \bar{x}_i \hat{\beta}_{FE} \quad (2.2.12)$$

The intercepts $\hat{\alpha}_i$ are consistent estimates for the fixed effects α_i as T goes to infinity. If T is fixed, the individual effects do not converge since \bar{y}_i and \bar{x}_i do not converge if the number of individuals increases. Since we assume that ε_{it} are i.i.d. across individuals and time periods, the variance matrix for the fixed effects estimator is given by the following expression:

$$V(\hat{\beta}_{FE}) = \sigma_\varepsilon^2 (\sum_{i=1}^I \sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)')^{-1}, \quad (2.2.13)$$

if T is not large enough to estimate the true individual intercepts, the estimate for covariance matrix will underestimate the true variance. The reason behind this is that in the transformed regression equation the error covariance matrix is singular, and the variance of $(\varepsilon_{it} - \bar{\varepsilon}_i)$ is $(T-1)/T\sigma_\varepsilon^2$ instead of σ_ε^2 . A consistent estimate for σ_ε^2 can be obtained by estimating the sum of the squared within error terms divided by $N(T-1)$. Hence, the estimator for σ_ε^2 takes the following expression:

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{N(T-1)} \sum_{i=1}^I \sum_{t=1}^T (y_{it} - \hat{\alpha}_i - x'_{it} \hat{\beta}_{FE})^2 \quad (2.2.14)$$

And it can be rewritten as follows:

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{N(T-1)} \sum_{i=1}^I \sum_{t=1}^T (y_{it} - \bar{y}_i - (x_{it} - \bar{x}_i) \hat{\beta}_{FE})^2 \quad (2.2.15)$$

We can apply the freedom degrees correction by subtracting K number of parameters to the denominator in the latter equation. If we estimate β using equation (2.2.8), it is consistent since there is a correction of the degrees of freedom of the N parameters corresponding to the time-invariant individual effects. Additionally, under weak regularity conditions the estimator is

asymptotically normal, and thus statistical inference can be used on them through hypothesis testing with methods such as the T-test and the Wald test.

2.2.3 Random effects model

This subsection is based on Verbeek (2008). The random effects model assumes that α_i are random thus they cannot be treated as parameters. It takes the following form:

$$y_{it} = \alpha + f(\text{Age}_{it}) + x'_{it}\beta + \alpha_i + \varepsilon_{it} \quad (2.2.16)$$

This model assumes that α_i is i.i.d. with mean zero and variance σ_α^2 , and ε_{it} is i.i.d. with mean zero and variance σ_ε^2 . Then, there is a composite error term which consist of $(\alpha_i + \varepsilon_{it})$, a part which contains the unobserved heterogeneity due to time invariant individual effects, and a part which refers to the remaining idiosyncratic error term, respectively. We assume that ε_{it} is not correlated over time, and that α_i and ε_{it} are mutually independent and independent of x_{it} . Hence, the OLS estimates are unbiased and consistent. Unless $\sigma_\alpha^2 = 0$, Generalized Least Squares (GLS) estimator are more efficient and exploits the structure of the error covariance matrix. In this case, OLS estimates would be incorrect since they would not control for autocorrelation in the error term. The error term covariance matrix can be expressed as follows:

$$V(\alpha_i l_T + \alpha_i) = \Omega = \sigma_\alpha^2 \alpha_i l_T + \sigma_\varepsilon^2 I_T, \quad (2.2.17)$$

where I_T is the identity matrix. We can transform the data to obtain the GLS estimator for β by multiplying all y_i vectors by a square matrix P such we can write $\Omega^{-1} = PP'$. That way, $\Omega = (PP')^{-1} = P^{-1}P^{-1}$, and $P\Omega P = I$. We assume Ω^{-1} to be known and takes the following expression:

$$\Omega^{-1} = \frac{1}{\sqrt{\sigma_\varepsilon^2}} \left[\left(I_T - \frac{1}{T} l_T l_T' + \psi \frac{1}{T} l_T l_T' \right) \right], \quad (2.2.18)$$

where $\psi = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\alpha^2}$. Thus, the GLS for estimator can be written as follows:

$$\hat{\beta}_{GLS} = \left(\sum_{i=1}^I \sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' + \psi T \sum_{i=1}^I (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \left(\sum_{i=1}^I \sum_{t=1}^T (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i) + \psi T (x_{it} - \bar{x})(y_{it} - \bar{y}_i) \right) \quad (2.2.19)$$

Notice that if $\psi=0$, we obtain the fixed effects estimator for β , and if $\psi=1$ we get the OLS estimator and Ω is now the diagonal matrix and accounts for the heterogeneity across individuals. In addition, ψ tends to zero, and T tends to infinity, the fixed effects and random effects estimators are equivalent, it is to say, they converge to the same values given that all sources of heterogeneity come from α_i . From (2.2.19) it can be derived:

$$\hat{\beta}_{GLS} = W\hat{\beta}_B + (I_k - W)\hat{\beta}_{FE}, \quad (2.2.20)$$

where $\hat{\beta}_B$ denotes the between estimator for β which is the OLS estimator in the model for individual means presented in equation (2.2.9). W refers to the weighting matrix and it is the inverse of the covariance matrix of $\hat{\beta}_B$. The GLS estimator is the matrix-weighted average of the within estimator and between estimator, where the weight depends on the relative variances of the two coefficients from the two estimators. The GLS estimator is the optimal combination of the fixed effects and the OLS estimator. However, the assumptions needed for GLS are stronger than the ones for OLS and FE to work, since for OLS we need independence and zero correlation between the error term and x_{it} within the same period, and for fixed effects we need strict exogeneity of x_{it} and no assumptions for α_i . Also, we assume that we know σ_α^2 and σ_ε^2 when they are unknown in practice. Thus, the GLS estimator is unfeasible. We need to estimate σ_α^2 and σ_ε^2 through a two-step procedure to obtain a feasible GLS estimator for β (FGLS). First, we estimate σ_ε^2 from the fixed effect estimation. Note that for the between regression equation the error variance is specified as $\sigma_\alpha^2 + (\frac{1}{T}) \sigma_\varepsilon^2$, which is consistently estimated as follows:

$$\sigma_B^2 = \frac{1}{I} \sum_{i=1}^I (\bar{y}_i - \hat{\alpha}_B - \bar{x}'_{it} \hat{\beta}_B)^2 \quad (2.2.21)$$

Then, we estimate σ_α^2 as follows:

$$\hat{\sigma}_\alpha^2 = \hat{\sigma}_B^2 - \frac{1}{T} \hat{\sigma}_\varepsilon^2 \quad (2.2.22)$$

As the case for fixed effects estimator, it is possible to apply a degrees of freedom correction, subtracting $K+1$ in the denominator of equation (2.2.21). Under weak regularity conditions, the random effects estimator is asymptotically normal, and its covariance matrix is as follows:

$$V(\hat{\beta}_{RE}) = \hat{\sigma}_\varepsilon^2 ((\sum_{i=1}^I \sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' + \psi T \sum_{i=1}^I (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)'),^{-1} \quad (2.2.22)$$

which reflects that the random effects estimator is more efficient than fixed effects if $\psi > 0$.

2.2.4 Hausman test

We follow the contents of Verbeek (2008). We make use of the test developed by Hausman (1978) to decide whether to estimate by fixed effects estimator or random effects estimator. The Hausman test compares whether the two estimators are significantly different. The difference between the fixed effects model and the random effects model lies in the assumption about α_i . The null hypothesis consists

on the assumption that x_{it} and α_i are uncorrelated. If this is true, fixed effects and random effects are consistent and random effects estimator is more efficient. On the opposite, the alternative hypothesis states that x_{it} and α_i are correlated. Then, only the fixed effects estimator is consistent. The Hausman estimator is expressed as follows:

$$(\hat{\beta}_{FE} - \hat{\beta}_{RE})' [V(\hat{\beta}_{FE}) - V(\hat{\beta}_{RE})]^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE}), \quad (2.2.23)$$

which under the null hypothesis follows a Chi-squared distribution with K degrees of freedom.

2.2.5 Instrumental variables approach and causality of the estimated effects

This subsection uses explanations from Verbeek (2008). The fixed effects model eliminates the source of bias from unobserved individual effects through the within transformation. There might be also other sources of bias coming from the composite error term such as the fact that respondents with higher BMI prefer retiring rather than working part-time or full-time (reverse causation), which make the fixed effects estimator inconsistent.

The use of the instrumental variables approach solves the endogeneity problems and allows for causal interpretation of β . We use the two-stage least squares estimation method. In the first stage, we regress the suspected endogenous variables (working part-time and working full-time) on the exogenous variables and instruments. Following Neuman (2008) and Kantarci (2017, 2018) we use retirement eligibility ages of respondent and spouse as instrumental variables. That way, we obtain a linear probability model since the dependent variables are binary indicators. In a second stage, the predicted values are used to estimate the coefficients for β from the within transformed equation (2.2.10).

The validity of the instruments lies in the compliance of the exogeneity and relevance restrictions. It is to say, they are not correlated with the error term and must be relevant predictors of working part-time and working full-time. Furthermore, given that we have two endogenous variables, we need that the instruments provide independent sources of exogenous variation for each of them to identify their causal effects on BMI. If this is not the case, the endogenous variables could be weakly identified (Angrist and Pischke, 2009).

2.3 Exploratory graphical analysis

One of the aims of this thesis is to study the effects of working full-time and working part-time on BMI for the elderly who have different income levels and distinct education levels. In this section, we study graphically the relationships between age and BMI for each income group for all income measures and, also for each education level group. We then seek graphical evidence of the effects of working full-time and working part-time with respect to these variables. Hereby we provide graphical evidence of the differentials on BMI for individuals between 50 and 75 years old who work part-time, full-time and those who are retired.

In Figure 5 and Figure 6, we present univariate nonparametric regressions for the variable BMI against the variable age for part-time workers (red), full-time workers (blue) and retired respondents (grey). To disentangle the effects of BMI against age for individuals with different income levels, we also considered each income group for each income measure. Furthermore, we draw 95% confidence intervals around each of the resulting curves. The first relevant finding is that most of the curves for full-time workers and part-time workers do not cross each other until the age of 65. This result suggests that for these individuals the difference in the groups for all income measures are statistically significant at the 5% level of significance until that age.

The second noticeable finding, and very related to the previous one, is that the BMI decreases with age for retired individuals. There might be several reasons for this result. For instance, it might occur that this group of individuals is still doing some exercise. Also, their way of eating and time spent of different activities could be related to this result.

Another result which is worthy to note is that overall, on average, BMI is lower for the high income groups than for the low income groups. Therefore, we obtain graphical evidence for our hypothesis: individuals with higher income present lower BMI. Likewise, we find confirmation about the findings shown in the literature. American individuals who are wealthier can afford buying expensive food which is generally healthier (Young et al., 2002), and they take care of their health since they can afford to do so (Meara et al., 2008). When we specifically focus on the differences between income groups across labor market participation status, we find that retirees have on average higher BMI than part-time workers and full-time workers, and that overall part-time workers present lower BMI than full-time workers.

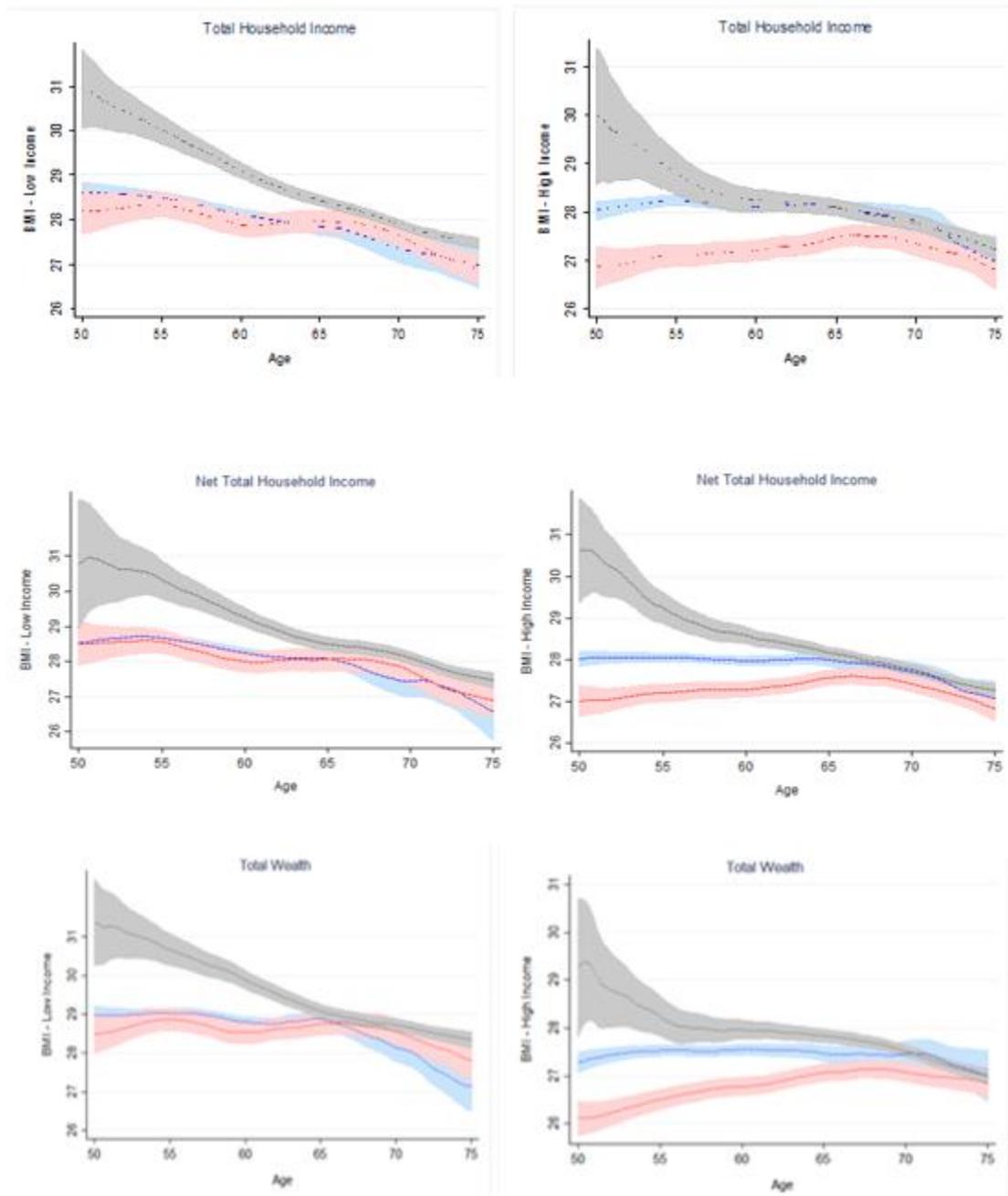


Figure 5: BMI average across age of respondent among part-time workers (red), full-time workers (blue) and retired respondents (grey) by low income level (left) and high income level (right) for each income measured considered in the analysis. Kernel-smoothed local polynomials with 95% confidence intervals.

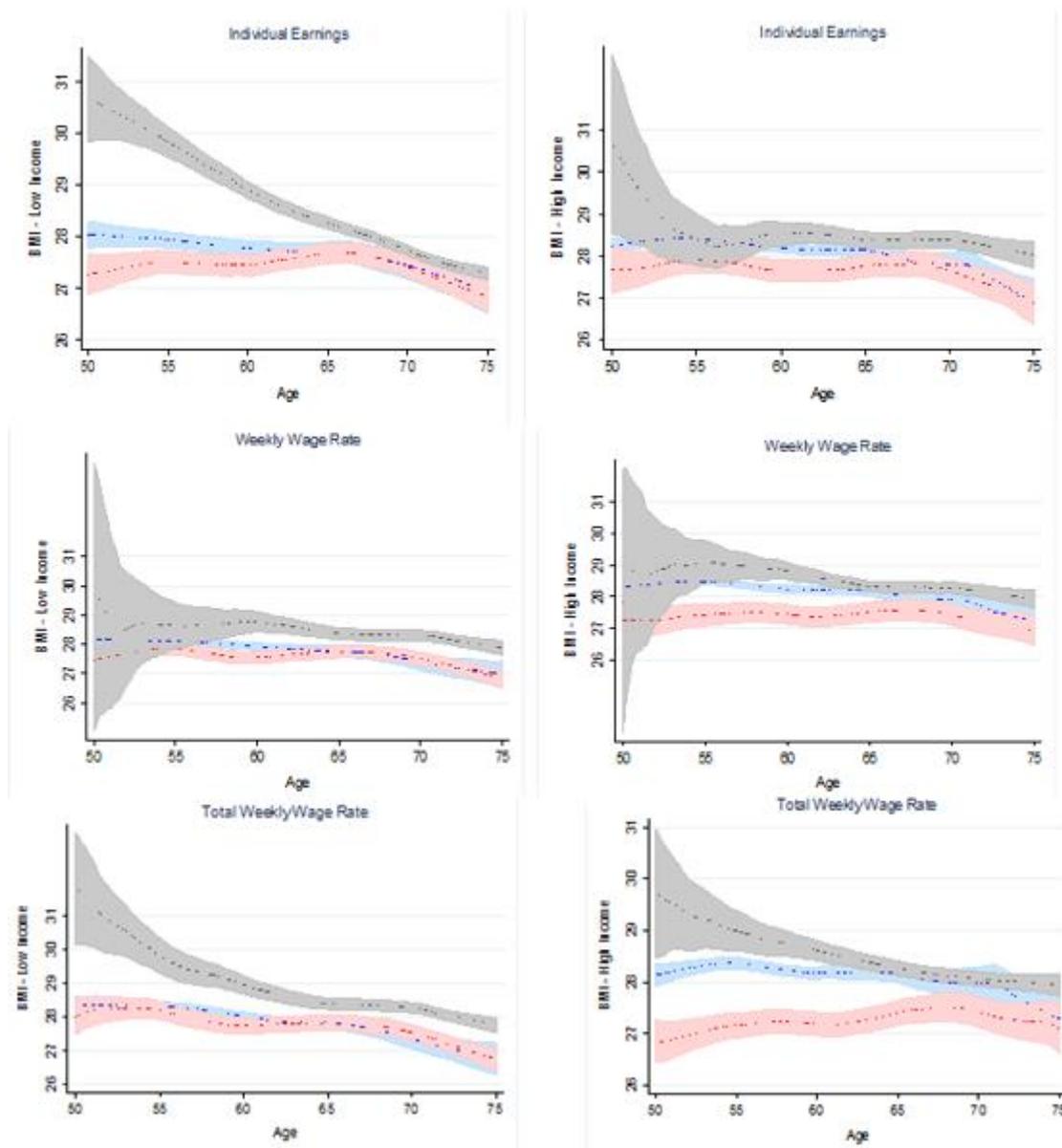


Figure 6: BMI average across age of respondent among part-time workers (red), full-time workers (blue) and retired respondents (grey) by low income level (left) and high income level (right) for each income measured considered in the analysis. Kernel-smoothed local polynomials with 95% confidence intervals.

