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Abstract

A growing body of literature is analyzing the effect of retirement on physical and mental health. We distinguish between working full-time and part-time and analyze their effects on the body weight of Americans between the ages 50 and 75. We take an instrumental variable approach to study the causal effects of working part-time and full-time. We explore a rich set of instrumental variables to find independent sources of exogenous variation to separately identify these effects. The results show that, compared to being retired, both working full-time and part-time reduce the body mass index, but the effect of working part-time is much larger. Using very different instrument sets consistently lead to the same conclusion.

1 Introduction

In industrialized countries the population is aging rapidly, which has two main causes: declining fertility rates and increasing longevity. As a consequence, the dependency ratio in these countries is increasing, which greatly affects health care costs and pension payments. In many European countries, this has already lead to an increase in the statutory retirement age. For instance, Belarus has increased the retirement age for both men and women by three years, the United Kingdom is gradually increasing the retirement age to 69 and the Netherlands will increase the retirement age to at least 67 by 2021. In 1983, the US Congress has passed legislation that will gradually increase the Social Security retirement age from the age of 65 to the age of 67, and policy makers consider increasing it even further. The increase in the retirement age aims to alleviate the impact of the population aging on the public finances, but it also means that there will be a larger population of older workers.

A growing number of studies are analyzing how working in old age affects physical and mental health. Most of the studies in this literature has so far focused on the effect of retirement on various health outcomes, but has not considered the possibility that working part-time can have a different effect on health than working full-time. For example, Dave et al. (2008), Coe and Zamarro (2011) and Insler (2014) estimate the effect of retirement on physical and mental health in Europe and in the United States. Coe et al. (2012), Bonsang et al. (2012), Mazzonna and Peracchi (2012) and Mazzonna and Peracchi (2017) study the effects of retirement on cognitive abilities in Europe and in the United States. Neuman (2008) and Eibich (2015) study the effects of retirement on subjective health status. Chung et al. (2009) and Godard (2016) consider the effects of retirement on body weight.

The main methodological difficulty in this literature is to identify the causal effect of retirement on health. The listed studies typically take an instrumental variable approach to address the endogeneity of retirement.

Few studies make a distinction between the health effects of working part-time and of working full-time. Dave et al. (2008) split their dataset in two parts, one part excludes all fully retired respondents and the other part excludes all partially retired respondents, and they conclude that partial retirement alleviates the adverse effects of complete retirement on physical and mental health outcomes. Forbes et al. (2015) show that Australian part-time workers have better mental health than retirees, but they do not account for endogeneity of the labor force status, and therefore do not analyze a causal effect.

We separate the effects of working part-time and full-time and explore a rich set of instrumental variables that provide independent sources of exogenous variation for the two distinct work decisions. The most commonly used instruments for the work decision in the subject literature are dummy variables for reaching retirement eligibility ages, which offer an exogenous source of variation for the full retirement decision, but not independent sources of exogenous variation for the part-time and full-time work decisions. Another disadvantage of the retirement eligibility ages as instruments has to do with the interpretation of the estimation results. Instrumental variable analysis estimates the Local Average Treatment Effect (LATE) (Imbens and Angrist, 1994), which means that the estimation results only apply to those who comply with the instruments. Most individuals work for an employer where they face institutional restrictions. One of these restrictions is mandatory retirement at the retirement eligibility ages. However, this restriction does not apply to self-employed workers, which means that self-employed workers are ignored when identifying the effects of part-time and full-time work. Therefore, the retirement eligibility ages as instruments might lead to selection bias. We explore a rich set of labor market and personal characteristics as determinants of the part-time and full-time work decisions. We then analyze to which extent these determinants act as instruments and provide independent sources of exogenous variation for the part-time and full-time work decisions to identify the causal effects of working part-time and full-time on the body weight.

We use data on a representative sample of American individuals of the ages 50 to 75, who are interviewed in the Health and Retirement Study (HRS). We exploit the panel structure of the HRS to employ panel data methods, while we analyze the causal effects of working part-time and full-time on the BMI. We also perform a number of diagnostic tests to check whether the instruments are valid.

Our results show that people who work have a lower BMI than retirees, but the effect of working part-time is much larger than that of working full-time.

This paper is organized as follows. Section 2 discusses the empirical approach we use. Section 3 describes the data and the sample restrictions. Section 4 discusses the descriptive statistics. Section 5 discusses the results. Section 6 performs several sensitivity checks and discuss their results and implications. Section 7 analyzes heterogeneous treatment effects and compares the results between men and women. Section 8 discusses the policy implications and concludes.

2 Empirical approach

2.1 Controlling for heterogeneity

The data we use is panel data, allowing us to apply panel data methods. In particular we use the fixed effects (FE) and the random effects (RE) models.

The random effects model takes the form:

$$y_{it} = \mu + x_{it}'\beta + f(A_{it}) + \alpha_i + \epsilon_{it} \tag{2.1}$$

y_{it} includes values for the outcome variable BMI and x_{it} contains two indicators of full-time and part-time work. β represents the effect of x_{it} on y_{it} and $f(A_{it})$ is a polynomial function for age. α_i is a time-invariant individual-specific intercept and ϵ_{it} is the idiosyncratic error term. The FE model has the same form, except the FE model does not consider μ, which is the average BMI of the whole population.