Similarly, in Figure 7 we consider the low education group and the high education group. We observe that the curves for low educated individuals do not cross each other until the age of 65 approximately. Hence, the differences between part-time workers, full-time workers, and retired individuals are statistically significant until that moment. Again, we find that BMI diminishes with age. For both low education and high education groups, on average, BMI of retirees is higher than the BMI of full-time and part-time workers. For highly educated individuals, the curves do not cross each other until the age of 65 approximately so that the differences among part-time workers, full-time workers and retired are statistically significant until that age. Here, we also find that BMI decreases with age. However, it is worthy to note that BMI of retirees, full-time workers and part-

time workers, is on average lower than that for the low educated groups. Likewise, we find that for low educated respondents, on average, the BMI of full-time workers is slightly higher than the BMI of part-time workers while, for the highly educated individuals, the BMI of those who work full-time is higher than the BMI of those who work part-time.

From these findings, we can conclude that BMI diminishes with age for retired individuals, that those with higher income level present on average lower body weight and, that low educated individuals have higher body weight than those who are highly educated. Furthermore, we can conclude that overall retirees with low- income have larger BMI than part-time workers and full-time workers, and that this difference is larger for those respondents within the high income group. Additionally, for low income respondents part-time workers have, in general, slightly higher BMI than those who work full-time, and we observe that the difference is larger for the high income group. Finally, we can also conclude that BMI is larger for low educated individuals than the BMI for respondents who attained a higher level of education. Particularly, retirees overall have higher BMI than part-time and full-time workers. We conclude that for low educated respondents, full-time workers present slightly higher than those who work part-time, and for high educated respondents, the difference between these groups of workers is higher.

These conclusions seem to be in line with the literature. Drewnowski and Specter (2004) find that individuals with low income level usually buy unhealthy food with high levels of fat and sugar because of their low prices. Related to this finding Young et al. (2002) finds that American consumers are more attracted to high portions of food with low prices and do not care about their body weight. Education might be crucial to address the obesity problem. In line with our findings, and in the literature, education appears to be negatively correlated with BMI. Meara et al. (2008) finds this relationship and states that promoting education might diminish obesity of Americans and relieve income disparities. Higher educated and wealthier individuals will take healthier food options since they can afford it. Then, higher socio-economic status implies lower levels of BMI. Additionally, there are some mechanisms that might drive these relationships, and we investigate these matters along the contents of this paper.

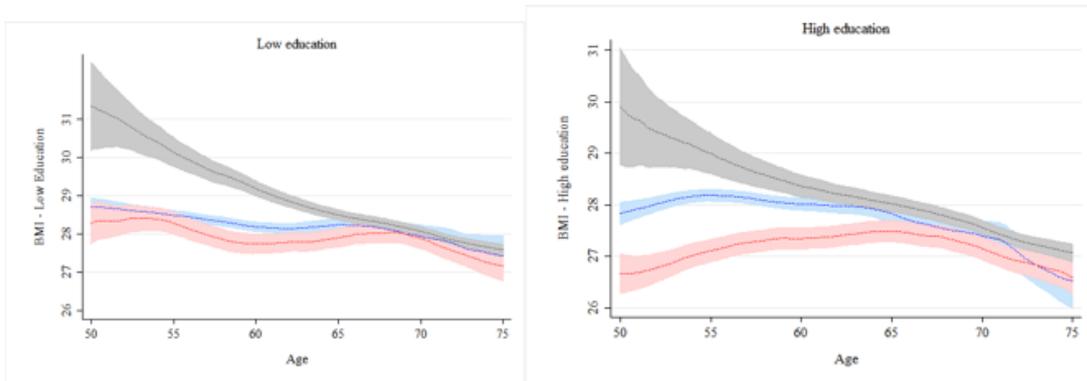


Figure 7: BMI average across age of respondent among part-time workers (red), full-time workers (blue) and retired respondents (grey) by low income level (left) and high income level (right) for each income measured considered in the analysis. Kernel-smoothed local polynomials with 95% confidence intervals.

2.4 Results

2.4.1 Instrument relevance and validity

In Table 2, we present the first stage estimation of the linear probability model from the second stage equation. Consequently, the predictions of the model might fall outside the unit interval, and standard errors are heteroskedastic by construction. Therefore, we correct for heteroskedasticity and obtain standard errors robust to heteroskedasticity (Eicker-White standard errors). This model assumes that residuals are not normally distributed. However, since our sample is large, we can use traditional tests for inference based on normal distributions

As described in Section 2.2, we use two set of instruments which corresponds to indicators for retirement eligibility ages of respondent and retirement eligibility ages of spouse (or partner). According to the estimates from Table 2, we conclude that both sets of instruments have a statistically significant effect on the probability of working part-time and working full-time. The effect is more pronounced for the probability of working full-time. The economic intuition behind this result is that most workers stop working full-time once they become eligible for retirement and thus for social security benefits and other pension payments. Retirement eligibility ages for both respondent and spouse are statistically significant at 1% of significance level. Hence, we can state that they are relevant predictors for labor market participation of older people. Estimates for retirement eligibility ages of respondent are statistically significant at standard levels of confidence, but they do differ in signs and magnitude size for working part-time and working full-time. It is also worthy to note that the spouse's retirement decision is a relevant predictor of respondent's retirement choice, and this finding is line with the literature (Gustman and Steinmeier, 2000, 2004, 2014).

The use of instrumental variables approach solves the endogeneity problems and allows for causal interpretation of β . We use the two-stage least squares estimation method. In the first stage, we regress the suspected endogenous variables (working part-time and working full-time) on the exogenous variables and instruments. Following Neuman (2008) and Kantarci (2017, 2018) we use retirement eligibility ages of respondent and spouse as instrumental variables. That way, we obtain a linear probability model since the dependent variables are binary indicators. In a second stage, the predicted values are used to estimate the coefficients for β from the within transformed equation (2.2.10). Also, we find that there is a nonlinear effect of age on the probability of working part-time and working full-time.

The validity of instruments is proven through the Angrist and Pischke (2009) first-stage conditional F test statistic for the endogenous regressors. This statistic tests for weak identification of each endogenous regressor, it is to say, for the fact that each instrument must provide independent sources of exogenous

variation for each endogenous regressor so their causal effect on BMI can be identified. A second test that we perform is the Sanderson and Windmeijer test (2016), which is an improvement of the latter described F statistic. Sanderson and Windmeijer (2016) find that the variance expression in the denominator of the F statistic should be adjusted to obtain the right asymptotic distribution when the null hypothesis is tested with two endogenous regressors in a model. This test consists of a two-stage methodology. First, an endogenous regressor is regressed on the first stage fitted values of the regressors (endogenous and exogenous). Second, the residuals, which come from the latter regression, are regressed on the instruments. If the instruments are jointly significant, then there is empirical evidence against the null hypothesis, that is, instruments weakly identified for a considered endogenous regressor. Furthermore, Sanderson and Windmeijer (2016) state that their proposed F statistic is equivalent to the Cragg-Donald (1993) minimum eigenvalue statistic. Results from Table 2 suggest that our instruments are not weakly identified for any of the two endogenous regressors. Therefore, our instruments provide independent sources of variation for each endogenous variable and, they alone allow identifying the causal effect of the endogenous variables on BMI. In Table 3, we present the results for the Sargan-Hansen test based on the Hansen J statistic, which follows a Chi-Squared distribution under the null hypothesis, and tests for the null hypothesis that all moment restrictions are valid of the overidentification test. According to the results, we fail to reject the null hypothesis and hence we do not have overidentifying restrictions and they are orthogonal to the error term. Therefore, we conclude that our instruments are valid.

Table 2: Baseline FE – First stage results

	Part-time	Full-time
Bet. early and normal ret. age	0.036*** (0.005)	-0.162*** (0.007)
Bet. normal ret. age and age 70	0.045*** (0.008)	-0.242*** (0.009)
Over age 70	0.031*** (0.011)	-0.207*** (0.012)
Bet. early and nor. ret. age (P)	-0.011** (0.006)	-0.027*** (0.006)
Bet. nor. ret. age and age 70 (P)	-0.040*** (0.008)	-0.021** (0.009)
Over age 70 (P)	-0.084*** (0.012)	0.012 (0.013)
Age	0.016** (0.006)	0.001 (0.007)
Age ²	-0.000** (0.000)	-0.000*** (0.000)
Constant	-0.343* (0.189)	1.354*** (0.202)
F test quadratic age	5.31***	542.70***
F test for excluded instruments	18.91***	176.93***
Weak identification test	12.682***	37.223***
N. Obs.	68, 151	
N. Ind.	14, 556	

Notes: 1. Linear probability model with fixed effects. 2. First stage results. 3. (P) refers to married or unmarried partner. 4. Weak identification test is based on Sanderson Windmeijer F statistic. It tests the null hypothesis that the endogenous variable alone is not identified. 5. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 6. *** p<0.01, ** p<0.05, * p<0.1.

2.4.2 Effects of working part-time and working full-time on BMI

In Table 3, we present the second stage estimates for the fixed effects baseline equation (2.2.7). We find statistically significant results at the standard levels of statistical significance for the effects of working part-time and working full time on BMI. Additionally, we reject the equality of working part-time and working full-time at 5% level of significance. This means that labor market participation has a significant effect on BMI and that this effect varies with the number of hours worked.

It is relevant to notice that the impact of working part-time on BMI is almost three times larger than the effect of working full-time, in absolute value. That is, part-time workers have on average lower BMI than full-time workers and retirees.

Working full-time also has a negative impact on BMI in comparison to individuals who are retired. The mechanisms will be further analyzed in the second part of the paper.

Table 3 also shows significant results for the age terms. We conclude that the effect of age on BMI is nonlinear. Age seems to have an average positive impact on BMI, keeping everything else constant, until a certain age when the effect substantially decreases and becomes negative and very close to zero.

Table 3: Baseline FE – Second stage results

	BMI
Part-time	-3.021***‡ (1.003)
Full-time	-0.846*** (0.275)
Age	0.556*** (0.054)
Age ²	-0.004*** (0.000)
Endogeneity test	13.813***
Overidentification test	1.394
F test for work status	10.543***
F test for quadratic age	187.750***
N. Obs.	65,865
N. Ind.	13,001

Notes: 1. Linear probability model with fixed effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is based on the C statistic. It tests the null hypothesis that "part-time" and "full-time" are exogenous. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

2.4.3 Effects of working part-time and working full-time on BMI by income level

To capture the differences in the studied treatment effects across individuals with different socio-economic status we first analyze these effects for individuals with different income levels. As mentioned in Section 2.3, we consider several income measures: total household income; individual earnings; net total household income; weekly wage rate and total weekly wage. For each of these measures, we consider a dummy indicator for low income and high income. We perform separate

fixed effects regressions for each income measure considered corresponding to the first stage and second stage of the regression equation (2.2.7).

In Table 4 and Table 5, we present the second stage results for the two levels of each income measure. For all income groups, we fail to reject the null hypothesis of overidentifying restrictions at the standard levels of significance. Hence, the instruments are valid. However, we fail to reject the endogeneity test in some cases. For the low income group from the following measures total household income, net total household income and total wealth, we find that working part-time and working full-time are not endogenous. Therefore, for these cases, we can treat the latter two regressors as exogenous variables. Also, for the high income group, we observe that from individual earnings, weekly wage rate and total weekly wage rate, working part-time and working full-time are not endogenous either.

Besides, the effects of working part-time and working full-time on BMI are overall similar to those obtained in Table 3. We comment first on the effects for high income groups. For total household income, we find that working part-time has a significant impact on BMI at 5% of significance level whilst the effect of working full-time is not significant. As in the baseline results, the impact of age is non-linear and is also statistically significant at 1% level of significance. Also, we find significant results for the effect of work status and quadratic age. Likewise, we reject the null hypothesis of the equality of working part-time and working full-time at 1% level of significance. For net total household income, we find similar results to the baseline results but as mentioned in the previous paragraph working part-time and working full-time can be considered exogenous regressors. With regards to individual earnings, we do not find significant impacts of working part-time and working full-time on BMI and we can consider these regressors as exogenous. The impact of quadratic age though is statistically significant at the standard levels of significance. For total wealth, the results are very similar to those from Table 3. For both weekly wage rate and total weekly wage rate, we do not observe significant effects of working part-time and working full-time on the dependent variable and, also the result from the endogeneity test we can consider these two variables as exogenous.

We can conclude that, as in Table 3, for most of income measures, we find that the impact of working part-time on body weight is larger than working full-time. It is to say, that working part-time is related to lower BMI while working full-time has low impact on BMI. Hence, for individuals with high income level, working less hours is linked with lower body fat.

For low income groups, we observe that for total household income the impact of working part-time is not statistically significant while the effect of working full-time is significant at 10% level and it presents similar size to the effect of this regressor in the baseline regression equation from Table 3. Additionally, the impact of age is non-linear and is also statistically significant at 1% level of significance. We also find a statistically significant effect for quadratic

age, but we fail to reject the endogeneity test so that we can treat working part-time and full-time as exogenous regressors. For net total household income, we do not find significant results for working part-time either, and we do find a statistically significant at 10% level of significance which is similar to the result in Table 3 for working full-time. As we previously explained, working part-time and working full-time can be considered exogenous regressors. For individual earnings, we find a statistically significant effect of working part-time at 1% level. The average impact of working part-time is larger (-3.519) than the effect of this regressor in Table 3 (-3.021). The impact of working full-time on BMI is though not statistically significant at the standard levels of confidence. The estimates for age are statistically significant at the standard levels of significance, and the results are very similar to those from Table 3. In relation to the weekly wage rate, the effect of working part-time is on average lower (-2.015) than the average effect of this regressor in Table 3 (-3.021). Moreover, the effect of working part-time is significant at 10% level of significance. The effect of working full-time is slightly larger (-0.919) than the impact of this variable in the baseline results. Likewise, the results are both statistically significant at 1% level of confidence. For total weekly wage rates, the effect of the two indicators for labor market participation are significant and larger than the baseline results and the estimates for other income measures (-3.578 for working part-time and -1.439 for working full-time). The estimate for age and squared age are also larger and statistically significant at 1% level. These findings show that for individuals with low income level, the impact of working part-time and working full-time on BMI is larger than for those individuals with high income level. We find statistically significant results for the effect of working part-time for the income groups measured by individual earnings, weekly wage rate and total weekly wage rate. The impact of working part-time for these groups is larger than the impact we found in Table 3. It is to say, the effect of working part-time on BMI is negative and larger than the effect we found for the baseline results. The effect of working full-time is also similar to the effect we observed in the baseline results, low and negative. In summary, for low income groups, working part-time and working full-time have negative impact on BMI, and the size of these effects is larger than for the high income groups.

Table 4: Income heterogeneity FE – Second stage results (1)

	BMI					
	Total household income		Net total household income		Earnings	
	Low income	High income	Low income	High income	Low income	High income
Part-time	-2.804 (2.717)	-2.733*** (1.081)	-2.737 \ddagger (2.591)	-2.317*** \ddagger (0.829)	-3.519*** \ddagger (1.338)	-4.595 (3.213)
Full-time	-0.920* (0.498)	-0.596 (0.381)	-0.806* (0.436)	-0.719** (0.294)	-0.962 (0.601)	-1.122 (0.823)
Age	0.505*** (0.091)	0.473*** (0.064)	0.534*** (0.152)	0.539*** (0.053)	0.378*** (0.089)	0.633*** (0.162)
Age ²	-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.004*** (0.000)	-0.003*** (0.001)	-0.005*** (0.001)
Endogeneity test	4.269	8.319**	4.209	9.590***	9.223**	3.610
Overid. test	1.937	2.316	1.022	1.342	2.997	1.542
F test quadratic age	35.82***	147.33***	27.87***	147.78***	24.27***	115.96***
F test work status	4.26	6.52**	3.53	8.56**	7.41**	2.06
F test for equality	0.66	6.31**	0.70	5.51**	4.16**	1.97
N. Obs.	24,578	37,853	14,129	48,137	30,353	32,637
N. Ind.	6,383	8,406	4,000	10,472	7,234	7,363

Notes: 1. Linear probability model with fixed effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. \ddagger indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is based on the C statistic. It tests the null hypothesis that "part-time" and "full-time" are exogenous. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Income heterogeneity FE – Second stage results (II)

	BMI					
	Total wealth		Weekly wage rate		Total weekly wage rate	
	Low income	High income	Low income	High income	Low income	High income
Part-time	-1.023 (1.725)	-3.165*** (1.079)	-2.015* (1.040)	-2.739 (3.209)	-3.578* (1.942)	-1.275 (1.158)
Full-time	-0.455 (0.478)	-0.718** (0.338)	-0.919*** (0.336)	-0.105 (0.365)	-1.439*** (0.557)	0.017 (0.286)
Age	0.458*** (0.102)	0.586*** (0.065)	0.563*** (0.092)	0.468*** (0.088)	0.678*** (0.129)	0.411*** (0.061)
Age ²	-0.003*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	-0.003*** (0.001)
Endogeneity test	1.180	11.116***	7.816**	0.741	8.380**	1.201
Overid. test	0.966	6.433	1.644	1.996	2.475	3.545
F test quadratic age	66.83***	103.34***	62.71***	78.73***	48.28***	128.38***
F test work status	1.02	8.92**	7.60**	0.88	6.95**	1.82
F test for equality	0.17	6.91***	1.57	0.78	2.00	1.57
N. Obs.	24,177	32,832	22,145	28,163	21,488	34,225
N. Ind.	6,321	7,052	4,715	5,906	4,959	7,090

Notes: 1. Linear probability model with fixed effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. † indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is based on the C statistic. It tests the null hypothesis that "part-time" and "full-time" are exogenous. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

2.4.4 Effects of working part-time and working full-time on BMI by education level

Education level is one of the determinants of the socio-economic status. In this subsection, we intend to capture the differences in the effects of working part-time and working full-time on BMI for groups of individuals with differentials in education attainment level. We construct a binary indicator which groups respondents into the category of low education if those who at least obtained a high school graduate diploma or similar diploma, and groups respondents into the category of high education if they attained a higher education level. As in the previous subsection, we estimate separate fixed effects regressions for each education group for the first stage and second stage of the regression equation (2.2.7).