We will estimate β, which measures the effects of working part-time and full-time on the BMI. To approach longitudinal data, simple linear regression models usually do not suffice, as they assume that the regressors and the error term are independent of each other, which might be a problem with longitudinal data. Heterogeneity across individuals could pose an issue, since there are many factors that influence the BMI that are different for each individual. For instance, there are no two individuals who eat the same food in the same amounts and basal metabolic rates (BMR) differ per individual as well, so food intake has an individual influence on BMI. Also, each individual has their own preferences about retirement. Some want to work as long as possible, while others prefer the freedom that retirement gives. In simple linear regression models, these individual preferences are ignored and therefore can cause a bias in the results. To account for unobserved heterogeneity, we use panel data methods. The main difference between linear regression and panel data models is their treatment of the α_i. The fixed effects model allows for correlation between the regressors and the α_i. In the random effects model, it is assumed that α_i is independent of the regressors. The α_i are an independent and identically distributed (iid) draw from a distribution with zero mean and variance σ^2_α, which can be interpreted as an individual attribute that does not change over time. It is also uncorrelated with the regressors. In both models, we assume that ϵ_{it} is iid, uncorrelated over time, with zero mean and variance σ^2_ϵ. As in simple linear regression models, it is assumed that x_{it} is independent of ϵ_{it}.

In both the fixed effects and random effects models, we apply a transformation on the data, so we can then perform simple OLS on the transformed data. The transformed equation for both the fixed effects and random effects model can be stated as:

$$\widetilde{y}_{it} = \widetilde{x}'_{it}\beta + f(\widetilde{A}_{it}) + \widetilde{\epsilon}_{it} \tag{2.2}$$

The fixed effects model is estimated by applying the within transformation. In the within transformation, we substract the individual means to eliminate the α_i. Then, simple OLS is applied on the transformed data, which leads to consistent estimates of β.

In the random effects model, following Verbeek (2004), the transformation is done by premultiplying vectors y_i by:

$$\Omega^{-1} = \sigma_\epsilon^{-2}\left(I_T - \frac{\sigma^2_\alpha}{\sigma^2_\epsilon + T\sigma^2_\alpha}\iota_T\iota'_T\right) \tag{2.3}$$

where σ^2_ϵ can be estimated by the residuals of the within estimation and σ^2_α can be estimated by:

$$\widehat{\sigma}^2_\alpha = \frac{1}{N}\sum_{n=1}^{N}(\bar{y}_i - \widehat{\mu}_B - \bar{x}'_i\widehat{\beta}_B)^2 - \frac{1}{T}\widehat{\sigma}^2_\epsilon \tag{2.4}$$

where $\widehat{\mu}_B$ and $\widehat{\beta}_B$ are the between estimators of β and μ, respectively. The between estimator exploits the differences between individuals, whereas the within estimator exploits differences within individuals. In the estimation of the random effects model, we need to account for autocorrelation over time in $\alpha_i + \epsilon_{it}$, which can be done by implementing the GLS estimator that accounts for autocorrelation.

2.2 Controlling for endogeneity

We analyze the effects of working part-time and full-time on BMI, but there can also be an effect in the opposite direction. For instance, considering the BMI as an explanatory variable of interest, Greve (2008) has found that BMI affects the employment status of Danish women, Kinge (2016) found that BMI affects the probability of not working due to disability and Renna and Thakur (2010) have found that older workers with a BMI of at least 35 have a higher likelihood of retiring early.

To address the endogeneity of the part-time and full-time work decisions in our models, we use an instrumental variable (IV) analysis. In particular, we estimate a two-stage least squares model. In the first stage, the endogenous variables are regressed on suitable instruments. In the second stage, the first-stage predictions are used to obtain consistent estimates for the coefficients of the endogenous variables.

For an instrument to be suitable, it must satisfy two requirements: it is strongly correlated with the endogenous variables and it is not correlated with the error term. However, since we are working with multiple endogenous regressors, we have an additional requirement. This is that different instrumental variables should provide independent sources of exogenous variation for different endogenous variables. We require this to separately identify the effects of the endogenous regressors. In this section, we explain the first-stage and second-stage regressions.

The instruments are transformed in the same way as the other variables. In the first stage we regress the transformed endogenous variables on the transformed instrumental variables and exogenous variables. We estimate the following regression equation:

$$\widetilde{x}_{it}^{j} = \widetilde{z}_{it}'\delta^{j} + f(\widetilde{A}_{it}) + \widetilde{\nu}_{it}^{j} \tag{2.5}$$

where $\widetilde{z}_{it}$ are the transformed instrumental variables, index j refers to each of the endogenous variables and ν_{it} is the error term. Simple OLS for both endogenous variables will give estimates for $\widetilde{x}_{it}$, the probabilities of working part-time and full-time, which we denote as $\widehat{\widetilde{x}}_{it}$. We use these estimates in Equation (2.2) to obtain the following second-stage regression equation:

$$\widetilde{y}_{it} = \widehat{\widetilde{x}}_{it}'\beta + f(\widetilde{A}_{it}) + \widetilde{\epsilon}_{it} \tag{2.6}$$

Since we have two endogenous variables, a minimum of two instrumental variables is required to prevent underidentification. Therefore, it is impossible to use the instrumental variables one by one. To account for this, we use indicators of reaching the retirement eligibility ages as our baseline instruments and add these to the instrument set of all models.

Indicators of reaching the retirement eligibility ages have been used repeatedly as determinants of the labor market status in the studies analyzing the effect of retirement on health (Coe and Zamarro, 2011; Mazzonna and Peracchi, 2017; Charles, 2004). However, these instruments have two potential drawbacks, both of which concern the identification of the effects of the endogenous variables. First, identification of two endogenous variables require instruments that provide independent sources of exogenous variation for each endogenous variable. This is not provided by the retirement eligibility ages, as they provide an independent source of exogenous variation mostly for the full-time work decision. Therefore, we consider a rich set of pension, socio-demographic and employment characteristics, that have been shown to be strong determinants of the part-time and full-time work decisions and hence present themselves as potential instruments. Some of these determinants have also been used as instruments in other studies.