Table 6: Education level heterogeneity FE – Second stage results

	BMI	
	Low education	High education
Part-time	−3.331** (1.482)	−2.789**‡ (1.374)
Full-time	−0.991*** (0.362)	−0.624 (0.438)
Age	0.568*** (0.073)	0.536*** (0.077)
Age ²	−0.004*** (0.001)	−0.004*** (0.001)
Endogeneity test	8.582**	5.812*
Overid. test	1.219	3.394
F test quadratic age	81.98***	106.08***
F test work status	7.52**	4.16***
F test for equality	3.65*	4.04***
N. Obs.	32,689	33,174
N. Ind.	6,512	6,488

Notes: 1. Linear probability model with fixed effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is based on the C statistic. It tests the null hypothesis that "part-time" and "full-time" are exogenous. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

In Table 6, we indicate the second stage results for each education attainment level. For both groups, we fail to reject the null hypothesis of overidentifying restrictions. Thus, the instruments are orthogonal to the error term. Furthermore, we reject the null hypothesis that working part-time and working full-time are exogenous. Overall results are similar to the baseline results. The effect on BMI is larger for part-time workers and the difference between the

effects of working part-time and working full-time is significant. These results are in line with the findings observed in Figure 7. The curves for part-time workers and full-time workers are lower than the curves for the retired- The effect of working part-time is negative and larger for the low educated individuals. We observe that on average and *ceteris paribus* part-time workers have lower BMI respect to retirees, and this effect is larger for individuals with low education. We find a statistically significant negative effect of working full-time on BMI for individuals with low education level which is lower than the effect of working part-time. We then conclude that, on average and keeping everything else equal, working part-time has a larger and negative impact on BMI for low educated individuals than for highly educated individuals, while working full-time has a negative and statistically significant impact at standard levels of significance on BMI for low educated respondents. We expect that the analysis of the behavioral mechanisms which might drive these relationships help to explain these results.

2.5 Robustness checks

In this paper, we make several assumptions with respect instrument identification and model specification. In this section, we check the sensitivity of our results to the set of instruments. We use in addition to our set of instrumental variables, an alternative set of instruments which consist of binary indicators for having ever been able to reduce work hours, ever worked in a large firm and ever been self-employed. We also check the sensitivity of the results to model specifications by studying whether the results are sensitive to age specification and the definition of income level groups. Finally, we check the sensitivity of the results to the econometric model.

2.5.1 Set of instrumental variables

In Section 2.1, we describe alternative instrumental variables to retirement eligibility ages of respondent and partner. We consider dummy indicators for ever have been able to reduce paid work hours within the regular work schedule, ever have worked in a large firm, and have ever been self-employed. In this section, we perform the analysis using these alternative instruments in addition to the baseline instrumental variables. That way, we can study the sensitivity of our results to the introduction of new instruments. Because of the introduction of these new instrumental variables, we shall change the model assumption about unobserved time-invariant individual characteristics (α_i). The fixed effects model is not valid this time because these additional variables have a high level of variation over time for respondent i . Furthermore, Hausman test indicates that the random effects model is appropriate. Additionally, these new instrumental variables are not independent of each other. The HRS asks about being able to reduce work hours only if the respondent is not self-employed. We hence include these variables in two different set of instruments and check the sensitivity of the results for both sets of variables.

We first consider a set of instruments which consist of retirement eligibility ages of respondent and partner, an indicator for have ever been able to reduce work hours and an indicator for having ever worked in a large firm. In Table 7 and Table8, we include the first stage and second stage baseline results for the random effects model. The effects of ever have been able to reduce paid work hours and ever have worked in a large firm on the probabilities of working part-time and working full-time are statistically significant at 1%. The interpretation of the coefficients is as follows: if an individual can reduce paid work hours within her/his regular schedule, she/he is more likely to work part-time; and, if an individual is working on a large firm, she/he is more likely to work full-time. The instruments are jointly significant at 1% level of significance. Then, instruments are powerful and if we look at the weak identification test (Sanderson and

Windmeijer, 2016), each instrument provides exogenous variation to explain the effects of the two endogenous regressors independently. Also, results from the test of overidentifying restrictions in Table 8 show that the instruments are orthogonal to the error term. Hence, we have valid instruments. Furthermore, results for the retirement eligibility ages in Table 6 and Table 7 are very similar to the fixed effects baseline results. This information suggests that our baseline results are robust to the set of instruments and the assumption over the unobserved individual effects.

Table 7: Robustness check – Baseline RE – First stage results

	Part-time	Full-time
Bet. early and normal ret. age	0.046*** (0.007)	-0.167*** (0.008)
Bet. normal ret. age and age 70	0.057*** (0.011)	-0.246*** (0.012)
Over age 70	0.037** (0.017)	-0.189*** (0.018)
Bet. early and nor. ret. age (P)	0.006 (0.006)	-0.055*** (0.007)
Bet. nor. ret. age and age 70 (P)	-0.014* (0.009)	-0.064*** (0.010)
Over age 70 (P)	-0.042*** (0.012)	-0.048*** (0.013)
Age	0.015* (0.009)	0.064*** (0.009)
Age ²	-0.000 (0.000)	-0.001*** (0.000)
Ever been able to red. work hours	0.136*** (0.006)	-0.019*** (0.007)
Ever worked in large firm	-0.106*** (0.006)	0.064*** (0.007)
Constant	-0.319 (0.256)	-0.483* (0.256)
F test quadratic age	7.28**	7774.83***
F test for excluded instruments	124.97***	109.34***
Weak identification test	167.85***	183.68***
N. Obs.	45,207	
N. Ind.	8,544	

Notes: 1. Linear probability model with random effects. 2. First stage results. 3. (P) refers to married or unmarried partner. 4. Weak identification test is based on Sanderson Windmeijer F statistic. 5. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 6. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Robustness check – Baseline RE – Second stage results

	BMI
Part-time	−3.724***‡ (0.682)
Full-time	−1.234*** (0.295)
Age	0.598*** (0.065)
Age ²	−0.005*** (0.001)
Constant	10.817*** (1.695)
Endogeneity test	34.79**
Overidentification test	3.62
F test for work status	30.14**
F test for quadratic age	144.29***
N. Obs.	44,650
N. Ind.	8,516

Notes: 1. Linear probability model with random effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner, indicator for being able to reduce working hours and indicator for having ever worked in a large firm. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is computed by hand since there is no package in Stata to do so. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

With regards, to the heterogeneous effect of working part-time and working full-time across groups with differences in income levels, we perform separate random effects regressions for each income measure considered corresponding to the first stage and second stage. In Table 9, we present the second stage results. For all income groups, we fail to reject the null hypothesis of overidentifying restrictions at the standard levels of significance. Thus, the instruments are orthogonal to the error term, and hence, they are valid instruments. Furthermore, we reject the endogeneity test in all cases. We then have empirical evidence that working part-time and working full-time can be treated as endogenous regressors for the two income levels and all the considered income measures. We find significant effects of working part-time and working full-time on BMI. However, as it happened in Table 4 and Table 5, the interpretation for working part-time and working full-time across income levels is somehow cumbersome since the effects are not equivalent for all income measures. In general, we can find that the effect of working part-time is larger than working full-time in comparison to retirees for those who have high income level in comparison to individuals with low income level. Overall, we observe that the impact of both endogenous regressors is more

pronounced in high income level groups. However, the size of the effect of working full-time on BMI across income levels depends on the analyzed income measure. In general terms, we could conclude that the effect of working full-time is more pronounced for low income individuals.

Furthermore, the effect of the variables age and squared age are statistically significant at the standard levels of significance, and their size is pretty similar to the coefficients obtained in Table 4 and Table 5. It is also worthy to note that the use of these instrumental variables gives statistically significant results for most of the income level groups and income measures. We then can conclude that the IV estimator is more efficient when we add these instruments. In addition, all of these findings suggest that our results are robust to the new set of instruments.

In Table 10, we present the second-stage results for each education attainment level using the new set of instruments. For both low education group and high education group we fail to reject the null hypothesis of overidentifying restrictions. Then, the set of instruments is orthogonal to the error term. Besides, we reject the null hypothesis that both working part-time and working full-time are exogenous at the standard levels of significance. Overall, results are similar to those obtained in Table 6. The effect of working part-time and working full-time are larger and more pronounced in comparison to retirees for low educated individuals. Overall part-time workers have lower BMI than full-time workers. We, therefore, conclude that our results for the differences across education level groups are robust to the new set of instruments.

Now we consider another set of instruments which consist of retirement eligibility ages of respondent and partner, an indicator for have ever worked in a large firm and an indicator for have ever been self-employed. If we look at tables A1 and A2 from the Appendix, we find empirical evidence that these instruments are good predictors of labor market participation. As it occurred when we used the previous set of instruments, we obtain statistically significant results for most of the income measures and education level groups (tables A3 and A4). Hence, we conclude that the IV estimator is more efficient, and this set of instruments is more powerful. Moreover, most of the results remain the same in terms of the sign and size of the coefficients. Thus, all these findings suggest that our results are robust to the new set of instruments.

Table 9: Robustness check - Income level heterogeneity RE – Second stage results

	BMI																								
	Total household income				Net total household income				Earnings				Total wealth				Weekly wage rate				Total weekly wage rate				
	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income			
Part-time	-2.716*** (0.813)	-4.059*** (0.789)	-3.663*** (1.245)	-2.973*** (0.622)	-2.004*** (0.662)	-3.259*** (1.078)	-3.508*** (1.021)	-3.555*** (0.687)	-2.842*** (0.732)	-5.691*** (1.882)	-2.550*** (0.830)	-3.426*** (0.934)	Part-time	-2.716*** (0.813)	-4.059*** (0.789)	-3.663*** (1.245)	-2.973*** (0.622)	-2.004*** (0.662)	-3.259*** (1.078)	-3.508*** (1.021)	-3.555*** (0.687)	-2.842*** (0.732)	-5.691*** (1.882)	-2.550*** (0.830)	-3.426*** (0.934)
Full-time	-1.181*** (0.358)	-1.222*** (0.411)	-1.238*** (0.440)	-1.032*** (0.323)	-0.736 (0.535)	-1.529*** (0.466)	-1.508*** (0.515)	-0.862*** (0.351)	-1.368*** (0.393)	-0.524 (0.347)	-1.498*** (0.442)	-0.421 (0.311)	Full-time	-1.181*** (0.358)	-1.222*** (0.411)	-1.238*** (0.440)	-1.032*** (0.323)	-0.736 (0.535)	-1.529*** (0.466)	-1.508*** (0.515)	-0.862*** (0.351)	-1.368*** (0.393)	-0.524 (0.347)	-1.498*** (0.442)	-0.421 (0.311)
Age	0.430*** (0.094)	0.548*** (0.079)	0.579*** (0.135)	0.561*** (0.066)	0.370*** (0.100)	0.657*** (0.102)	0.609*** (0.127)	0.601*** (0.070)	0.547*** (0.094)	0.474*** (0.081)	0.541*** (0.110)	0.450*** (0.069)	Age	0.430*** (0.094)	0.548*** (0.079)	0.579*** (0.135)	0.561*** (0.066)	0.370*** (0.100)	0.657*** (0.102)	0.609*** (0.127)	0.601*** (0.070)	0.547*** (0.094)	0.474*** (0.081)	0.541*** (0.110)	0.450*** (0.069)
Age ²	-0.004*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	Age ²	-0.004*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	
Constant	16.493*** (2.855)	11.847*** (2.023)	12.646*** (3.551)	11.074*** (1.824)	16.837*** (3.520)	9.337*** (2.486)	11.659*** (3.184)	9.418*** (2.070)	12.710*** (2.637)	13.378*** (2.267)	12.987*** (3.013)	13.850*** (1.887)	Constant	16.493*** (2.855)	11.847*** (2.023)	12.646*** (3.551)	11.074*** (1.824)	16.837*** (3.520)	9.337*** (2.486)	11.659*** (3.184)	9.418*** (2.070)	12.710*** (2.637)	13.378*** (2.267)	12.987*** (3.013)	13.850*** (1.887)
Endogeneity test	13.13***	32.72***	12.49***	26.37***	9.15***	26.66***	14.56***	29.88***	17.90***	12.55***	12.98***	18.70***	Endogeneity test	13.13***	32.72***	12.49***	26.37***	9.15***	26.66***	14.56***	29.88***	17.90***	12.55***	12.98***	18.70***
Overid. test	6.09	3.845	3.679	7.204	2.369	2.530	14.640**	2.478	5.176	3.243	10.297	6.058	Overid. test	6.09	3.845	3.679	7.204	2.369	2.530	14.640**	2.478	5.176	3.243	10.297	6.058
F test quadratic age	20.75***	112.80***	21.73***	117.50***	14.14***	118.45***	48.05***	90.27***	39.21***	61.42***	28.56***	92.31***	F test quadratic age	20.75***	112.80***	21.73***	117.50***	14.14***	118.45***	48.05***	90.27***	39.21***	61.42***	28.56***	92.31***
F test work status	14.10***	26.58***	11.26***	22.96***	9.38***	23.89***	12.39***	26.77***	17.18***	9.41***	12.37***	13.53***	F test work status	14.10***	26.58***	11.26***	22.96***	9.38***	23.89***	12.39***	26.77***	17.18***	9.41***	12.37***	13.53***
F test for equality	5.11**	20.79***	4.78***	15.51***	3.16*	23.89***	8.36***	19.55***	6.30**	8.29***	3.04*	12.61*	F test for equality	5.11**	20.79***	4.78***	15.51***	3.16*	23.89***	8.36***	19.55***	6.30**	8.29***	3.04*	12.61*
N. Obs.	15,227	29,423	12,422	32,228	14,464	30,186	18,900	23,005	18,042	23,840	15,356	28,087	N. Obs.	15,227	29,423	12,422	32,228	14,464	30,186	18,900	23,005	18,042	23,840	15,356	28,087
N. Ind.	4,743	7,125	4,520	7,540	4,249	7,449	5,631	5,485	4,528	5,641	4,383	6,357	N. Ind.	4,743	7,125	4,520	7,540	4,249	7,449	5,631	5,485	4,528	5,641	4,383	6,357

Notes: 1. Linear probability model with random effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner; indicator for being able to reduce working hours and partner; indicator for having ever worked in a large firm. 4. † indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is computed by hand since there is no package in Stata to do so. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Robustness check – Education level heterogeneity RE – Second stage results

	BMI	
	Low education	High education
Part-time	−4.045***‡ (0.937)	−3.207***‡ (0.967)
Full-time	−1.392*** (0.386)	−0.916** (0.448)
Age	0.586*** (0.095)	0.578*** (0.086)
Age ²	−0.005*** (0.001)	−0.004*** (0.001)
Constant	11.945*** (2.564)	10.478*** (2.182)
Endogeneity test	21.63***	12.98***
Overid. test	4.830	4.561
F test quadratic age	52.27***	96.44***
F test work status	19.47***	11.21***
F test for equality	13.20***	10.12***
N. Obs.	20,890	23,758
N. Ind.	3,940	4,575

Notes: 1. Linear probability model with random effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner, indicator for being able to reduce working hours and indicator for ever having worked in a large firm. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is computed by hand since there is no package in Stata to do so. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

2.5.2 Age specification

We have observed empirical evidence that the relationship between age and BMI is nonlinear, which is in line with the findings in the literature. It appears that the effect of age on BMI is positive until a certain point at which the direction of the relationship reverses and turns negative. In this part, we investigate the sensitivity of the results to higher-order polynomials. We analyze the results for linear, quadratic and cubic functions of age. We only explore the relationships until cubic age since higher-order polynomials might lead to overfitting the model. We present in Table 11 and Table 12 the first stage and second stage fixed effects results.

In the first stage results, we find that the coefficients for working part-time and working full-time do not vary much between a model in which we consider a linear function of age and the model with a quadratic function of age. However, when we control for cubic age, the size of these coefficients decreases. Also, we find that the coefficient for cubic age is virtually zero. We also observed that the coefficients for the two endogenous variables are also lower for the regressions with a linear function of age. Then, this model might not be capturing well nonlinear effects of age on BMI and instruments have lower predictive power. Therefore, we conclude that the results with the quadratic specification of age captures the nonlinear relationship between age and BMI adequately and allows the instruments to maintain their predictive power.

With regards to second stage results, the effects of working part-time and working full-time are positive and statistically significant at standard levels of significance when we control for linear age. The effect of working part-time is larger than working full-time as in the rest of the specifications. When we control for quadratic age, we obtain a smaller coefficient for working part-time. The estimate for working full-time is statistically significant at 1%, and the effect is negative and lower than working part-time in comparison with retirees. There is empirical evidence of a nonlinear concave relationship between age and BMI. We find that when we control for cubic age, the effect of working part-time is lower. Likewise, the effect of working full-time is also smaller and not statistically significant at standard levels of significance. Also, the term for cubic age is virtually zero and not statistically significant. The J statistic is more powerful when we control for linear age, and we reject the null hypothesis of overidentifying restrictions. Thus, our instruments are not valid since they are not orthogonal to the error term.

In summary, our instruments lose predictive power when we introduce a quadratic term and they become even less powerful when we include a cubic term. We consider that the model with a quadratic age function specification captures well the nonlinearity between the variable age and the variable BMI.

Table 11: Robustness check – Age specification – First stage results

	Linear age		Quadratic age		Cubic age	
	Part-time	Full-time	Part-time	Full-time	Part-time	Full-time
Bet. early and normal ret. age	0.034*** (0.005)	-0.166*** (0.007)	0.036*** (0.005)	-0.162*** (0.007)	0.024*** (0.006)	-0.107*** (0.007)
Bet. normal ret. age and age 70	0.037*** (0.008)	-0.257*** (0.010)	0.045*** (0.008)	-0.242*** (0.009)	0.023** (0.010)	-0.146*** (0.011)
Over age 70	0.011 (0.011)	-0.245*** (0.013)	0.031*** (0.011)	-0.207*** (0.012)	0.013 (0.013)	-0.127*** (0.014)
Bet. early and nor. ret. age (P)	-0.011** (0.005)	-0.027*** (0.006)	-0.011** (0.006)	-0.027*** (0.006)	-0.012** (0.006)	-0.023*** (0.006)
Bet. nor. ret. age and age 70 (P)	-0.041*** (0.008)	-0.023** (0.009)	-0.040*** (0.008)	-0.021** (0.009)	-0.042*** (0.008)	-0.015 (0.009)
Over age 70 (P)	-0.087*** (0.012)	0.006 (0.013)	-0.084*** (0.012)	0.012 (0.013)	-0.085*** (0.012)	0.014 (0.013)
Age	0.002*** (0.001)	-0.024*** (0.001)	0.016** (0.006)	0.001 (0.007)	-0.263*** (0.079)	1.213*** (0.085)
Age ²			-0.000** (0.000)	-0.000*** (0.000)	0.004*** (0.001)	-0.020*** (0.001)
Age ³					-0.000*** (0.000)	0.000*** (0.000)
Constant	0.058 (0.039)	2.105*** (0.046)	-0.343* (0.189)	1.354*** (0.202)	5.352*** (1.624)	-23.412*** (1.759)
F test quadratic age			5.31***	542.70***		
F test cubic age					8.58***	385.39***
F test for excluded instruments	23.750***	141.059***	10.635***	106.383***	10.490***	42.379***
Weak identification test	28.367***	129.183***	12.682***	37.223***	13.067***	60.070***
N. Obs	68, 151					
N. Ind	14, 556					

Notes: 1. Linear probability model with fixed effects. 2. First stage results. 3. (P) refers to married or unmarried partner. 4. Weak identification test is based on Sanderson Windmeijer F statistic. 5. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 6. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Robustness check – Age specification – Second stage results

	BMI		
	Linear age	Quadratic age	Cubic age
Part-time	2.468***‡ (0.650)	-3.021***‡ (1.003)	-2.878***‡ (1.005)
Full-time	0.343*** (0.214)	-0.846*** (0.275)	-0.469 (0.409)
Age	0.085*** (0.009)	0.556*** (0.054)	-0.594 (0.875)
Age ²		-0.004*** (0.000)	0.014 (0.014)
Age ³			-0.000 (-0.000)
Constant	22.134*** (0.703)	10.494*** (1.426)	33.457* (17.474)
Endogeneity test	23.236***	13.813***	10.530***
Overid. test	51.906***	1.394	1.037
F test quadratic age		187.73***	
F test cubic age			189.44***
N. Obs	67,382		
N. Ind	14,518		

Notes: 1. Linear probability model with fixed effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test based on the C statistic. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

2.5.3 Income threshold

In this section, we study the sensitivity of our results to a change in the definition of the heterogeneous income groups. That way, we redefine the income threshold to build up sample groups with differentials in income level. In Section 2.1, we used as a threshold the median of each income measure to create binary indicators for high- and low income levels. We now set the threshold as the average income for each income measure. Thus, we create binary indicators which are equal to one if the respondent's income level is higher or equal to the average income level of our sample and zero elsewhere.

Table 13 presents the second stage results of this robustness check. The first relevant finding is that instruments are orthogonal to the error term according to the results from the overidentifying restriction test for all income measures and groups. The second finding is that, as in Table 4 and Table 5, we fail to reject the endogeneity test in some cases. For the low income group from a couple of income measures such as net household income and total wealth, we fail to reject the null hypothesis of the endogeneity test. That is, the variables working part-time and working full-time can be treated as exogenous. Likewise, for the high

income group from the income measure individual earnings and weekly wage rate those regressors can also be considered exogenous. Furthermore, the effects of working part-time and working full-time are overall similar to the estimates from Table 3. Another finding is that signs of the coefficients do not vary across income measure specifications with respect to the results from Table 4 and Table 5. Also, the significance and magnitude of the results vary slightly with respect to Table 4 and Table 5. For high total household income respondents, the impact of working part-time is statistically significant at 5% level of significance while the effect of working full-time is only significant at 10%. For respondents with a high level of net total household income, we find similar results. For individuals with a high level of earnings, working full-time and working part-time are exogenous variables as we mentioned, and they do not have a significant impact on BMI. For respondents with a high level of total wealth, the impact of working part-time is statistically significant at 5% while working full-time does not have a significant impact. For high total weekly wage rate, respondents working part-time and working full-time are exogenous, and their effects on BMI are not statistically significant. For respondents with low total household income, working part-time is statistically significant at 5% and working full-time is statistically significant at 1%. For individuals with low level of net total household income the variables working part-time and working full-time are exogenous, and their impact on BMI is not statistically significant. For individuals with low earnings, both working part-time and working full-time are statistically significant at 1%, and we reject the equality of the estimates of these two variables at 5%. Overall, the magnitude of the estimates is slightly larger. Standard errors are also larger for most of the coefficients. The effect of age is nonlinear and statistically significant at 1% for all income groups and very similar to results in Table 4 and Table 5. Standard errors are also larger for most of the coefficients. Since these results do not lead to different conclusions, we could state that our results are robust to changes in the income threshold definition.

Table 13: Income threshold – Second stage results

	BMI																								
	Total household income				Net total household income				Earnings				Total wealth				Weekly wage rate				Total weekly wage rate				
	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income	Low income	High income			
Part-time	-3.618** (1.611)	-2.504** (1.149)	-2.752 (2.059)	-2.563** (1.022)	-3.270*** (1.176)	-1.351 (4.406)	-2.397* (1.363)	-3.695** (1.660)	-1.955* (1.022)	-0.637 (2.838)	-4.920*** (1.605)	0.897 (1.412)													
Full-time	-0.945*** (0.340)	-0.949* (0.563)	-0.581 (0.381)	-0.858** (0.390)	-0.978*** (0.370)	-0.255 (1.106)	-0.705* (0.378)	-0.575 (0.512)	-0.653** (0.310)	0.296 (0.432)	-1.559*** (0.426)	0.416 (0.383)													
Age	0.541*** (0.075)	0.458*** (0.076)	0.578*** (0.106)	0.494*** (0.061)	0.485*** (0.063)	0.545*** (0.194)	0.522*** (0.072)	0.587*** (0.112)	0.578*** (0.080)	0.369*** (0.091)	0.720*** (0.112)	0.316*** (0.073)													
Age ²	-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.000)	-0.004*** (0.002)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.006*** (0.001)	-0.002*** (0.001)													
Constant	11.658*** (2.058)	13.006*** (1.909)	10.030*** (2.594)	11.686*** (1.842)	13.100*** (2.171)	9.859** (4.315)	11.855*** (1.784)	8.310** (3.374)	9.628*** (2.024)	14.322*** (2.414)	7.477*** (2.795)	15.238*** (1.950)													
Endogeneity test	9.688***	5.876*	2.058	8.189**	10.879***	0.336	3.868	8.968**	5.315*	0.270	20.102***	0.941													
Overid. test	0.750	2.548	3.408	1.653	1.435	0.890	1.022	2.346	0.600	3.495	0.280	1.035													
N. Obs	42,220	25,102	32,620	34,762	42,462	24,920	42,410	18,572	34720	18,114	35,037	23,763													
N. Ind	11,706	7,808	10,317	10,079	11,349	7,594	11,640	5,359	8,092	4,717	8,889	6,101													

Notes: 1. Linear probability model with fixed effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. † indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test based on the C statistic. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

2.5.4 Econometric model

As we have previously indicated, retirement decision and thus the number of hours worked are endogenous variables in our econometric model. We make use of instrumental variables to address the endogeneity problem. Likewise, we also take advantage of the longitudinal component of the HRS dataset which allows us to estimate by fixed effects and address the sources of endogeneity originated by the unobserved time-invariant individual effects. We include three additional models to check for the sensitivity of our results to different model estimation methods and model assumptions. Results for these sensitivity tests are presented in Table 14. The first model considers cross-section information and does not use panel data information. It is a pooled regression model estimated by OLS. It does not deal with the endogeneity problem through instrumental variables either. The second model presented exploits the nature of the panel dataset and allows for fixed effects. Here we deal with the endogeneity which might come from time-invariant individual effects. However, we do not consider instruments as in the first model. The third model presented is a pooled instrumental variable (IV) model estimated by the two-stage least squares estimator (2SLS). This model approaches the endogeneity problem in our model caused by the number of hours worked, but it does not account for the endogeneity coming from unobserved heterogeneous individual effects. The last model considers both the panel dimension of the HRS data and instrumental variables. It estimates by 2SLS after the within-group transformation.

On the one hand, results across the models do not lead to different conclusions. Working part-time and working full-time with respect to retirees have lower BMI. The effect on BMI is larger for part-time workers. Nonetheless, results from the pooled IV show a positive impact of working part-time and working full-time on BMI. On the other hand, the size of the coefficients does vary across the considered models. The magnitude of the coefficients decreases substantially when we consider the panel data dimension in comparison with the pooled OLS and decreases when we compare pooled IV model with IV-FE panel data model.

Table 14: Robustness check - Econometric model

	BMI			
	Pooled OLS	FE	Pooled IV	IV-FE
Part-time	-0.932***‡ (0.057)	-0.027 (0.042)	8.421***‡ (3.194)	-3.021***‡ (1.003)
Full-time	-0.542*** (0.052)	-0.034 (0.039)	0.744 (0.676)	-0.846*** (0.275)
Age	0.394*** (0.053)	0.443*** (0.032)	0.128 (0.097)	0.556*** (0.054)
Age ²	-0.004*** (0.000)	-0.003*** (0.000)	-0.001 (0.001)	-0.004*** (0.000)
Constant	18.129*** (1.677)	12.266*** (1.011)	22.240*** (2.349)	10.494*** (1.426)
End. test			16.719***	6.58***
Ove. test			0.452	1.394
N. Obs	90,328	90,328	67,382	67,382
N. Ind		18,398		14,518

Notes: 1. Linear probability model with and without fixed effects, and linear probability model with and without instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test based on the C statistic. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses (the latter is only indicated for FE and IV-FE models). 8. *** p<0.01, ** p<0.05, * p<0.1.

3. Mechanisms: Time use channels

3.1 Data description

3.1.1 General description of the survey data

To investigate the mechanisms which might drive the effects of the number of work hours on BMI for older people, we make use of time use data from the American Time Use Survey (ATUS) linked with the Eating and Health module from the Compendium of Physical Activities (Tudor-Locke et al., 2009). The ATUS is a survey carried out by telephone by the U.S. Census Bureau. This survey is based on the Current Population Survey (CPS) collected by the United States Census Bureau for the Bureau of Labor Statistics (BLS). The CPS interviews randomly about 60,000 households every month. During this interview process, a portion of the interviewed is excluded from the survey because they do not comply with the requirements we describe further below. Every month they gather data on labor market statistics and several topics such as school enrollment, child support, and volunteerism. It takes between 2 and 5 months to fulfill the survey interviews. This final sample is common to the ATUS.

The ATUS collects information on demographic characteristics, respondent's market labor time and non-market activities such non-paid work, exercising, eating, sleeping, socializing among others. The requisite to be interviewed is to be an American resident, at least 15 years old, not being in the active military forces and those who are not permanent residents in nursing homes and prisons. From each household, one person is chosen randomly from the CPS final sample to be the respondent of the ATUS survey interview. The respondent is asked by phone about how she/he spends her/his time between 04:00 of the previous day and 04:00 of the interview day. For each time use question, the respondent must report where and with whom she/he was doing the activity. We make use of the survey data collected between the period 2003 and 2015³.

In similarity with the restrictions we imposed on the HRS dataset, we execute the following restrictions: we only consider respondents between 50 and 70 years old, we drop respondents with missing observations, we drop from the sample those individuals who report being unemployed, disabled or who are not in the labor force for any other reason, we only keep observations from the years 2006, 2007, 2008, 2014 and 2015 for a reason which will be explained later on this section. We also exclude pregnant women from the sample because their reported BMI might not be representative of the population. This results in a sample size of

³ For further information please see the U.S. Bureau of Labor Statistics and U.S. Census Bureau, 2016. American Time Use Survey User's Guide - Understanding ATUS 2003 to 2015, <http://www.bls.gov/tus/atususersguide.pdf>.

170,842 observations, which are around 12,000 observations each year considered.

The ATUS does not contain information about one of our variables of interest, BMI. Nevertheless, there are supplementary modules to this survey which contain health-related information. The already mentioned Eating and Health module from the Compendium of Physical Activities is collected in the years 2006, 2007, 2008, 2014 and 2015. That way, we can make use of this information to analyze the time use patterns and their relationship with BMI and employment status. Furthermore, the inclusion of this data allows studying descriptive information about the rate of energy spent on physical activities (Ainsworth et al., 1993). The Compendium of Physical Activities links a five-digit code that provides information about the intensity of physical activities which is measured by the Metabolic Equivalent of Task (MET) defined as the ratio of work metabolic rate to a resting metabolic rate. For an average adult, one MET is equivalent to one kcal/kg/hour. This measure ranges intensity of physical activities from 0.9 METs (sleeping) to 23 METs (running) (Ainsworth et al., 2011).

Furthermore, since the ATUS survey gathers information of different demographic groups, sample weights are provided along with the data to obtain a representative sample of the underlying population for statistical and inference purposes. Additionally, the sample is not uniformly distributed across the days of the week. There are differences in the response rate and distribution of time spent on activities across each day of the week. Because of that, each day of the week is weighted using the sample weights. That way, each day is equally represented among the total number of days of the week and one can obtain meaningful results. Likewise, BLS draws a set of random subsamples each month to calculate variances estimates and creates replicate weights using the regular estimation method for each of the subsamples. Standard errors are calculated with the replicate variance method⁴.

3.1.2 Measuring hours worked

Analogously to the HRS labor market status definition and considering the information available in the ATUS, we define full-time work as working 35 hours or more per week and part-time as working less than 35 hours per week. The definition of a full-time worker and part-time worker are based on the following survey questions: *"How many hours per week do you usually work at your job?"* These definitions comprise the total number of hours spent in all jobs. Moreover, we only account for those hours worked during work days since half of the respondents were interviewed during the weekend and this information is not

⁴ For further information on this matter please see Chapter 7 from the U.S. Bureau of Labor Statistics and U.S. Census Bureau, 2016. American Time Use Survey User's Guide - Understanding ATUS 2003 to 2015. <http://www.bls.gov/tus/atususersguide.pdf>. Also, see Chapter 14 of CPS Technical Paper 66 at <https://www.census.gov/prod/2006pubs/tp-66.pdf> for further information on the replicate variance method.

representative because respondents usually do not work on Saturday and Sunday. Retired individuals are also defined as those who do not work any hour per week.

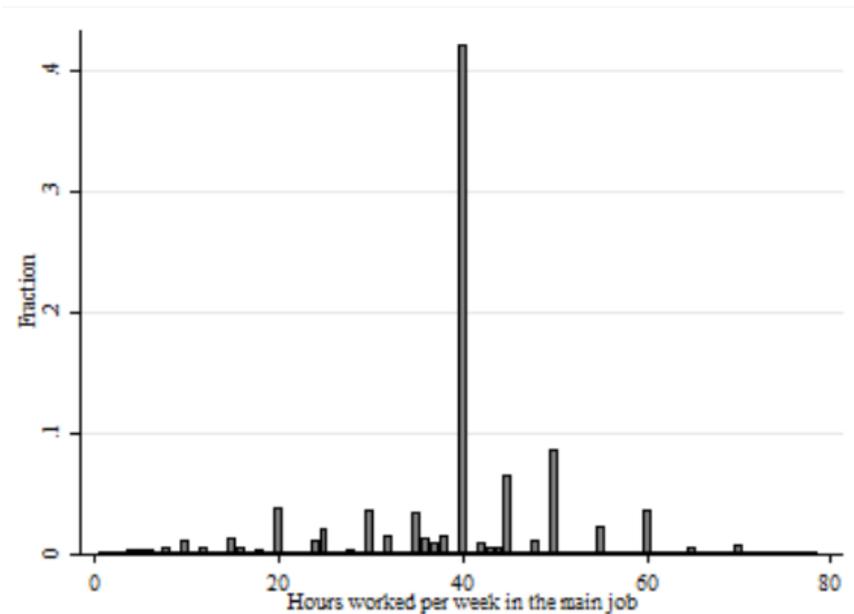


Figure 8: Distribution of hours worked per week (after sample restrictions)

Figure 8 displays the distributions of number of hours worked per week in all the chosen survey years (2006, 2007, 2008, 2014 and 2015). We observe that the majority of the respondents work more 35 or more hours per week. Among these respondents, 78% work 35 hours or more while and among those respondents who work less than 35 hours per week, 12% of individuals work less than 20 hours per week. Hence, the distribution of hours worked per day are similar in the two surveys (see Figure 2). Taking all this information into consideration, we can say that the definition of labor market status is consistent across the samples from the HRS survey and the ATUS survey.