Second, using only the retirement eligibility ages as instruments identifies only the effects of the endogenous variables for the subgroup of the population that is affected by the retirement eligibility ages. It is often the case that people who work for an employer face mandatory retirement when they reach one of the retirement eligibility ages. Self-employed people, however, do not face this mandatory retirement and can continue working. Therefore, estimation results from models that just consider the retirement eligibility ages as instruments are limited in their interpretation. That is, the effects estimated in the instrumental variable analysis represent the Local Average Treatment Effects (LATE) (Imbens and Angrist, 1994). The LATE interpretation implies that the estimation results only hold for those who are affected by the instrumental variables. This interpretation is also used in many other studies about the effects of retirement on (mental) health (Bonsang et al., 2012; Insler, 2014; Eibich, 2015; Godard, 2016).

We investigate the validity of the new instrumental variables we use as follows. First, we consider formal hypothesis tests to find whether the instruments weakly identify the effects of the two endogenous variables. Second, we consider a baseline instrument set that includes only the retirement eligibility ages of the respondent. We then construct a series of new instrument sets where each set augments the baseline instrument set with an additional instrumental variable. We carry out formal hypothesis tests of exogeneity on both the baseline and alternative instrument sets, and study how the test results differ between the baseline and the alternative sets of instruments.

2.3 Diagnostic tests

Identification of working part-time and full-time hinges on finding suitable instruments. We consider several formal hypothesis tests to investigate whether the instruments we use are valid. As discussed in Section 2.2, there are three requirements for the instrumental variables to be suitable. First, the instrument should be a strong predictor of the endogenous variable. Second, the instrument should not be correlated with the error term of the reduced form regression. Third, the instruments should provide independent sources of exogenous variation for both of the endogenous regressors. These requirements are tested using five formal hypothesis tests carried out in the first and second stage of the two-step least squares estimation method. In the first stage, we address the relevance and weak identification of the instruments. In the second stage, we perform an endogeneity test and we test for validity of the instruments. Note that these tests are performed on the transformed data (see Section 2.1).

2.3.1 First-stage tests

As mentioned above, the first stage tests address the issue the relevance and weak identification of the instruments. Weak identification occurs when the instruments are not strongly correlated with the endogenous variables, which can lead to biased results and misleading inference (Stock et al., 2002).

Sanderson-Windmeijer statistic. Studies employing instrumental variable analysis typically use an F-test of joint significance on the coefficient estimates of the instruments, where the null hypothesis is that the coefficient of the instruments are equal to zero. A rule of thumb is that if the F-statistic is higher than 10, the instruments are strong. However, in the case of multiple endogenous variables, the standard first-stage F-statistic is not valid. The standard F-statistic can be high even though the model is weakly identified, the endogenous variables can be correlated

(Sanderson and Windmeijer, 2016; Markussen and Røed, 2017). Therefore, from the F-test alone we cannot tell which endogenous variable is affected by which instrument(s).

We employ the statistic developed by Sanderson and Windmeijer (2016). The test is based on the standard F-statistic, as the test is a 'conditional F-statistic' and gives information about each endogenous variable conditional on the other endogenous variable(s). The statistic is calculated as follows: regress one of the endogenous variables on the predicted values of the first-stage regression of the other endogenous variables and on exogenous regressors. Then regress the residuals on the instruments and test for joint significance of the instruments.

Various other studies have used this statistic to test whether the instruments provide independent sources of exogenous variation. Examples include Markussen and Røed (2017), Brogaard et al. (2017), Bertoni et al. (2017), Alvarez-Cuadrado et al. (2015), Huang and Petkevich (2016), Freeman et al. (2017), Anton et al. (2018) and Buchheim and Watzinger (2017). Specifically, Markussen and Røed (2017) are interested in the peer effects on the gender gap in entrepreneurship. In their model, they have two endogenous variables and they use the Sanderson-Windmeijer statistic to support the argument that their instruments separately identify the effects of their endogenous variables.

Shea's partial R^2 measure. Shea's Partial R^2 statistic is a measure of instrument relevance, introduced by Shea (1997). The statistic is calculated by a procedure proposed by Godfrey (1999). First, we regress the outcome variable on the endogenous variables while we control for the exogenous variables. From this regression, we save the R^2, which we denote as R^2_{OLS}, and the variance of both endogenous variables, which we denote as V_1^{OLS} and V_2^{OLS}. In the third step, we perform the second-stage instrumental variable regression and save the same regression statistics as in the second step, which we denote as R^2_{2SLS}, V_1^{IV} and V_2^{IV}, respectively. Then, as derived in Godfrey (1999), Shea's partial R^2 is calculated as

$$\frac{V^i_{OLS}}{V^i_{IV}} * \frac{1 - R^2_{IV}}{1 - R^2_{OLS}} \tag{2.7}$$

where i is an index for part-time work or full-time work.

The statistic gives a result for each endogenous variable, like the Sanderson-Windmeijer statistic. Hence, it can be used as an indicator of whether the instruments separately identify the effects of full-time and part-time working. It is an adaptation of the classical R^2 measure. This statistic is less formal than the other statistics we use, as it is not a hypothesis test. However, the statistic is still useful as it can be compared across model specifications to investigate the validity of a particular instrument specification. This means that the exact value of the statistic is of little concern.

Cragg-Donald minimum eigenvalue statistic. The Cragg-Donald F-test is also a test for weak identification. However, this statistic is not used to investigate whether each endogenous variable is weakly identified. Instead, it tests the overall strength of the instrumental variables. This statistic was developed by Cragg and Donald (1993) and is closely related to the Anderson (1951) canonical correlations test.

Poskitt and Skeels (2002) show that the Cragg-Donald test is equivalent to testing the significance of the smallest canonical correlation. Canonical correlation analysis is a way to obtain information from cross-covariance matrices, first described by Hotelling (1936). Canonical correlation analysis finds linear combinations of entries of multiple vectors with maximum correlation with each other (Härdle and Simar, 2007). Canonical correlation analysis is performed on the residuals obtained after regressing the instrumental variables on the exogenous variables and the residuals obtained after regressing the endogenous variables on the exogenous variables. The Cragg-Donald statistic is then calculated, according to Poskitt and Skeels (2002), as:

$$N * \frac{C^2}{1 - C^2} \tag{2.8}$$

where N is the number of observations and C the minimum canonical correlation. After a small correction for the degrees of freedom, we have our statistic.

Originally, the Cragg-Donald test is used to test for underidentification. Stock and Yogo (2005) have tabulated critical values for the test statistic under the null hypothesis of weak instruments. They consider two definitions of weak instruments and give critical values for both. First, if the bias of the IV estimator relative to the OLS estimator is high, then the instruments are weak. Second, if the size of the Wald test on all elements of β is large, the instruments are weak. A smaller test size means the probability that we incorrectly reject the null is smaller. We will use the second definition, as critical values of the first are not tabulated for models with two endogenous variables and three instruments, which is our baseline model. In case of four instruments, as is the case in most of our models, the critical values for the test statistic are 16.87, 9.93 and 7.54, for respectively 10%, 15% and 20% maximal IV size. In models with three instruments, such as our baseline models, these critical values are 13.43, 8.18 and 6.40, respectively.

2.3.2 Second-stage tests

Endogeneity test. There are several types of hypothesis tests we can use for testing whether the endogenous variables are in fact endogenous. We choose the Durbin-Wu-Hausman F-test, as the test can account for heteroskedasticity and serial correlation. The test statistic is calculated is as follows. First, each endogenous regressor is regressed on the instrumental variables. The residuals of this regression are saved. Second, the outcome variable is regressed on the endogenous variables, the residuals and the exogenous variables. Finally, a test of the joint significance is carried out. If the null is rejected, this indicates inconsistency of the estimator.

Hansen's over-identifying restrictions test. We use this test to test whether instruments offer exogenous sources of variation for the endogenous regressors. The null hypothesis is that the instruments are jointly uncorrelated with the error term. The statistic was introduced by Sargan (1958) and an extension was made by Hansen (1982). The statistic requires that there are more instruments than endogenous variables. It is calculated by evaluating the GMM objective at the efficient GMM estimator[1].

We use this statistic in two ways. We first consider a baseline instrument set and obtain the statistic. We then augment the instrument set with an additional instrumental variable. Failing to reject the later statistic provides evidence that the additional instrumental variable is exogenous. Second, the difference between the two statistics indicates to which extent the additional instrument is exogenous to the error of the reduced form regression.

[1]In Baum et al. (2002), a simple algorithm is described to calculate this efficient GMM estimator and the GMM objective is derived.

3 Data

We use data from the Health and Retirement Study (HRS). HRS is a survey of a representative sample of more than 20,000 Americans older than 50, performed every two years by the Survey Research Center at the University of Michigan. Since 1992, respondents were asked about various topics, including their financial situation, pensions, health and a range of other topics. We make use of the survey data collected from 1992 to 2014 which correspond to the first twelve waves of the survey.

For the purposes of this study, we restrict the sample in several respects. First, we drop all respondents who have never held a job for at least five years and we drop respondents where this information is missing. Second, we drop those who did not have a job since the age of 50 and those with missing observations. Third, we drop respondents who reported a labor market state other than being retired after being retired in any earlier survey year. Fourth, we drop all observations where the respondent is neither employed nor retired. Finally, we drop observations of respondents younger than 50 or older than 75. This results in an unbalanced panel of 91,379 observations for 18,449 individuals.

3.1 Variable definitions

In this section, we define and discuss all variables that are included in our models.

3.1.1 Dependent variable

BMI. The Body Mass Index (BMI) is used as a measure of the body weight. BMI is given by the body weight of the respondent in kilogram divided by the height in meters squared. Burkhauser and Cawley (2008) argue that a problem of this measure is that a high BMI does not necessarily imply a high fat mass, as a high BMI can also be explained by a high muscle or bone mass. Other indicators of body composition are for instance waist circumference and fat mass, which are used for instance by Johansson et al. (2009). However, due to lack of availability of these indicators in the HRS, we use the BMI as a measure.

3.1.2 Exogenous variables

Age. As specified in Section 2.1, we include a polynomial function for age in our models. We control for two variables of age; age and age squared, which captures (non-linear) changes in the probabilities of working part-time and full time, as well as the changes in BMI with age. The respondent's age is reported in years and the decimals indicate the number of months past this age.

3.1.3 Endogenous variables

We aim to explain the effects of working part-time and full-time on body weight, with retirement as the base outcome.

Full-time work. Full-time work is defined as working for at least 36 weeks per year and at least 35 hours per working week. This includes hours made at a second job.

Part-time work. We consider the respondent to work part-time if he works at most 34 hours per week or if he works for at most 35 weeks per year and at least 35 hours per working week. As with full-time work, this includes hours worked at a second job. The HRS considers two categories of part-time: part-time workers and part-time retirees. A respondent is a part-time retiree if he works part-time and mentions retirement in at least one of the following two questions:

> "Are you working now, temporarily laid off, unemployed and looking for work, disabled and unable to work, retired, a homemaker, or what?"

and

> "At this time do you consider yourself partly retired, completely retired, or not retired at all?"

A respondent is a part-time worker if he works part-time but does not mention retirement in these questions. In this variable, we combine both categories.

Being retired. This is our base outcome, against which the results for full-time workers and part-time workers are compared. We consider as retired the respondents who are not currently working, are not looking for work and mention retirement in at least one of the two HRS questions quoted in the description of part-time work.

3.1.4 Instrumental variables

Here, we discuss all variables that we consider as instrumental variables. As discussed in Section 2.2, it is important that the instrumental variables provide independent sources of exogenous variation and that they affect the whole American population between the ages 50 and 75, leaving no subpopulations unaccounted for. These two aspects are the main objectives of our analysis, as discussed in Section 2.2.