3.1.3 Measuring health

As in the HRS sample, we use BMI as a measure of physical health. Information for this measure is not contained in the ATUS data but in the Eating and Health supplementary modules from the Compendium of Physical Activities, which is only available for the periods 2006-2008 and 2014-2015. Again, we define BMI as respondent's weight in kilograms divided by the square of their height in meters, and we also consider other indices such as being obese and overweight.

3.1.4 Income measure

The CPS provides information about family income. To address patterns in time use on activities of the elderly who work part-time and full-time with income differentials, we consider family income as the indicator of income level. That way,

we classify our sample into two categories: low income and high income. Analogously to the construction of the indicator for the HRS sample, we make use of the average income, and we set as a threshold the median. Notice that ATUS also provides information about weekly earnings and hourly earnings. However, for brevity, we only focus on family income.

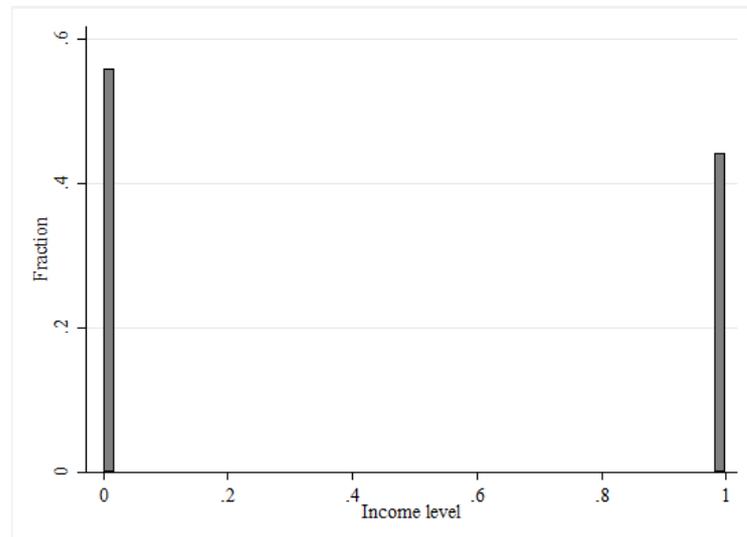


Figure 9: Distribution of the variable income level (after sample restrictions)

3.1.5 Education measure

Information on educational attainment is collected in the CPS. To explore the difference in the patterns in time use of the elderly who are working part-time and working full-time and have different education levels, we create a binary indicator for "low education" and "high education". We group those individuals who at least attended high school, and we group those with higher qualifications in the category "high education." Then, our indicator takes the value of one if the respondent belongs to the category "high education" and zero otherwise.

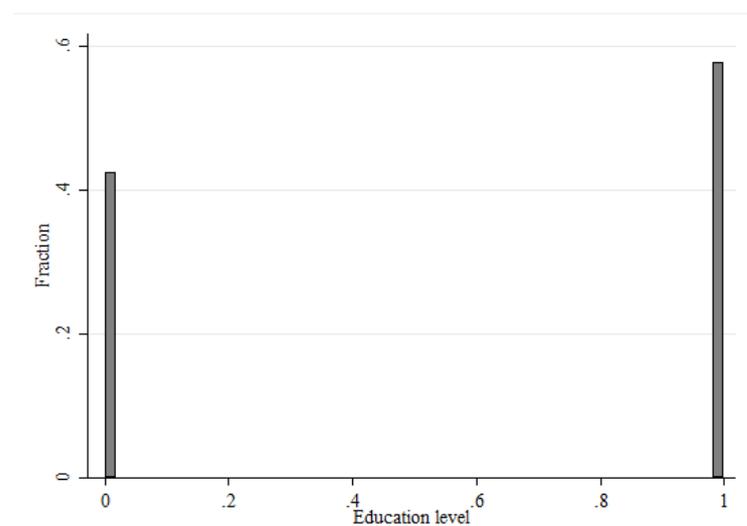


Figure 10: Distribution of the variable education level (after sample restrictions)

3.1.6 Set of instrumental variables

As in the previous analysis using the HRS sample, we use retirement eligibility ages as instrumental variables for retirement decision. Given the information available in the ATUS, we make use of a set of three instruments: indicators to whether the respondent is between early and normal retirement age, between normal retirement age and age of 70, and above the age of 70.

3.1.7 Descriptive statistics

In Table 15, we present the descriptive statistics of the main demographic variables and labor market information for the restricted sample. Across the survey years of study, the average age is 46.69. Our ATUS sample is, on average, younger than our HRS sample. 56.29% of the respondents are women, 77.40% are under early retirement eligibility age, 50.63% are between the early and regular retirement eligibility ages, 48.08% are between normal and the age of 70, and 12.73% are over the age of 70, 57.64% have higher education, the average BMI is 27.43, 48.26% are overweight and 27.62% are obese, 53.30% are married or in a relationship. Regarding labor force information, 11.67% are working part-time, 49.31% are working full-time, and 17.63% are retired.

Table 15: Descriptive statistics (ATUS)

	Mean
<i>Demographics</i>	
Age (50-75) (average)	46.89
Female (%)	56.29
Under early ret. age (%)	77.40
Bet. early and nor. ret. age (%)	50.63
Bet. nor. ret. age and age 70 (%)	48.08
Over age 70 (%)	12.73
High education (%)	57.64
BMI	27.43
Overweight (%)	48.26
Obese (%)	27.62
Married or partnership (%)	53.30
<i>Labour market information</i>	
Part-time worker (%)	11.67
Full-time worker (%)	49.31
Retired (%)	17.63
N.Obs.	170,842

Notes: 1. Averages are calculated using ATUS population representative-weights. 2. The values presented in percentages might not add up to 100% due to rounding. 3. The percentages (are averages) and averages are calculated with out considering missing values.

3.1.8 Time use activities

The target of this part of the analysis is to find how time use on different activities works as a mechanism between time spent working and BMI for old individuals with differentials in income and education. The ATUS contains information about the time spent in 485 activities organized into 17 major categories. Since we use BMI as a measure of physical health, we only focus on those activities that seem related to this indicator. We follow Abramowitz (2016) for the selection of health-related activities which could have an impact on BMI. The chosen channels can be classified into three categories: eating, physical activities, and health. Table 15 depicts descriptive statistics of time use on activities by income level in minutes and Table 16 presents the summary statistics for the time use on activities by education groups.

Among the activities within the eating category, we distinguish primary and secondary eating, preparing food, grocery shopping and purchasing prepared food. We consider that this set of activities are relevant for our analysis since the way of eating is very related to the number of hours working and health. Individuals who work more hours tend to spend less time cooking food, and it is more likely that they consume prepared food. In addition, individuals who are busier tend to have less time to eat and they do it while working or doing something else. The kind of food that they eat is usually high on sugar and very caloric (Satia et al., 2004; Jeffry et al., 2006; Chou et al., 2004). Physical activities are also a relevant factor for body weight. We consider time spent in sleeping, exercise, housework, screen time (includes watching TV and personal computer usage) and commuting. The time spent in these non-working activities allows the analysis of how the time spent working impacts physically demanding and sedentary activities. If individuals replace time at work by sedentary activities such as sleeping or watching TV, we expect that if they work more hours, they will have higher BMI. On the contrary, if individuals substitute time at work by demanding physical activities, they will have lower BMI. With regards to health, we consider the time spent on own medical care which refers to investment in own health such as visits to the doctor. People that work more hours usually have less time to take care of their own health.

Table 16: Time use on activities by income level

	Low income						High income											
	Percent of sample reporting any time on activity			average minutes spent on activity if >0			Percent of sample reporting any time on activity			average minutes spent on activity if >0								
	Full	Part	Ret.	Full	Part	Ret.	Full	Part	Ret.	Full	Part	Ret.						
Primary eating	94.6	95.6	96.9	65.7	70.2	72.5	62.6	67.1	70.3	96.4	97.8	98.5	74.8	77.8	84.8	72.1	76.1	83.5
Secondary eating	49.9	52.6	47.2	126.3	112.2	104.5	63.0	59.0	49.3	58.4	60.6	54.2	105.6	95.9	80.4	61.6	58.1	43.6
Food preparation	52.1	58.5	61.1	45.4	51.7	54.0	23.7	30.3	33.0	50.1	59.5	59.4	46.5	51.5	55.5	23.3	30.7	33.0
Grocery shopping	17.1	17.6	17.0	43.3	40.8	47.0	7.4	7.2	8.0	16.0	20.6	19.0	43.7	41.3	44.1	7.0	8.5	8.4
Purchasing prepared food	10.6	8.6	6.2	10.6	10.0	11.4	1.1	0.9	0.7	12.4	10.8	7.7	10.7	10.5	12.0	1.3	1.1	0.9
Sleeping	99.9	99.9	99.8	504.8	516.5	533.5	504.1	515.9	532.6	99.9	100.0	100.0	491.0	504.4	514.8	490.4	504.4	514.6
Exercise	11.2	12.8	16.4	90.3	86.5	90.5	10.6	11.1	14.8	19.4	21.5	23.8	91.1	91.7	96.2	17.6	19.7	22.9
Housework	37.4	46.9	45.7	102.8	108.7	108.4	38.5	51.0	49.5	34.9	48.4	45.8	96.2	98.8	102.8	33.6	47.8	47.1
Screen time	82.8	85.8	91.1	220.0	236.0	318.6	182.2	202.6	290.1	81.2	82.8	90.0	191.1	199.6	265.1	155.3	165.3	238.8
Commuting	88.7	86.3	72.4	81.3	78.9	75.8	72.2	68.1	54.9	90.5	88.8	79.8	92.5	89.4	89.0	83.7	79.4	71.9
Own medical care time	2.2	3.0	4.9	94.8	78.9	92.3	2.1	2.4	4.4	2.5	3.9	4.5	80.0	71.5	83.0	2.1	2.8	3.7

Note: Time use channels descriptive statistics are calculated using ATUS population-representative weights.

Table 17: Time use on activities by education level

	Low education						High education											
	Percent of sample reporting any time on activity			average minutes spent on activity if >0			Percent of sample reporting any time on activity			average minutes spent on activity if >0								
	Full	Part	Ret.	Full	Part	Ret.	Full	Part	Ret.	Full	Part	Ret.						
Primary eating	95.2	95.8	96.9	66.5	66.9	70.7	63.3	64.1	68.5	95.9	97.0	97.7	73.2	77.0	81.1	70.2	74.7	79.3
Secondary eating	44.6	49.1	44.5	113.3	123.6	107.3	50.5	60.6	47.7	59.7	59.8	53.6	113.7	96.1	88.6	67.9	57.5	47.6
Food preparation	50.3	59.2	60.5	49.3	56.3	54.0	24.8	32.9	34.0	51.3	58.6	60.8	44.4	49.2	52.7	22.8	28.9	32.0
Grocery shopping	15.1	16	15.6	46.1	48.5	47.0	6.9	7.0	7.6	17.2	20.6	19.4	42.4	39.7	44.2	7.3	8.2	8.6
Purchasing prepared food	8.2	8.6	5.7	10.2	11.8	11.4	1.0	0.8	0.7	12.4	10.3	7.6	10.9	10.5	11.4	1.4	1.1	0.9
Sleeping	99.9	99.9	99.8	507.1	536.9	533.5	506.4	517.7	536.1	99.9	99.9	99.9	491.9	507.5	519.8	491.2	507.2	519.1
Exercise	10.1	9.4	15.0	99.2	93.9	90.5	10.0	8.4	14.1	19.1	20.6	21.9	88.7	89.2	91.6	17.0	18.4	20.1
Housework	34.6	48.3	46.8	106.6	113.6	108.4	36.9	55.5	53.2	36.7	84.0	44.7	95.7	98.1	99.8	35.1	46.1	44.7
Screen time	83.8	85.7	91.6	228.3	329.3	318.6	191.3	231.9	301.6	81.0	84.0	90.0	190.9	203.9	278.0	154.6	171.2	250.2
Commuting	88.3	85.8	70.3	81.1	74.5	75.8	71.6	64.3	52.4	90.5	88.3	78.7	91.0	88.2	84.5	82.3	77.8	66.4
Own medical care time	2.2	2.8	4.2	94.4	92.7	92.3	2.1	2.3	3.9	2.5	3.7	5.1	82.1	71.8	87.4	2.1	2.7	4.4

Note: Time use channels descriptive statistics are calculated using ATUS population-representative weights.

3.2 Empirical methodology

The target of this section is to provide detailed explanations about the methodology we follow to investigate the effect of different mechanisms that might drive the effect of working part-time and working full-time on BMI for the elderly across groups with differentials in income level and education level attainment. We identify different physical health-related mechanisms through time use information on several activities for these groups of the population. These mechanisms are identified using pooled cross-sectional data from the ATUS for the period 2006-2008 and 2014-2015. We follow Abramowitz (2016) for the identification of these health-related channels and the identification of these mechanisms.

Abramowitz (2016) investigates the effect of time spent working on BMI for men and women using data from 2006, 2007 and 2008 ATUS survey linked with the Eating and Health modules and the Compendium of Physical Activities. Furthermore, he analyzes the mechanisms which could explain the relationship between the impact of the number of hours worked on BMI. He first estimates a baseline ordinary least squares specification model to study the effect of time spent working and BMI and he controls for individual characteristics. Furthermore, he also controls for strenuous and non-strenuous job. Then, following the approach described in Fertig et al. (2009), he estimates a series of equation models including controls for time use channels related to eating, working time and health. Likewise, Abramowitz (2016) considers that time use on each activity is an omitted variable and checks if its inclusion impacts significantly on the effect of time spent working on BMI. That way, he attempts to capture the direct causal effect of hours worked on BMI and the effect of unobservable individual characteristics which might cause correlations and reverse causation (Abramowitz, 2016). That way, Abramowitz (2016) re-estimates the baseline specification model including control variables for time spent on each of the potential channels. He then follows the specification model used by Fertig et al. (2009). He estimates a regression model for each of the potential time use channels. That is, he augments the model adding one control for each time use channel. He estimates each regression model for women and men separately to study whether we obtain different results for each group.

In contrast to the approach of Abramowitz (2016), we differentiate between working part-time and working full-time instead of considering the total number of work hours. Hence, we focus on labor market participation. Besides, we investigate the effects of working part-time and working full-time on different income and education groups. We include controls for time use on selected activities on a baseline equation which is similar to the baseline equation presented in Section 2. Following the approach of Fertig et al. (2009) and Abramowitz (2016), we augment this model adding one control for time channels each time and regress each equation for each income and education level group.

We then estimate the model controlling for all time activities for each income and education level group. Following the literature, we apply the instrumental variable approach using retirement eligibility ages of respondent as instruments to find a causal relationship of working part-time and working full-time on BMI.

3.2.1 Implementation

Analogously to Section 2.2, we start the analysis from a baseline equation model using OLS to identify the causal effect of labor market participation on BMI for different income and education groups:

$$y_i = \alpha + f(\text{Age}_i) + \text{Part_time}_i\beta_1 + \text{Full_time}_i\beta_2 + c_i\beta_3 + \varepsilon_i, \quad (3.2.1)$$

where i refers to the respondent ($i= 0, 1, 2, \dots, I$), y_i is BMI of respondent i , $f(\text{Age}_i)$ is defined as a continuous polynomial in age for individual i to capture the non-linear relationship between age and BMI. c_i refers to a set of demographic characteristics such as race, ethnicity, marital status, season of the year, place of residence (non-metropolitan or metropolitan area) and state of residence. Part_time_i is defined as a dummy variable which takes a value of 1 if respondent i works part-time and 0 elsewhere. Full_time_i refers to a dummy variable which is equal to 1 if respondent i works full-time and 0 otherwise. The variable retirement is left as category of reference to avoid perfect multicollinearity. The parameters of interest are β_1 and β_2 which measure which measures the effects of working part-time and working full-time on BMI, respectively. We assume that ε_i is i.i.d. with mean zero and variance σ_ε^2 . We use a variance replicate method to calculate standard errors as suggested by the ATUS Guide (Chapter 7).