All variables are binary variables, with few exceptions as described below. For some of the instruments we consider, it might be argued that a version taking continuous values might also be used, for instance for household net worth. There are two main reasons for considering instruments as binary variables. First, binary variables simplify the interpretation of the coefficient estimates. Second, an increase of one unit in a given continuous variable that takes a large range of values can have a very small effect on the work decision at the intensive or extensive margin making it difficult to capture a statistically significant effect.

Retirement eligibility ages of respondent. As mentioned in Section 2.2, this instrument is used in a large number of studies. Example studies are Charles (2004), Neuman (2008), Coe and Zamarro (2011), Bonsang et al. (2012), Eibich (2015) and Mazzonna and Peracchi (2017). We define three binary variables for the retirement eligibility ages. Each dummy takes a value of 1 if the respondent has reached an early, normal or late retirement age and takes a value of 0 otherwise. The early and late retirement ages are fixed to one age for all respondents, but the normal retirement age depends on the birthyear of the respondent. The early retirement age is 62 and the late retirement age is 70. The normal retirement age is between the ages of 65 and 67, with (non-linear) increments of two months, as displayed in Table 1. The normal retirement age of people born before 1938 is 65, while that of people born in 1960 or later is 67. To illustrate that retiring at different eligibility ages has a large impact on the pension benefit payouts, in Table 1, we present the changes in benefit payouts based on the moment of retiring. Retirement benefits can be reduced by as much as 30% for early retirement, while late retirement provides considerably large increases in pension benefits, up to 8% per year after the normal retirement age.

Expected probability of working past 62. In Insler (2014), the subject of interest is the effect of retirement on general health and he also uses an instrumental variable approach to estimate this effect. He uses six instruments: the respondent's expected probability of working past the age of 62, that of working past the age of 65, two retirement eligibility age indicators and two interactions between the retirement eligibility age indicators and the variables for expected probability of working past 62 and 65. These expected probabilities can be correlated with the current health status of the respondent and because of this, he has formed an approach to orthogonalize these expected probabilities to several indicators of the current health status of the respondent. We also follow this approach, which we explain below. His results show that these orthogonalized variables are valid instruments. Information required to create these variables is obtained from the following question in the HRS:

> "(Thinking about work in general and not just your present job,) what do you think the chances are that you will be working full-time after you reach age 62?"

This question is asked to all working respondents who are younger than 62. As Insler (2014), we orthogonalize this to the health status of the respondent by taking only the first observation of an answer to this question and regress this (via simple OLS) on several variables for health indicators and behaviors and the age of the respondent's parents. These are binary variables for self-reported health, high blood pressure, diabetes, cancer, lung problems, heart problems, strokes, psychiatric problems, arthritis, vigorous physical activity and smoking. The parents' age variables are the mother's age if deceased or if still alive and the same for the father. The residual term of this regression is orthogonal to the health status of the respondent.

Since we have used only the first available answer to the above HRS question, there is no information about expected probabilities in other survey years. Therefore, we also use this residual term in all other years that the respondents participates in the survey, still following the approach of Insler (2014).

We also impute information in a number of other variables where we structurally have missing observations, similar to Peters (2007), who uses the last known response to a question about union coverage to impute the variable in later years. For instance, we do this if the corresponding HRS question is only asked to respondents who have a job at the time of an interview. These variables are: expected probability of working past 65, usual retirement age, employer pension coverage, average firm size, union coverage and undesirable working conditions.

Expected probability of working past 65. Immediately after the question about expected probability of working past 62, the HRS asks the following:

> "And what about the chances that you will be working full-time after you reach age 65?"

This question is only asked if the respondent currently has a job and if he is younger than 65 years. We perform the same orthogonalization process as in the expected probability of working past 62 to obtain the instrument.

Average usual retirement age. In all survey years of the HRS, respondents are asked:

> "On your main job, what is the usual retirement age for people who work with you or have the same kind of job?"

Brown (2006) finds that people are more likely to retire around the usual retirement age. In particular, he finds considerable spikes in retirement hazards around the usual retirement age. He argues that using the usual retirement age has two main advantages over using the statutory retirement ages. First, the usual retirement age allows to distinguish between respondents to whom the early retirement age is important and those to whom the normal or late retirement age is important. Second, it allows to distinguish those who do not follow the statutory retirement ages. A disadvantage can be that it may overlook the professions for which there are no usual retirement ages. We expect this variable to behave in a way similar to the retirement eligibility age variables.

Answers accepted in most years of the HRS are between 40 and 94, since values of 95 as assigned to respondents who reported they had no usual retirement age. Therefore, we only use values between 40 and 94. In cases where a respondent reported several different usual retirement ages (in different survey years), we used the average of the reported usual retirement ages. We create a dummy variable that takes a value of 1 in survey years where the respondent is past this average usual retirement age.

Retirement eligibility ages of partner. One's own retirement decision is correlated with the retirement decision of the spouse, as Henretta and O'Rand (1983), Blau (1998) and Gustman and Steinmeier (2000) have shown, and therefore, this variable might be a good instrument for the respondent's retirement decision. Similar to the variable for retirement eligibility of the respondent, we define three binary variables. Each dummy takes a value of 1 if the respondent's partner has reach an early, normal or late retirement age and takes a value of 0 otherwise.

Labor force status of the partner. We consider the labor force status of the partner as an instrument. This variable is similar to the variable indicating the retirement eligibility ages of the partner. The main difference is that the retirement eligibility ages of the partner are an indirect measure of the labor force status, while this variable is a more explicit determinant of the labor force status. This variables takes a value of 0 if the respondent's spouse is a full-time worker, a part-time worker or a part-time retiree and takes a value of 1 if the respondent's spouse is a full-time retiree.

Marital status. Ekerdt et al. (1996) found that the marital status is a significant determinant of the retirement decision. The variable they define is slightly different from the one we use, however. Ekerdt et al. (1996) distinguish between respondents with a partner and respondents who are married. However, we consider them as one group, since an initial comparison of retirement behavior across respondents with a partner and those married showed very similar retirement behavior. It might be that both groups are more likely to be working fewer hours so that they can invest more time in household activities or taking care of children. Therefore, these responses would be more likely to be working part-time and less likely to be working full-time. We define a dummy variable where a value 1 indicates in the respondent is with a partner or is married, and a value of 0 indicates if the respondent does not have a partner or is not married.

Ever covered by employer pension. Being included in a pension plan from an employer was earlier shown to be a determinant of retirement in Ekerdt et al. (1996)[2]. The main economic argument that he uses to motivate this variable is as follows. The income from the pension plan can help the pensioner meet his ends, so that he is less dependent on labor income. In the HRS, respondents are asked about pension plans on their job and whether they are included in such plans. The corresponding questions are:

> "Were you included in a pension or retirement plan, or in any tax deferred savings plan, through your work when you worked for [company]?"

or, if the respondent was self-employed in the previous wave:

> "Aside from IRAs not sponsored by your business or KEOGH plans, were you included in a pension or retirement plan?"

These questions are only asked to respondents who are employed at the time of the survey. Based on these questions, we consider three categories of respondents which we use to create two instruments. In the first category, we consider the respondents who answer 'yes' to at least one of the two above questions in all survey years. In the second, we consider those who answer 'yes' to at least one of the above questions in at least one survey year, but not in all survey years. Finally, we consider those who always answer 'no' to the above questions.

In the first instrument, we create a dummy variable that takes a value of 1 for respondents in category 1 or 2 and it takes a value of 0 for respondents in category 3.

This variable and other variables about job characteristics restrict the sample to the subsample of respondents who were not retired in at least one of the survey years, since most HRS questions about job characteristics are only asked to respondents who have a job. However, the share of respondents who are retired in all waves of the survey is small (5.09%), and we therefore expect this not to influence our results significantly.

Always covered by employer pension. This variable is very similar to the variable 'Ever covered by employer pension', since the only difference is the classification of the categories. We create a dummy variable that takes a value of 1 for respondents in category 1 and it takes a value of 0 for respondents in category 2 or 3.

Ever offered a retirement window. In the USA, employers can offer their employees an early retirement window. The HRS asks the respondents:

> "Employers sometimes encourage older workers to leave a firm at a particular time by offering a special financial incentive, like a cash bonus or improved pension benefits. These are often called 'early retirement windows.' Have you been offered such an early retirement window at any time since [previous wave]?"

[2] Although they refer to this variable as 'private pensions', the information used is the same

Brown (2002) indicates that a third of early retirement offers is accepted by respondents in the first five waves of the HRS. Coe and Lindeboom (2008) also use retirement window offers as an instrument in their paper to examine the effect of retirement on general health. However, since our methodology is entirely different from theirs, we had to change the definition of the variable somewhat. One of the main differences in the methodology that causes the need to change the definition is that Coe and Lindeboom (2008) only consider the effects two to four years after a potential retirement decision, while we consider the effects over the all survey periods. Therefore, we have missing observations for people who are retired. We define a dummy variable that takes a value of 1 for respondents who ever indicated (in any of the survey years) that they have received an early retirement window offer, and a value of 0 for those who have never indicated that they have received an early retirement window offer.

Currently covered by employer-provided health insurance. As stated in Rogowski and Karoly (2000), it is difficult for people close to the retirement age to get access to health insurance other than the health insurance provided by their employer, mainly due to high premiums. Access to Medicare/Medicaid also is not available for this group, since they are only available for people older than 65 and people who are blind or disabled. They find that people with access health insurance after retirement retire earlier than those who don't have this access. This finding is supported by Rust and Phelan (1997), who argue that Medicare has a big impact on the retirement decision. French and Jones (2011) also find that retirement decision is significantly affected by access to health insurance. They use several categories of health insurance, which we also make use of to generate our health insurance variables.

Results by French and Jones (2011) show that workers who have health insurance provided by their employer stay in the work force 0.41 years longer than those who do not have employer-provided health insurance. We expect that this effect will hold more strongly for full-time workers, since full-time workers are more likely to be offered employer-provided health insurance, as discussed by Currie and Madrian (1999). They argue that providing health insurance to part-time workers is more expensive than providing it to full-time workers and that health insurance must, by a non-discrimination law, be provided to nearly all full-time workers, while there is no such law for part-time workers.

The HRS has several questions concerning whether the respondent has health insurance and who provides this health insurance. First, the interviewer asks several questions regarding Medicare/Medicaid (through a health maintenance organization or otherwise) and any military health care plans the respondent might have. Then, the following question is asked:

> "Do NOT include long-term care insurance, or anything that you have just told me about. How many other such plans do you have?"

In case the answer is zero, the dummy takes a value of 0 for the corresponding respondent in the corresponding wave. If the answer is larger than zero, the interviewer asks further questions about at most three of these plans. The next questions of interest are the following two:

> "Do you obtain this health insurance through your (own business or professional organization/current employer)?"

and

"Do you obtain this health insurance through a former employer of yours?"

If the respondent answers 'yes' to at least one of these questions for at least one of his three primary pensions, the dummy variable takes a value of 1. If the respondent always answers 'no', the dummy takes a value of 0.

It can be argued that having health insurance may be correlated with the BMI. For instance, individuals with health insurance can more easily go to the doctor when suffering from a BMI-related disease, or individuals with health insurance can have better access to preventive care which helps keep their BMI low. Therefore, we orthogonalize the health insurance variable in the same way as the variable 'Expected probability of working past 62': we regress this variable on the health indicators and behaviors, as well as the parents' age dummy variables and save the residuals.