Following Fertig et al. (2009) and Abramovitz (2016), for each time use channel we consider time spent on certain activity in hours and we introduce time use channels (t) as controls in the baseline equation (3.2.1):

$$y_i = \alpha + f(\text{Age}_i) + \text{Part_time}_i\beta_1 + \text{Full_time}_i\beta_2 + c'_i\beta_2 + t'_i\beta_3 + \varepsilon_i \quad (3.2.2)$$

We then estimate equations (3.2.1) and (3.2.2) for each income level group and each education level group. In each regression, we augment (3.2.2) with a control variable related to the time spent on a certain activity. In other words, we estimate several regressions in which each of them we add a new control variable related to the time spent on a selected activity. This way, we can compare estimates from (3.2.1) with each of these regressions and interpret the change in the coefficients from the omitted variable bias point of view. Thus, the omitted variable bias can be expressed as follows:

$$\delta_{\text{Part-time}} = \beta_1 + \beta_3\rho, \quad (3.2.3)$$

$$\delta_{\text{Full-time}} = \beta_2 + \beta_3\gamma, \quad (3.2.4)$$

where ρ and γ refers to the correlation between working part-time and working full-time, respectively, and the potential time use channel. It is to say, these parameters refer to the coefficient estimates of working part-time and working full-time, respectively, in each augmented regression. The omitted variable bias can be interpreted follows: a positive (negative) result from $(\delta_{Full-time} - \beta_2)$, implies that $\beta_3\gamma > 0$ ($\beta_3\gamma < 0$). We then conclude that the impact of the time spent on the chosen activity on BMI and the effect of working full-time on the time spent on the selected activity have the same (the opposite) sign. The interpretation of the omitted variable bias for working part-time and working full-time are similar. We discuss the case for the effect of working full-time. If $(\delta_{Full-time} - \beta_2)$ is positive, γ and β_3 present opposite signs and $\beta_3\gamma > 0$. Then, the impact of the time use channel on BMI (β_3) and the correlation between the working full-time and the time use channel (γ) has the opposite sign. For instance, the difference controlling for screen time is positive. The more hours the respondent works, the less time she/he spends on screen time (negative γ) but given that this is a sedentary activity, it leads to a higher BMI (positive β_3). Hence, if $(\delta_{Full-time} - \beta_2)$ is significant, working full-time could lead to a higher BMI since the respondent is sedentary for a longer amount of time. Then, if we omit the variable screen time, we would underestimate the effect of working full-time on BMI. If $(\delta_{Full-time} - \beta_2)$ is negative, γ and β_3 present the same sign and $\beta_3\gamma < 0$. For example, the difference controlling for time spent on household tasks is negative. The more hours the respondent works, the less time she/he spends on housework (negative γ). Moreover, we could state that time spent on household tasks is negatively correlated with BMI (negative β_3) since it involves certain physical activity. Therefore, the effect of working full-time on BMI is higher when we add time spent on household task in the model equation. Hence, if $(\delta_{Full-time} - \beta_2)$ is significant, the direct impact of working full-time on BMI is intensified when we include the time spent on housework in the model equation. If we omit the control for time spent on household tasks, we would overestimate the impact of working full-time on BMI.

It is important to notice that all the activities selected add up to a total of 24 hours and time use channels could be correlated with each other., we control for all time channels spent on the activities. We specify similar omitted variable bias equations as we did in equations (3.2.3) and (3.2.4) by adding an extra term to these equations which accounts for the correlations between the time spent in all time use channels for working part-time and working full-time, respectively. If the differences between the coefficients for the variables of interest and the latter correlations are significant then we can conclude the effects of working part-time and working full-time on BMI when we are considering the time spent in a day in all the selected activities.

3.2.2 Instrumental variables approach and causality of the estimated effects

As already mentioned, part-time and full-time working appears to be endogenous. Following Neuman (2008) and Kantarci (2017, 2018), we consider retirement eligibility ages of respondent as instruments. In the first stage, we regress the endogenous variables (working part-time and working full-time) on the exogenous variables and retirement eligibility ages. Then, in the second stage, the predicted values are used to estimate the coefficients for working part-time and working full-time on BMI. These instrumental variables must comply the exogeneity and relevance restrictions. The instruments must provide independent sources of exogenous variation for part-time and full-time working to identify their causal effects on the BMI to avoid that the endogenous variables could be weakly identified (Angrist and Pischke, 2009).

From the first stage results (see Table B1 in the Appendix) we find these instruments are good predictors of working part-time and working full-time. However, the endogeneity test from the second stage results shows that working part-time and working full-time can be considered exogenous variables since we do not reject the null hypothesis that these instruments are exogenous ($\chi^2(2) = 0.695$). Then, we expect that the incorporation to the model of variables related to individual characteristics and time allocation can help us to find the causal effects of working part-time and working full-time on BMI and the effect of time use allocation.

3.3 Results

3.3.1 Effects of working part-time and full-time on BMI

Table 18 shows the results for the baseline equation (3.2.1). We observe the results from a linear regression model which indicates the effects of working part-time and full-time for two groups of income and two groups of education. For full-time workers, we find a negative relationship, although we do not find significant results except for the low education group at 1% of significance level. The estimated effects of working part-time on BMI are more pronounced than the effects of working full-time. We find statistically significant results for part-time workers with high income level, low education, and high education at 1% level of significance. For these groups, there is a significant negative correlation between working part-time and BMI. According to the results, working part-time and having a higher income level shows a negative relationship with BMI. We also find a significant and negative impact of working part-time on BMI at 10% level of significance for the group of low income level. However, the impact on BMI is lower than for the group of part-time workers with high income level. Part-time workers with lower education level present slightly higher BMI than those with higher education. In other words, the higher is the education level, the lower will be, on average, their BMI. Individuals who attain a higher level of education are more aware of the consequences of overweight and obesity and the importance of having a balanced diet. These results are in line with Kantarci (2017, 2018) who finds that the effect of working part-time is substantially higher than the effect of working full-time. We find empirical evidence that respondent's age has a non-linear and significant effect on BMI.

With regard to the set of demographic characteristics, it is worthy to note that black respondents have on average higher BMI than respondents with other ethnicities. The effect for Hispanic respondents is similar. Other ethnicities such as Asians present the lowest coefficient for BMI. We also find positive and significant results for those individuals who live in a non-metropolitan area. That is, individuals who live in rural areas tend to weight more than those who live in metropolitan areas. Intuitively, we could conclude that people who live in rural areas might be less socially pressured to stay physically active than those who do not live far from their neighbors.

Table 18: Effects of working part-time and working full-time on BMI

	BMI			
	Low income	High income	Low education	High education
Part-time	-0.385* (0.232)	-1.282*** (0.244)	-0.778*** (0.271)	-0.729*** (0.228)
Full-time	-0.391* (0.217)	-0.129 (0.197)	-0.507** (0.235)	-0.242 (0.183)
Age	0.407** (0.184)	0.374** (0.168)	0.236 (0.199)	0.557*** (0.154)
Age ²	-0.003** (0.001)	-0.003** (0.001)	-0.002 (0.002)	-0.004*** (0.001)
Black	2.008*** (0.204)	2.045*** (0.297)	1.530*** (0.238)	2.388*** (0.231)
Hispanic	0.976*** (0.219)	1.376*** (0.311)	0.522* (0.278)	1.285*** (0.302)
Other race	-1.201** (0.479)	-1.844*** (0.326)	-2.144*** (0.497)	-1.239*** (0.315)
Married	-0.129 (0.129)	0.342** (0.152)	-0.202 (0.159)	-0.059 (0.129)
Non metropolitan	0.441** (0.195)	0.827*** (0.234)	0.592** (0.201)	0.508** (0.220)
Constant	15.03** (5.914)	16.81*** (5.168)	21.09*** (6.434)	11.64** (4.818)
N. Obs	9,384	7,833	6,623	10,594

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under high school graduate level and high income to levels higher than high school graduate. 3. Fixed effects for survey year, state dummies and season of the year are included in the model. 4. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 5. *** p<0.01, ** p<0.05, * p<0.1.

3.3.2 Effects of time use channels on working part-time and full-time

As we explained in Section 3.3, we augment equation (3.2.2) by including at a time as a control variable a given time spent on a selected activity. We compare the estimates from equation (3.2.1) with each of the augmented regression equations and observe the resulting omitted variable bias. It is to say, we analyze the results of $(\delta_{Part-time} - \beta_1 = \beta_3\rho)$ and $(\delta_{Full-time} - \beta_2 = \beta_3\gamma)$. The omitted variable bias can be interpreted as the product between the correlation between a specific time use channel and working part-time or full-time ρ and γ , respectively, and the correlation between the time use channel and BMI.

In Table 19 we present the results for the effects on time use channels on working part-time and full-time for low income and high income categories, and low education and high education groups. This way, we can analyze the correlation between the time use channels and working part-time, and the correlation between the time use channels and working full-time. Overall, for full-time workers, we find a negative relationship with most of the time spent on the considered activities. However, there are some exceptions. For individuals who have a low income level, grocery shopping is positively correlated with working full-time, but this effect is not statistically significant. For individuals with high income level, food and drink preparation at home, grocery shopping, sleeping, and housework are positively correlated with working full-time. These results might seem counterintuitive since full-time workers have less time to do groceries, cooking their own food, sleeping or doing housework. However, we might explain these effects for working full-time by looking at the results for the education groups. Individuals who have attained a high education level, food preparation, grocery shopping, and sleeping have a positive correlation with working full-time. If we look to the results for low education, we observe that the effects of the different time use channels on working full-time are smaller than the effects for highly educated individuals. From these results, we can conclude that education level is a relevant factor when we talk about how individuals organize their time. Even though full-time workers have a fewer amount of time to spend on non-working related activities, highly educated individuals might organize better their time and spent more time on health-related activities than low educated workers since they are more likely to be aware of the implications on how the allocation of time among activities can affect health.

Regarding part-time workers, we find a negative and statistically significant correlation between most of the activities and working part-time for the low income and low education groups at standard levels of significance (1%, 5% and 10%). For the rest of the considered heterogeneous categories, we do not find any significant negative impact of time spent in each of the selected activities on working part-time. The size of the effects is higher for all activities for all heterogeneity groups with respect to working full-time. That is, for the coefficients with a negative sign the size of the coefficients is lower and for those with a positive sign are bigger. For the effect of time use channels on being retired, we can extract the same conclusions as for the effect of time use channels on working part-time. The size of the coefficients is also similar to the effects on working part-time.

Table 19: Effects of time use channels on working full-time and working part-time.

	Low income			High income			Low education			High education		
	Full-time	Part-time	Retired	Full-time	Part-time	Retired	Full-time	Part-time	Retired	Full-time	Part-time	Retired
Primary eating	-0.021*** (0.006)	-0.019** (0.006)	-0.006 (0.006)	-0.005 (0.005)	0.028*** (0.006)	0.024*** (0.005)	-0.021** (0.007)	-0.019** (0.006)	-0.005 (0.006)	-0.006 (0.005)	0.025*** (0.007)	0.025*** (4.77)
Secondary eating	-0.001 (0.002)	-0.002 (0.003)	0.001 (0.002)	0.000 (0.002)	-0.000 (0.002)	0.002 (0.002)	-0.003*** (0.002)	0.003 (0.002)	0.002 (0.002)	-0.001 (0.001)	0.004* (0.002)	-0.002 (-1.10)
Food preparation	-0.048*** (0.007)	-0.052*** (0.008)	0.015** (0.007)	0.019** (0.007)	0.033*** (0.033)	0.023*** (0.007)	-0.046*** (0.009)	-0.056*** (0.007)	0.018** (0.008)	0.017** (0.007)	0.028*** (0.007)	0.039*** (6.08)
Grocery	0.002 (0.013)	-0.025 (0.175)	-0.002 (0.011)	0.030** (0.015)	-0.000 (0.012)	-0.005 (0.013)	0.011 (0.016)	-0.037* (0.015)	-0.000 (0.014)	0.030** (0.012)	-0.011 (0.014)	0.007 (0.62)
Prepared food	-0.059 (0.082)	0.001 (0.071)	-0.072 (0.052)	-0.029 (0.045)	0.131 (0.075)	0.028 (0.028)	-0.060 (0.095)	-0.000 (0.007)	-0.103* (0.053)	-0.024 (0.047)	0.162* (0.094)	0.024 (0.40)
Sleeping	-0.018*** (0.005)	-0.024*** (0.003)	-0.000 (0.002)	0.006** (0.003)	0.019*** (0.002)	0.017*** (0.002)	-0.021*** (0.003)	-0.023*** (0.002)	0.001 (0.002)	0.006** (0.002)	0.021*** (0.003)	0.017*** (7.81)
Exercise	-0.031*** (0.005)	-0.036*** (0.007)	-0.002 (0.005)	0.005 (0.005)	0.033*** (0.007)	0.031*** (0.006)	-0.033*** (0.007)	-0.032*** (0.006)	-0.010* (0.006)	0.007 (0.005)	0.043*** (0.008)	0.027*** (4.85)
Household	-0.028*** (0.004)	-0.036*** (0.005)	0.004 (0.004)	0.011** (0.004)	0.024*** (0.004)	0.025*** (0.004)	-0.031*** (0.004)	-0.033*** (0.004)	0.011** (0.004)	0.00591 (0.003)	0.020*** (0.004)	0.027*** (7.51)
Screen	-0.024*** (0.002)	-0.023*** (0.002)	-0.004** (0.001)	-0.001 (0.002)	0.028*** (0.001)	0.023*** (0.002)	-0.026*** (0.002)	-0.024*** (0.002)	-0.000 (0.001)	-0.004** (0.001)	0.026*** (0.002)	0.028*** (16.35)
Commute	-0.011** (0.001)	-0.017*** (0.005)	0.005 (0.004)	0.005 (0.004)	0.006* (0.004)	0.012*** (0.004)	-0.013** (0.005)	-0.014*** (0.004)	0.006 (0.004)	0.004 (0.003)	0.007 (0.004)	0.010** (2.82)
Own medical care	-0.061*** (0.011)	-0.040** (0.019)	-0.004 (0.010)	-0.002 (0.015)	0.064*** (0.126)	0.043** (0.016)	-0.053** (0.016)	-0.052** (0.016)	0.003 (0.015)	-0.009 (0.011)	0.050*** (0.014)	0.061*** (4.27)
N. Obs	9,747	8,106	9,747	8,106	9,747	8,106	6,870	10,983	6,870	10,983	6,870	10,983

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under high school graduate level and high income to levels higher than high school graduate. 3. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 4. Time spent on activities is measured in hours. 5. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 6. *** p<0.01, ** p<0.05, * p<0.1.

3.3.3 Effects of working part-time and working full-time on BMI and separate time use channels

In the previous section, we analyze the correlations of time use channels on working part-time and working full-time. As we explained in Section 3.2, we augment equation (3.2.2) by including controls for each time spent on a selected activity at each time. We compare the estimates from equation (3.2.1) with each of the augmented regression equations and observe the resulting omitted variable bias. It is to say, we analyze the results of $(\delta_{part-time} - \beta_1 = \beta_3\rho)$ and $(\delta_{Full-time} - \beta_2 = \beta_3\gamma)$. The omitted variable bias can be interpreted as the product between the correlation between a specific time use channel and working part-time or full-time ρ and γ , respectively, and the correlation between the time use channel and BMI. In the present section, we include separately controls for time use channels to study the omitted variable bias. Then, in tables 20 and 21 we present the results for the effects on time use channels separately on working part-time and full-time for income groups and education groups. In the first line of both tables it is presented the effect from the baseline equation. Table 20 includes the results of $\delta_{part-time} - \beta_1$ for each time use channel added to the baseline equation (3.2.2), and in the same way, table 21 presents the results of $\delta_{Full-time} - \beta_2$ for each time use channel added to equation (3.2.2).

In Table 20, the most significant effect is screen time for all the groups considered. Intuitively, we expect that the more time individuals spend in front of a screen, the higher will be their body fat. Our results seem to confirm this hypothesis. We find significant and positive results on the effect of screen time on BMI. The impact is, on average, higher for individuals with high income level and high education level. There are some statistically significant effects of time use on different activities. The effect spending time on food preparation is negative and statistically significant for the high income group, low education group, and high education group. This effect is larger for those who have a high income level in comparison with those with lower income and second place for those who belong to the group of higher education. The effect for individuals with low education level is also negative but smaller. The impact of preparing food at home is positive and statistically significant at 1% significance level for respondents with high income level and education level. It appears that cooking at home for these individuals increases on average their BMI. Doing groceries is also significant and has a negative effect on BMI for the latter groups. Preparing food at home appears to have a positive impact which is statistically significant for high income and high education groups at 5% level of significance. Likewise, the sign of the coefficients for sleeping is also positive and significant for low income and low education groups. As expected, doing exercise reduces BMI and we observe statistically significant estimates for most of the analyzed groups. In addition, time spent at commuting seems to affect BMI positively.

Table 20: Effects of working part-time on BMI and separate time use channels

	BMI			
	Low income	High income	Low education	High education
Baseline part-time effect	-0.385* (0.232)	-1.282*** (0.244)	-0.778*** (0.271)	-0.729*** (0.228)
Primary eating	-0.163 (0.101)	-0.086 (0.093)	-0.198* (0.113)	-0.073 (0.089)
Secondary eating	0.009 (0.009)	0.037 (0.029)	0.032 (0.027)	0.017 (0.025)
Food preparation	-0.135 (0.118)	-0.461*** (0.086)	-0.242** (0.114)	-0.324*** (0.084)
Grocery	-0.284 (0.234)	-0.408* (0.176)	-0.270 (0.259)	-0.433* (0.182)
Prepared food	0.326 (0.326)	2.664** (0.977)	-0.605 (1.384)	3.193*** (0.891)
Sleeping	0.136*** (0.136)	0.035 (0.049)	0.084* (0.044)	0.089** (0.042)
Exercise	-0.255*** (0.076)	-0.364*** (0.069)	-0.148* (0.079)	-0.394*** (0.069)
Household	-0.082 (0.065)	-0.147** (0.069)	-0.125* (0.069)	-0.102* (0.058)
Screen	0.129*** (0.072)	0.264*** (0.031)	0.101** (0.031)	0.258*** (0.026)
Commute	0.189** (0.072)	-0.020 (0.052)	0.144* (0.081)	0.040 (0.040)
Own medical care	0.178 (0.202)	-0.070 (0.237)	0.140 (0.285)	0.013 (0.156)
N. Obs	8,101	6,927	5,820	9,208

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. First row refers to the coefficient from the baseline model specification. 3. First row refers to the coefficient from the baseline model specification. 4. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 5. Time spent on activities is measured in hours. 6. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

For the effects of time use channels on BMI for full-time workers, we shall look at Table 21. Like in Table 20, we find that the most remarkable result in terms of statistical significance is screen time. The magnitude of the effects is similar to the effects for part-time workers although is slightly higher for most of the heterogeneous full-time working groups considered.