Covered by employer-provided health insurance up to age 65. This variable is similar to the variable 'Employer-provided health insurance' described above. The difference is that in this variable, we will consider respondents who can keep the health insurance until the age of 65. For this variable, we define two groups: respondents who have health insurance provided by their employer until they are 65 and those who don't. If the answer to one of the two last questions presented in the description of that variable is 'yes' and the respondent is not yet 65 years of age, the interviewer will later ask:

"(Can/If you left your current employer now, could) you continue this insurance coverage for yourself up to the age of 65?"

We create a dummy variables that takes a value of 1 if the answer to this question is 'yes', and it takes a value of 0 if the respondent answers 'no' to this last question. Additionally, it takes a value of 0 if the respondent is not covered by health insurance provided by an employer. Finally, we perform the same orthogonalization as in the variable 'Currently covered by employer-provided health insurance'.

Covered by employer-provided health insurance past age 65. This variable is very similar to the variable for employer-provided health insurance up to 65. The only difference between this variable and the health insurance up to 65 variable is a small difference in the question asked during the survey. Here, the corresponding question is:

"(Does/If you left your current employer now, does) your employer offer some type of health insurance coverage for you after the age of 65?"

However, this question is not asked in the HRS until the survey year 2000. We define a dummy variable that takes a value of 1 if the respondent answers 'yes' to this question The variable takes a value of 0 if the respondent answers 'no'. Additionally, it takes a value of 0 if respondent is not covered by health insurance provided by an employer at the time of the survey or if the respondent is not covered until the age of 65. The motivation of this variable is similar to the motivation of the other health insurance variables, but we want to see if the effects carry on past the age at which respondents are Medicare- or Medicaid-eligible. Again, we orthogonalize this variable to the parents' age variables, health indicators and health behavior indicators.

Household income net of personal income. We define this variable as the total income of the household minus any income of the respondent himself or herself. This definition is similar to the one in Chung et al. (2009), who exclude the income of the respondent from the income variable to prevent endogeneity with the BMI. Included in this variable are for instance wages, any bonuses or overtime pay, social security and any other sources of income. If the respondent's spouse has a high income, the respondent might be less inclined to earn an income of himself and therefore to retire earlier. We therefore expect that the income of other people in the household of the respondent might influence the retirement decision of the respondent. The dummy takes a value of 1 if the value of this income is less than the median income and it takes a 0 otherwise. We use the median here rather than the mean, since the data is skewed.

Household net worth. This is the total worth of the household, meaning the sum of all household ownings minus debts. Included in this variable are for example the values of the primary residence, vehicles, businesses, IRAs, stocks, bonds and mortgages. This definition is the same as the definition of the same variable used by Peters (2007), whose results show that household net worth has a significant effect on both complete and partial retirement, but has a larger effect on partial retirement. We expect that this variable will show results similar to the household income net of personal income. However, household net worth is correlated with the respondent's own income, so we need to be careful with the interpretation. Much like the income variable above, the dummy takes a value of 1 if the value of their net worth is less than the median net worth and a value of 0 otherwise.

Race. Ekerdt et al. (1996) also consider race as a determinant of the retirement decision. He differentiates between the white and non-white population, where he finds results significant at the 10% significance level. He argues that non-white people have less options in the labor market, which would result in less early retirees. In our exploratory research, we have considered several definitions of this variable and we came to the conclusion that the retirement decision of white or Caucasian people is very similar to that of black or African Americans, but different from that of 'other' races. In the HRS, the answers to the race question are masked, so we can only distinguish between white, black or 'other'. The question asked is:

> "Do you consider yourself primarily White or Caucasian, Black or African American, American Indian, or Asian, or something else?"

However, the answers are grouped as 'White/Caucasian', 'Black/African American and 'other'. The 'other' category includes for example respondents of American Indian, Alaskan, Asian and Pacific islander descent. So this dummy takes a value of 1 if the respondent considers himself white/Caucasian or black/African American and it takes a value of 0 if he considers himself part of another race.

Education level. We distinguish between two categories for the education variable. The first category are respondents who have a degree, respondents with a high school diploma or GED and more than 12 years of education or respondents who are categorized as 'other' in the HRS question where they get asked about their degrees. The second category are respondents with a high school diploma or GED and 12 years of education or less and respondents with education at a level lower than high school. We chose this split, as it creates a 'natural' split of respondents into two categories of similar size in terms of number of observations. We have also considered to use education years as a variable, but the results were very similar to those of the education level variable. We generate a binary that takes a value of 1 for respondents in the first category and that takes a value of 0 for respondents in the second category.

Kim and DeVaney (2005) have found that education is a predictor of partial retirement. They argue that people with more education leads to more opportunities regarding the retirement decision. We therefore expect that higher educated people can retire earlier than lower educated people. This result is supported by Ekerdt et al. (1996), who conclude that education is a significant determinant of the retirement decision. However, we do need to be careful with this variable, as a more recent study has shown that BMI contributes to the effect of education on health (Brunello et al., 2016). Also, Cutler and Lleras-Muney (2006) note that, of respondents with more education, the percentage being overweight or obese is lower.

Difficulty with activities. Stenholm et al. (2014) find that elderly who are retired have in general lower physical abilities that those who are full-time working. We will also consider an instrument that indicates the respondent's level of physical ability. However, Stenholm et al. (2014) also find convincing evidence that this may be caused by chronic diseases or risks related to the lifestyle of the respondents. So we expect that while this might be an indicator of the retirement status, we will almost certainly have issues with endogeneity and therefore we will use this variable as a check to see if we obtain the results that are expected. The correlation of this variable with health status is also made clear in the formulation of the relevant questions in the HRS. In the HRS, there is a set of 10 questions that are about the physical functioning of the respondent. In this subsection, respondents are asked whether they have difficulty with walking one block, sitting for two hours, getting up from a chair, climbing one or several flights of stairs, stooping or kneeling, pulling or pushing large objects, lifting weights of over 10 pounds, picking up a dime from a table and if they can reach their arms above shoulder level. The questions asked are formulated as follows:

> "(Because of a health problem do you have any difficulty) with ...?"