Table 21: Effects of working full-time on BMI and separate time use channels

	BMI			
	Low income	High income	Low education	High education
<i>Baseline full-time effect</i>	-0.391* (0.217)	-0.129 (0.197)	-0.507** (0.235)	-0.242 (0.183)
Primary eating	-0.229** (0.098)	0.013 (0.140)	-0.206* (0.122)	-0.047 (0.115)
Secondary eating	-0.048 (0.031)	0.080** (0.034)	-0.016 (0.036)	0.028 (0.036)
Food preparation	-0.049 (0.129)	-0.543*** (0.124)	-0.103 (0.166)	-0.331*** (0.110)
Grocery	-0.290 (0.266)	-0.115 (0.345)	-0.043 (0.322)	-0.505* (0.257)
Prepared food	-0.399 (1.533)	3.752** (1.680)	-0.013 (1.928)	2.468* (1.450)
Sleeping	0.109** (0.050)	0.155* (0.082)	0.051 (0.054)	0.188*** (0.058)
Exercise	-0.217** (0.077)	-0.165 (0.116)	-0.025 (0.093)	-0.308*** (0.085)
Household	-0.123 (0.076)	-0.001 (0.086)	-0.104 (0.066)	-0.064 (0.086)
Screen	0.142*** (0.033)	0.286*** (0.039)	0.133*** (0.037)	0.247*** (0.034)
Commute	0.101 (0.079)	-0.007 (0.070)	0.132 (0.090)	0.013 (0.061)
Own medical care	0.188 (0.188)	-0.165 (0.288)	0.267 (0.228)	-0.099 (0.222)
N. Obs	5,582	2,720	3,697	4,605

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. First row refers to the coefficient from the baseline model specification. 4. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 5. Time spent on activities is measured in hours. 6. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

3.3.1 Effects of working part-time and working full-time and all time use channels on BMI

In Table 22 we present the results for the effects of working part-time and working full-time controlling for all time use channels considered. The most prominent result for the low income group is the effect on BMI of sleeping, exercise and screen time. The impact of time spent sleeping is positive as the effect of screen time. As in the previous sections, the impact of exercise on BMI is negative. Doing exercise reduces the probability of gaining weight. For individuals with high income, working part-time has a negative effect on BMI. In addition, when we control for all time use activities, we find that preparing food at home decreases BMI. On the contrary, eating prepared food impacts positively BMI. For these group of respondents, the effects of exercise and screen time are larger than for low income respondents. For individuals with high education level, working part-time has a negative effect on BMI. We find significant results for the effects of preparing food at home, exercise which impacts negatively BMI, and screen time which affects positively to BMI. Furthermore, we find that housework also impacts negatively BMI since it implies physical activity which might help to reduce BMI. We find similar results for the low educated individuals, but the sizes of the effects are overall smaller. Summarizing, our results when we control for all time use channels follow the same line as the previously observed results.

Table 22: Effects of working part-time and working full-time and all time use channels on BMI.

	BMI			
	Low income	High income	Low education	High education
Part-time	-0.235 (0.230)	-1.101*** (0.235)	-0.697** (0.269)	-0.552** (0.224)
Full-time	-0.230 (0.215)	-0.008 (0.202)	-0.334 (0.243)	0.121 (0.177)
Primary eating	-0.172* (0.093)	-0.104 (0.086)	-0.229** (0.102)	-0.071 (0.080)
Secondary eating	-0.005 (0.025)	0.036 (0.072)	0.019 (0.027)	0.008 (0.024)
Food preparation	-0.139 (0.103)	-0.499*** (0.083)	-0.234** (0.109)	-0.343*** (0.082)
Grocery	-0.192 (0.216)	-0.292 (0.180)	-0.096 (0.249)	-0.403** (0.172)
Prepared food	0.534 (1.196)	2.571** (0.923)	-0.495 (1.328)	3.025*** (0.843)
Sleeping	0.113*** (0.036)	0.053 (0.048)	0.071* (0.040)	0.093** (0.039)
Exercise	-0.254*** (0.072)	-0.346*** (0.068)	-0.156** (0.074)	-0.370*** (0.064)
Household	-0.101* (0.059)	-0.126** (0.062)	-0.132** (0.060)	-0.095* (0.053)
Screen	0.128*** (0.026)	0.273*** (0.028)	0.103*** (0.030)	0.263*** (0.025)
Commute	0.125* (0.069)	0.006 (0.048)	0.140* (0.074)	0.026 (0.037)
Own medical care	0.113 (0.190)	-0.026 (0.223)	0.083 (0.256)	0.024 (0.150)
N. Obs	9,329	7,799	6,582	10,546

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. First row refers to the coefficient from the baseline model specification. 4. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 5. Time spent on activities is measured in hours. 6. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

3.4 Robustness checks

In this section, we analyze the sensitivity of our results to the inclusion of different age specifications to the definition of income level groups. We also check the sensitivity of our results to a dependent variable which is closely related to BMI and could be also interpreted as an indicator of physical health. We take obesity as the dependent variable and check whether this choice leads to different conclusions.

3.4.1 Age specification

We have concluded in several sections of this paper, that there is a nonlinear relationship between the variables age and BMI. Specifically, we have observed that the impact of age on BMI is first positive and then it becomes negative. As in Section 2.5.2, we check the sensitivity of our results to age specification. We show the sensitivity of the effects of working full-time and working part-time on BMI by income level and education level to linear, quadratic and cubic age specifications in Tables 23 and Table 24, respectively. According to the significance of the results for the age terms, we conclude that the specification with the quadratic age variable is the most suitable for our analysis.

Table 23: Robustness check – Effects of working part-time and working full-time on BMI by income level: Age specification

	BMI					
	Linear age		Quadratic age		Cubic age	
	Low income	High income	Low income	High income	Low income	High income
Part-time	-0.379 (0.233)	-1.230*** (0.242)	-0.385* (0.232)	-1.282*** (0.244)	-0.355 (0.231)	-1.281*** (0.244)
Full-time	-0.405 (0.217)	-0.081 (0.196)	-0.391* (0.217)	-0.129 (0.197)	-0.313 (0.215)	-0.127 (0.194)
Black	1.997*** (0.205)	2.044*** (0.298)	2.008*** (0.204)	2.045*** (0.297)	2.001*** (0.204)	2.045*** (0.297)
Hispanic	0.957*** (0.218)	1.361*** (0.311)	0.976*** (0.220)	1.376*** (0.311)	0.973*** (0.220)	1.376*** (0.311)
Other race	-1.218** (0.482)	-1.850*** (0.325)	-1.201** (0.479)	-1.844*** (0.326)	-1.201** (0.478)	-1.844*** (0.326)
Married	-0.120 (0.129)	0.360** (0.152)	-0.129 (0.129)	0.342** (0.152)	-0.133 (0.129)	0.342** (0.152)
Non-metropolitan	0.438** (0.196)	0.834*** (0.234)	0.441** (0.195)	0.827*** (0.234)	0.446** (0.195)	0.827*** (0.235)
Age	-0.022 (0.014)	-0.012 (0.013)	0.407** (0.184)	0.374** (0.168)	-5.028* (2.560)	0.204 (0.042)
Age ²			-0.003** (0.001)	-0.003** (0.001)	0.084** (0.041)	-0.000 (0.042)
Age ³					-0.000** (0.000)	-0.000 (0.000)
N. Obs	9,384	7,833	9,384	7,833	9,384	7,833

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. Fixed effects for survey year, state dummies and season of the year are included all model specifications. 4. Time spent on activities is measured in hours. 5. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

Table 24: Robustness check - Effects of working part-time and working full-time on BMI by education level: Age specification

	BMI					
	Linear age		Quadratic age		Cubic age	
	Low education	High education	Low education	High education	Low education	High education
Part-time	-0.779** (0.272)	-0.741** (0.229)	-0.799** (0.270)	-0.790** (0.228)	-0.758** (0.267)	-0.783** (0.228)
Full-time	-0.455* (0.234)	-0.003 (0.184)	-0.455* (0.234)	-0.050 (0.182)	-0.370 (0.232)	-0.035 (0.183)
Black	1.542*** (0.237)	2.354*** (0.230)	1.541*** (0.238)	2.361*** (0.228)	1.529*** (0.237)	2.362*** (0.228)
Hispanic	0.524* (0.279)	1.320*** (0.304)	0.530* (0.279)	1.332*** (0.305)	0.513* (0.279)	1.333*** (0.304)
Other race	-2.175*** (0.500)	-1.286*** (0.321)	-2.176*** (0.498)	-1.267*** (0.321)	-2.172*** (0.496)	-1.268*** (0.320)
Married	-0.136 (0.157)	0.177 (0.129)	-0.146 (0.156)	0.163 (0.128)	-0.147 (0.157)	0.162 (0.128)
Non-metropolitan	0.598** (0.202)	0.501** (0.224)	0.596** (0.202)	0.495** (0.224)	0.597** (0.201)	0.497** (0.224)
Age	-0.0327** (0.016)	-0.004 (0.012)	0.224 (0.200)	0.546*** (0.154)	-5.581* (2.840)	-0.803 (2.274)
Age ²			-0.002 (0.002)	-0.005*** (0.001)	0.092** (0.046)	0.018 (0.037)
Age ³					-0.001** (0.000)	-0.000 (0.000)
N.Obs	6,623	10,594	6,623	10,594	6,623	10,594

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. Fixed effects for survey year, state dummies and season of the year are included all model specifications. 4. Time spent on activities is measured in hours. 5. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

3.4.2 Income threshold

In this section, we study the sensitivity of our results to a change in the definition of the heterogeneous income groups. That way, we redefine the income threshold to build up sample groups with differentials in income level. In contrast to Section 3.4, we set the threshold as the average income for each income measure. We present the robustness check for the results about the effects of working full-time and working part-time on BMI in Table 25, and for the effects of working full-time and working part-time on BMI considering all time use channels in Table 26. As we previously observed, there is no statistically significant effect of working full-time on BMI (Table 25). However, we do find again that the impact of the some of the considered time use channels is significant for full-time workers for both income groups considered (Table 26). For part-time workers, we can conclude that our results remain similar and they lead to the same conclusions we previously described in the results section. Thus, our results can be considered to be robust to the change in the income threshold.

Table 25: Robustness check – Effects of working part-time and working full-time on BMI: Income threshold

	BMI	
	Low income	High income
Part-time	-0.569** (0.262)	-0.957*** (0.204)
Full-time	-0.412* (0.243)	-0.132 (0.172)
Age	0.675*** (0.186)	0.265* (0.154)
Age ²	-0.005*** (0.001)	-0.002* (0.001)
Black	2.054*** (0.230)	2.011*** (0.232)
Hispanic	0.888*** (0.233)	1.456*** (0.242)
Other race	-1.348** (0.551)	-1.645*** (0.307)
Married	-0.140 (0.154)	0.186 (0.147)
Non-metropolitan	0.212 (0.221)	0.911*** (0.215)
N. Obs	7,016	10,201

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than average household income and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. Fixed effects for survey year, state dummies and season of the year are included in the model. 4. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 5. *** p<0.01, ** p<0.05, * p<0.1.

Table 26: Robustness check – Effects of time use channels on working full-time and working part-time: Income threshold

	Low income			High income		
	Full-time	Part-time	Retired	Full-time	Part-time	Retired
Primary eating	-0.027*** (0.006)	-0.016** (0.005)	-0.001 (0.007)	-0.007 (0.004)	0.027*** (0.007)	0.023*** (0.005)
Secondary eating	-0.002 (0.002)	-0.000 (0.002)	0.001 (0.002)	-0.000 (0.001)	0.001 (0.002)	0.001 (0.002)
Food preparation	-0.052*** (0.008)	-0.050*** (0.007)	0.019** (0.008)	0.015*** (0.006)	0.032*** (0.008)	0.035*** (0.006)
Grocery	-0.013 (0.148)	-0.012 (0.015)	-0.005 (0.011)	0.025* (0.013)	0.018 (0.013)	-0.013 (0.011)
Prepared food	0.038 (0.008)	-0.044 (0.069)	-0.146** (0.053)	-0.013 (0.043)	0.108 (0.080)	0.057 (0.069)
Sleeping	-0.019*** (0.002)	-0.021*** (0.003)	-0.000 (0.002)	0.005** (0.002)	0.020*** (0.003)	0.017*** (0.002)
Exercise	-0.034*** (0.006)	-0.033*** (0.006)	0.005 (0.007)	0.000 (0.004)	0.029*** (0.009)	0.032*** (0.005)
Household	-0.026*** (0.004)	-0.035*** (0.004)	0.003 (0.004)	0.010*** (0.004)	0.023*** (0.005)	0.025*** (0.004)
Screen	-0.024*** (0.002)	-0.024*** (0.002)	-0.003** (0.001)	-0.002 (0.002)	0.027*** (0.002)	0.025*** (0.002)
Commute	-0.014** (0.005)	-0.014*** (0.004)	0.006 (0.004)	0.004 (0.004)	0.008* (0.004)	0.011*** (0.003)
Own medical care	-0.055*** (0.013)	-0.049** (0.017)	-0.014 (0.010)	0.003 (0.013)	0.069*** (0.012)	0.046*** (0.015)
N. Obs	7,295	10,558	7,295	10,558	7,295	10,558

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than average household income and high income is defined as the opposite. Low education refers to under highschool graduate level and high income to levels higher than highschool graduate. 3. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 4. Time spent on activities is measured in hours. 5. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 6. *** p<0.01, ** p<0.05, * p<0.1.

3.4.3 Dependent variable

In this section, we analyze the sensitivity of our findings to a change in the dependent variable. To do so, we consider obesity as the dependent variable. We define a binary indicator for being obese which takes the value of 1 if the respondent surpasses a BMI of 30, and 0 otherwise. We repeat the analysis using this new dependent variable, so we get now linear probability model equations to estimate the effects of working full-time and part-time, and time use channels on being obese. Although we get different models, we obtain similar conclusions to the baseline analysis since BMI and obesity are closely related and it seems logical to find similar results.

Table 27: Robustness check - Effects of working part-time and working full-time on obesity

	Obese			
	Low income	High income	Low education	High education
Part-time	-0.042** (0.020)	-0.081*** (0.023)	-0.064** (0.027)	-0.057*** (0.020)
Full-time	-0.048*** (0.018)	-0.017 (0.019)	-0.045** (0.021)	-0.021 (0.017)
Age	0.035** (0.016)	0.019 (0.015)	0.028* (0.016)	0.030** (0.013)
Age ²	-0.000** (0.000)	-0.000 (0.000)	-0.000* (0.000)	-0.000** (0.000)
Black	0.128*** (0.019)	0.139*** (0.024)	0.105*** (0.021)	0.148*** (0.019)
Hispanic	0.058*** (0.021)	0.085*** (0.030)	0.041 (0.028)	0.059** (0.025)
Other race	-0.040 (0.038)	-0.094*** (0.028)	-0.096** (0.040)	-0.062** (0.026)
Married	-0.007 (0.013)	0.011 (0.013)	-0.021 (0.014)	0.007 (0.010)
Non-metropolitan	0.027* (0.018)	0.065*** (0.021)	0.043** (0.017)	0.036** (0.018)
N. Obs	9,384	7,833	6,623	10,594

Notes: 1. Linear regression model. 2. Regression results for the determinants of obesity across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. 3. Fixed effects for survey year, state dummies and season of the year are included in the model. 4. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 5. *** p<0.01, ** p<0.05, * p<0.1.

Table 28: Robustness check – Effects of working part-time and working and time use channels on obesity

	Obese			
	Low income	High income	Low education	High education
<i>Baseline part-time effect</i>	-0.042** (0.020)	-0.081*** (0.023)	-0.064** (0.027)	-0.057*** (0.020)
Primary eating	-0.015* (0.009)	-0.008 (0.008)	-0.016 (0.011)	-0.008 (0.008)
Secondary eating	0.001 (0.002)	0.004 (0.003)	0.004 (0.003)	0.001 (0.40)
Food preparation	-0.005 (0.009)	-0.016* (0.008)	-0.008 (0.010)	-0.013 (0.008)
Grocery	-0.010 (0.019)	-0.012 (0.016)	-0.005 (0.022)	-0.018 (0.016)
Prepared food	-0.053 (0.092)	0.311*** (0.087)	0.012 (0.099)	0.259*** (0.084)
Sleeping	0.012*** (0.003)	0.005 (0.004)	0.010** (0.004)	0.007** (0.003)
Exercise	-0.029*** (0.007)	-0.031*** (0.006)	-0.019*** (0.007)	-0.035*** (0.006)
Household	-0.004 (0.006)	-0.010 (0.006)	-0.008 (0.006)	-0.005 (0.005)
Screen	0.008*** (0.002)	0.018*** (0.003)	0.008*** (0.003)	0.016*** (0.002)
Commute	0.007 (0.006)	-0.004 (0.004)	0.005 (0.007)	-0.001 (0.004)
Own medical care	0.024 (0.173)	-0.009 (0.018)	0.034 (0.021)	-0.009 (0.016)
N. Obs	8,101	6,927	5,820	9,208

Notes: 1. Linear regression model. 2. Regression results for the determinants of obesity across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. 3. First row refers to the coefficient from the baseline model specification. 4. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 5. Time spent on activities is measured in hours. 6. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

Table 29: Robustness check – Effects of working full-time and time use channels on obesity

	Obese			
	Low income	High income	Low education	High education
Baseline full-time effect	-0.048*** (0.018)	-0.017 (0.019)	-0.045** (0.021)	-0.021 (0.017)
Primary eating	-0.017* (0.010)	0.000 (0.014)	-0.022* (0.013)	0.001 (0.009)
Secondary eating	-0.003 (0.003)	0.010** (0.004)	-0.002 (0.004)	0.008* (0.004)
Food preparation	-0.002 (0.117)	-0.013 (0.011)	-0.003 (0.0124)	-0.009 (0.010)
Grocery	-0.015 (0.023)	0.026 (0.032)	0.014 (0.029)	-0.021 (0.022)
Prepared food	-0.132 (0.117)	0.355** (0.149)	0.019 (0.149)	0.121 (0.148)
Sleeping	0.010** (0.004)	0.018** (0.007)	0.010** (0.005)	0.015*** (0.004)
Exercise	-0.021** (0.008)	-0.027** (0.010)	-0.005 (0.010)	-0.034*** (0.007)
Household	-0.010 (0.006)	-0.003 (0.008)	-0.011 * (0.006)	-0.003 (0.007)
Screen	0.008*** (0.003)	0.020*** (0.003)	0.009** (0.003)	0.014*** (0.002)
Commute	0.006 (0.007)	-0.000 (0.006)	0.010 (0.009)	-0.001 (0.005)
Own medical care	0.028 (0.019)	-0.013 (0.026)	0.029 (0.021)	-0.001 (0.021)
N. Obs	5,582	2,720	3,697	4,605

Notes: 1. Linear regression model. 2. Regression results for the determinants of obesity across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. 3. First row refers to the coefficient from the baseline model specification. 4. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 5. Time spent on activities is measured in hours. 6. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

Table 30: Robustness check – Effects of working part-time, working full-time and time use channels on obesity

	Obese			
	Low income	High income	Low education	High education
Part-time	-0.032 (0.027)	-0.071*** (0.023)	-0.056** (0.027)	-0.044** (0.020)
Full-time	-0.036* (0.019)	-0.006 (0.019)	-0.031 (0.022)	-0.011 (0.017)
Primary eating	-0.014 (0.008)	-0.009 (0.008)	-0.018* (0.010)	-0.007 (0.007)
Secondary eating	-0.000 (0.002)	0.003 (0.003)	0.002 (0.003)	0.001 (0.002)
Food preparation	-0.007 (0.008)	-0.021** (0.007)	-0.011 (0.009)	-0.016** (0.007)
Grocery	-0.006 (0.018)	0.003 (0.017)	0.008 (0.021)	-0.012 (0.015)
Prepared food	-0.037 (0.090)	0.293*** (0.085)	0.012 (0.098)	0.241*** (0.078)
Sleeping	0.010*** (0.003)	0.006 (0.004)	0.009** (0.004)	0.007** (0.003)
Exercise	-0.026*** (0.007)	-0.030*** (0.006)	-0.018** (0.007)	-0.032*** (0.006)
Household	-0.007 (0.005)	-0.009* (0.005)	-0.010* (0.005)	-0.006 (0.005)
Screen	0.007*** (0.002)	0.018*** (0.002)	0.007** (0.003)	0.015*** (0.002)
Commute	0.002 (0.005)	-0.002 (0.004)	0.005 (0.006)	-0.002 (0.004)
Own medical care	0.020 (0.017)	-0.005 (0.017)	0.030 (0.019)	-0.008 (0.015)
N. Obs	9,329	7,799	6,582	10,546

Notes: 1. Linear regression model. 2. Regression results for the determinants of BMI across heterogeneous treatment group effects: income level and education level. The income measurement refers to total household income. Low income category groups the sample that has an income level lower than the 50th percentile, that is below the median, and high income is defined as the opposite. 3. First row refers to the coefficient from the baseline model specification. 4. Individual characteristics such as age, quadratic age, race, marital status and living area, have been included in all specifications. Additionally, fixed effects for survey year, state dummies and season of the year are included all model specifications. 5. Time spent on activities is measured in hours. 6. Heteroskedasticity robust standard errors are in parenthesis and calculated using the replicate variance method. 7. *** p<0.01, ** p<0.05, * p<0.1.

4. Conclusions

In this paper, we first study the causal effect of working part-time and working full-time on body weight. Additionally, we investigate whether the effects are the same across different socio-economic status groups on the income and education dimensions. To investigate these issues, we make use of panel data from the Health and Retirement Study, which includes detailed information about a wide variety of topics such as labor participation, health-related characteristics and other demographic variables of the elderly American population. The time span used is 2000-2014. The sample consists of individuals between 50 and 75 years old. As indicated in previous literature, measuring the causal effect of labor market participation on health outcomes is difficult since retirement choice is often a source of endogeneity. To do so, we follow the instrumental variable approach. We make use of some instruments, which according to previous findings, are valid instruments. Following Neuman (2008) and Kantarci (2017, 2018), we use retirement eligibility ages as instruments of the number of hours worked. We distinguish between the fixed effects estimation model and the random effects estimation model, depending on the assumptions we make about unobserved time-invariant individual characteristics. Through the Hausman test, we decide that the fixed effects model is the best approximation to the true model. We then check the sensitivity of our results to the set of instrumental variables, to the age specification, the definition of the income level groups and to the econometric model.

Finally, we study which mechanisms might drive the effects working part-time and working full-time on Body Mass Index. Also, we investigate these mechanisms across individuals with differentials in income and education. For these analyses, we make use of time use data from the American Time Use Survey which is linked to the Compendium of Physical Activities. We consider a sample of individuals between 50 and 75 years old for the waves 2006, 2007, 2008, 2014 and 2015. We make use of the time spent on several activities as the time use channels which could have an impact on BMI. Using this data, we study the effect of working part-time and working full-time on Body Mass Index. Likewise, we investigate the impact across groups with differentials in income and education. We expect to obtain similar results to those obtained using the HRS information. Following the approaches of Fertig et al. (2009) and Abramovitz (2016), we include controls for time use channels. Then, we augmented this model adding one by one each time channel and regress each equation model for each income level group and education level group. Furthermore, we estimate the model controlling for all time channels. Here we also make use of retirement eligibility ages as instrumental variables to control for endogeneity. We also check for the sensitivity of our results to the age specification, the definition of the income level groups and to another indicator of physical health as dependent variable.

The main findings of this paper are the following. First, we find that retirement eligibility ages are relevant predictors of the labor market participation decision. Hence, this result is in line with the previous literature on the topic (Coile and Gruber, 2000; Neuman, 2008; Bonsang et al., 2012; Gustman and Steinmeier, 2000, 2004, 2014, Mazzona and Peracchi, 2012, 2017; Kantarci, 2017, 2018). Regarding to the effects of the number of hours worked on BMI, we find that both working part-time and working full-time have a statistically significant and negative effect on BMI. Individuals who work part-time have on average lower BMI than those working full-time or retired. This is in line with the findings of Kantarci (2017, 2018) who finds that the effect of working part-time on BMI is larger than the effect of working full-time. Likewise, we find the same result for those individuals with a high level of income. Hence, for individuals with high income level the lower is the number of hours worked, the lower their BMI is. The impact of working part-time on BMI is even larger for those individuals who have low income level. Analogously, we find that working part-time has a negative and larger effect for low educated individuals than for highly educated individuals.

Furthermore, relative to the study of the mechanisms that might help us to explain the differentials in the effects of working part-time and working full-time on body weight, we find interesting results. On average, individuals with a high income level present higher levels of screen time than those who have low income level. The impact on BMI is negative and larger for individuals with high income. For individuals highly educated, the impact of screen time on BMI is also larger than for those with lower level of education.

Additionally, for individuals with low income level, the most relevant findings in comparison to the high income level group are related to sleeping, exercise and screen time. It seems that the higher is the amount they spend on sleeping, the higher is their BMI. The same occurs with screen time. On the contrary, exercise shows a negative relationship with body fat. These findings make sense since doing exercise reduces the probability of gaining weight and sleeping and screen time are two of the activities with lowest MET. For individuals with high income level, we find that the time spent on food preparation, eating prepared food, exercise, household, and screen time are related to relevant findings in comparison to the results for low income individuals. For these individuals, cooking food at home decreases the chances to have higher levels of body fat. This might be given by the way of cooking their meals and the higher quality food they could buy. In contrast, eating prepared food seems to have a negative impact on their BMI. Exercise and taking care of their household help them to reduce their weight. Screen time seems to have a larger negative impact for wealthier individuals than for individuals with low income level. This is probably because they spend on average more time in front of a screen. For low educated individuals the findings appear to be very similar to those of low income individuals although the time spent on exercise has a smaller negative impact on

BMI. When we compare highly educated individuals and low educated individuals we find that food preparation, prepared food, exercise, household, screen time, sleeping and going grocery shopping are relevant activities. We suppose that individuals who have a high level of education, are more aware of the effects of diet and certain habits on health.

Our findings also suggest that old individuals with high income level are more sensitive to activities which have an impact on the effects of working full-time and working part-time on BMI than for those who have a lower level of income. Likewise, highly educated individuals are also more sensitive to activities which have an impact of the effects of working part-time and working full-time on body weight.

In the U.S., obesity is one of the major concerns since it is a factor which increases the likelihood of suffering other serious diseases such as diabetes, hypertension and cardiovascular diseases. It is forecasted that obesity will rise in the years to come. Then, it has then great implications for health-care costs but also has effects on demographic and economic factors. Life expectancy will diminish since current and future generations will follow the same behavioral pattern (Olshansky et al., 2005). If we add the decreasing trend of the fertility ratio affects negatively to the dependency ratio. Hence, all kind of public expenditures will need to adjust to this reality. We find that retirees have higher BMI than old workers. Furthermore, the allocation of time made by retirees and full-time workers seem to favor sedentarism. However, there is evidence that reducing the number of hours work might be positive for the physical health of those who still want to work. Additionally, we find that individuals with a higher socio-economic status usually have lower BMI. Educational programs on nourishment, healthy lifestyle, sport programs, and lowering the price of healthy food should be applied to reduce the obesity problem.

Regarding further research, analyses on other measures of physical health could be performed to study the differences between working part-time and working full-time for the elderly. Furthermore, we could investigate the effects of working part-time and working full-time on mental health which also might have implications on physical health. Besides, we could consider as another dimension of socio-economic status, the type of job occupation such as blue-collar or white-collar jobs among others. Job occupations are more physically and mentally demanding than others are. Therefore, it might be interesting to explore the effects of different job occupations on physical and mental health. Also, studying if these differences are the same for populations of different countries using longitudinal datasets could lead to interesting results. We could also use the same data of the present study but distinguish between nationalities. Moreover, using longitudinal data instead of pooled cross-sectional data for the time use analysis could allow us to make use of the fixed effects model.

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Appendix

A) Effects of working part-time and working full-time on BMI – Robustness checks

Table A1: Robustness check – Baseline RE & set of instruments – First stage results

	Part-time	Full-time
Bet. early and normal ret. age	0.039*** (0.006)	-0.159*** (0.007)
Bet. normal ret. age and age 70	0.048*** (0.010)	-0.237*** (0.011)
Over age 70	0.028* (0.015)	-0.183*** (0.016)
Bet. early and nor. ret. age (P)	0.007 (0.006)	-0.059*** (0.006)
Bet. nor. ret. age and age 70 (P)	-0.011 (0.008)	-0.067*** (0.009)
Over age 70 (P)	-0.033*** (0.011)	-0.054*** (0.012)
Age	0.011 (0.008)	0.048*** (0.008)
Age squared	-0.000 (0.000)	-0.001*** (0.000)
Ever been self employed	0.128*** (0.008)	-0.007 (0.008)
Ever worked in large firm	-0.090*** (0.006)	0.066*** (0.007)
Constant	-0.146 (0.231)	-0.086 (0.233)
F test quadratic age	3.44	822.56***
F test for excluded instruments	116.20***	126.76***
Weak identification test	150.32***	171.60***
N. Obs.	54,842	
N. Ind.	10,516	

Notes: 1. Linear probability model with random effects. 2. First stage results. 3. (P) refers to married or unmarried partner. 4. Weak identification test is based on Sanderson Windmeijer F statistic. 5. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 6. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Robustness check – Baseline RE & set of instruments – Second stage results

	BMI	
	Coefficient	SE
Part-time	-4.325***‡	(0.626)
Full-time	-1.280***	(0.271)
Age	0.608***	(0.057)
Age ²	-0.005***	(0.001)
Constant	10.620***	(1.526)
Endogeneity test	68.82**	
Overidentification test	4.329	
F test for work status	68.77**	
F test for quadratic age	230.28***	
N. Obs.	54,199	
N. Ind.	10,487	

Notes: 1. Linear probability model with random effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner, indicator for have ever being self-employed and indicator for having ever worked in a large firm. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is computed by hand since there is no package in Stata to do so. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Robustness check – Income level heterogeneity RE & set of instruments – Second stage results

	BMI																																																																																							
	Total household income			Net total household income			Earnings			Total wealth			Weekly wage rate			Total weekly wage rate																																																																								
	Low income	High income		Low income	High income		Low income	High income		Low income	High income		Low income	High income		Low income	High income																																																																							
Part-time	-4.018*** (0.769)	-4.546*** (0.748)	-4.845*** (1.003)	-3.483*** (0.603)	-2.529*** (0.908)	-7.342*** (0.968)	-4.143*** (0.988)	-3.580*** (0.638)	-2.039*** (0.777)	-5.880*** (0.875)	-4.243*** (0.886)	-3.813*** (0.758)	0.504*** (0.088)	0.557*** (0.071)	0.560*** (0.115)	0.568*** (0.059)	0.380*** (0.080)	0.702*** (0.102)	0.600*** (0.113)	0.606*** (0.062)	0.544*** (0.087)	0.484*** (0.068)	0.675*** (0.103)	0.461*** (0.063)																																																																
Full-time	-1.170*** (0.331)	-1.344*** (0.402)	-1.080*** (0.396)	-1.160*** (0.311)	-0.908*** (0.426)	-1.949*** (0.473)	-1.502*** (0.472)	-0.868*** (0.322)	-1.161*** (0.343)	-0.490 (0.328)	-1.761*** (0.412)	-0.416 (0.303)	Age ²	-0.004*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.006*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)																																																															
Constant	14.469*** (2.754)	11.727*** (1.830)	13.090*** (3.147)	11.102*** (1.652)	16.928*** (2.646)	8.571*** (2.513)	11.961*** (2.808)	9.261*** (1.833)	12.437*** (2.462)	13.017*** (1.995)	9.663*** (2.901)	13.504*** (1.745)	39.29	18.781	13.933	40.266	21.501	32.098	21.373	29.221	21.683	28.159	19.061	33.226	5.944	8.664	5.271	9.565	5.999	8.513	6.575	6.975	5.519	6.727	5.525	7.628																																																				
Endogeneity test	30.59	57.88	25.72	50.60	11.66	69.53	23.78	40.34	19.30	53.16	29.15	39.29	Overid. test	3.512	6.202	2.463	10.641	4.898	6.738	5.353	1.203	4.056	9.545	F test quadratic age	33.28***	126.39***	25.72***	132.38***	22.33***	119.23***	51.17***	113.56***	45.71***	79.60***	44.81***	104.80***	F test work status	28.97***	37.25***	23.91***	33.49***	10.42***	57.60***	17.60***	31.66***	17.45***	45.22***	25.79***	26.24***	F test for equality	17.31***	29.80***	17.06***	6.81***	3.06*	45.57***	13.67***	21.61***	2.26	40.32***	12.18***	24.94***	N. Obs	18,781	35,418	13,933	40,266	21,501	32,098	21,373	29,221	21,683	28,159	19,061	33,226	N. Ind	5,944	8,664	5,271	9,565	5,999	8,513	6,575	6,975	5,519	6,727	5,525	7,628

Notes: 1. Linear probability model with random effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner, indicator for have ever being self-employed and indicator for having ever worked in a large firm. 4. † indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is computed by hand since there is no package in Stata to do so. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hausen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness check – Education level heterogeneity RE & set of instruments – Second stage results

	BMI	
	Low education	High education
Part-time	−4.739***‡ (0.894)	−3.754***‡ (0.868)
Full-time	−1.399*** (0.358)	−1.043** (0.413)
Age	0.590*** (0.084)	0.600*** (0.076)
Age ²	−0.005*** (0.001)	−0.005*** (0.001)
Constant	11.831*** (2.322)	10.057*** (1.970)
Endogeneity test	40.36***	25.44***
Overid. test	2.830	6.282
F test quadratic age	61.23***	108.76***
F test work status	28.52***	18.93***
F test for equality	21.56***	16.39*
N. Obs	25,365	28,832
N. Ind	4,868	5,618

Notes: 1. Linear probability model with random effects and instrumental variables. 2. Second stage results. 3. Instruments: indicators for retirement eligibility ages of respondent and partner, indicator for have ever being self-employed and indicator for having ever worked in a large firm. 4. ‡ indicates that we reject the equality of the coefficients of part-time and full-time at the 0.05 level. 5. Endogeneity test is computed by hand since there is no package in Stata to do so. It tests the null hypothesis that part-time and full-time are exogenous variables. 6. Overidentification test is based on the Hansen J statistic. It tests the null hypothesis that all instruments are orthogonal to the error term. 7. Heteroskedasticity standard errors and clustering on panel groups are in parentheses. 8. *** p<0.01, ** p<0.05, * p<0.1.

B) Instrumental variables approach and causality of the estimated effects – Baseline results – First stage results

Table B1: Baseline results – First stage results

	Part-time	Full-time
Bet. early and normal ret. age	0.016** (0.006)	-0.199*** (0.008)
Bet. normal ret. age and age 70	0.0246*** (0.008)	-0.307*** (0.019)
Over age 70	0.009 (0.016)	-0.273*** (0.193)
Age	0.029*** (0.000)	-0.015* (0.008)
Age ²	-0.000*** (0.000)	-0.000 (0.000)
Black	-0.025*** (0.005)	0.024*** (0.005)
Hispanic	-0.014** (0.005)	0.001 (0.006)
Other race	-0.027*** (0.008)	0.016 (0.010)
Married	-0.005* (0.003)	-0.012*** (0.004)
Non metropolitan	0.008* (0.004)	-0.023*** (0.005)
Constant	-0.755*** (0.182)	1.829*** (0.219)
F test quadratic age	11.28***	622.15***
F test for excluded instruments	5.139***	131.139***
Weak identification test	0.262	0.271
N. Obs.	50,417	

Notes: 1. Linear regression model. 2. First stage results. 3. Weak identification test is based on Sanderson Windmeijer F statistic. It tests the null hypothesis that the endogenous variable alone is not identified. 4. Fixed effects for survey year, state dummies and season of the year are included in the model. 5. *** p<0.01, ** p<0.05, * p<0.1.