Similar to Avendano et al. (2009), Wahrendorf et al. (2013) and Stenholm et al. (2014) we make a score variable based on these questions. The score is equal to the number of tasks that the respondent has difficulty with, resulting in a score between zero and ten. If the respondent failed to answer any of the questions, the score is scaled to the number of questions that were answered. Based on this score variable, we make our binary variable. The dummy takes a value of 1 if his or her score is above the mean and it takes a value of 0 if it is below the mean.

Self-rated memory. Coe et al. (2012) consider self-rated memory as an outcome variable to see if it is influenced by the retirement decision. However, we argue that the relation could also work the other way around. For instance, as the memory declines it becomes increasingly difficult to make hard decisions or calculations at work or to keep up with work in general, thus making retirement more appealing. During the interview, the respondent is asked to rate their own memory:

> "First, how would you rate your memory at the present time? Would you say it is excellent, very good, good, fair or poor?"

We create a dummy that takes a value of 1 if the answer is good or better and it takes a value of 0 if the answer is fair or poor.

Word recall total. Part of the HRS questionnaire includes a more formal test of memory. In this part, the interviewer asks the respondent to recall a list of ten words. The first time this is done is immediately after hearing the list. Twenty minutes afterwards, the respondent is asked again to recall the list. We sum the number of words recalled correctly in both the immediate test and the delayed test. Bonsang et al. (2012) use this sum variable in their paper where they want to find out whether the retirement decision affects cognitive functioning. However, much like with the self-rated memory variable, we argue that the relation works the other way around too.

Based on the sum variable, we create a binary variable which takes a value of 1 if the respondent recalls more words than the average respondent and it takes a value of 0 if the respondent recalls less words than average. We expect that the dynamics of this variable are similar to those of self-rated memory.

Average firm size - respondent's location. Previous research by Montgomery (1988) has shown that the larger the company, the smaller the share of part-time workers, which is an indication that this might be a good predictor for the part-time work decision. In Dorn and Sousa-Poza (2005), company size is said to be related to the probability of early retirement, which they say can be caused by large companies having their own pension funds. However, the variable we create is categorized differently than their firm size variable. They consider three categories: people working at companies sized 0 to 10 employees, 11 to 100 employees and companies with more than 100 employees. Similar to the other instruments we have defined, we only consider two categories, people working at companies with 0 to 50 employees and those with more than 50 employees, which creates an almost even split of the data. To also obtain observations for retired respondents, we use the average of the reported company sizes and impute this also to the missing observations, the same as what we did in for instance the employer pension variable. This dummy variable is defined using the answers of two HRS questions. If the respondent is self-employed, we use the answers to the question:

> "Including yourself, how many people work in this business?"

and if the respondent works for someone else, we use the answers to the question:

> "About how many employees work for this company or organization at the location where you work?"

For respondents who give a mean answer of 50 or less across all survey years, the dummy variable takes a value of 0. For respondents who give a mean answer of more than 50 across all survey years, the dummy takes a value of 1.

Average firm size - all locations. This variable is similar to the variable about average firm size at the location where the respondent works, but this uses some additional information. While the firm size variable described above only considers the firm size at the location that the respondent works at, this variable considers the firm size at all locations. In the HRS, the following question is asked:

"About how many employees work for this company or organization at all locations?"

This question is asked only to those who are not self-employed. For respondents who give a mean answer of 50 or less across all survey years, the dummy variable takes a value of 0. For respondents who give a mean answer of more than 50 across all survey years, the dummy takes a value of 1. The share of respondents who do not know how many employees their firm has, has increased compared to the firm size variable described above. For respondents who did know the firm size at their location, but do not know the firm size at all locations, the dummy takes no value.

Years of experience. Based on the work of Dorn and Sousa-Poza (2005), where work experience has been shown to be an indicator of early retirement, we decided to include a similar variable in our models. They argue that those with more work experience tend to have a higher salary and better pension, which allows for earlier retirement than people with less working experience. This variable is created from the respondent's reported job history. This variable is prone to reporting errors, as respondents are asked to recall all durations of their previous and current occupations. Unfortunately, the amount of missing information increases almost every survey year. Therefore, we need to be very careful when drawing conclusions about this variable. We first define a variable that counts the number of years worked by the respondent in all previous (and current) jobs. Then, we create a dummy variable that takes a value of 1 if the respondent has worked for more than thirty years and it takes a value of 0 if the respondent has worked for thirty years or less. We have considered a large amount of threshold values (including non-binary ones), but eventually settled on thirty, as it created a split in the data that is quite even and there are clear differences in retirement behavior across the groups, as presented in Table 3.

Union coverage. Peters (2007) shows that union membership has a significant effect on partial retirement for both men and women. She mentions that unions help the workers to fund their retirement. The definition of this variable is the same as that of the variable that she uses. In all waves of the HRS, the respondent is asked whether he is covered by a union or employee-association contract. The exact question is:

"Are you covered by a union or employee-association contract?"

If the answer is 'yes', the dummy takes a value of 1 and if the answer is 'no', it takes a value of 0. For this variable, we make the same imputations as those mentioned in the description of the employer pension variable.

Blue-collar worker. Dorn and Sousa-Poza (2005) find that the type of work performed by the respondent is a determinant of the early retirement decision. They state that blue-collar workers have lower income and therefore fewer opportunities to go into early retirement. Respondents are grouped into two clusters; white-collar workers and blue-collar workers. For respondents who were a blue-collar worker in their job with the longest tenure, the dummy takes a value of 1. For respondents with a white-collar job as their job with the longest tenure, the dummy takes a value of 0.

Job in tertiary sector. For the definition of this variable, we use the well-known three-sector theory, most notably developed by Fisher (1939). The tertiary sector of the economy is also known as the service industry. We consider every industry outside of agriculture, mining, utilities, construction and manufacturing to be part of the service industry. For respondents who had their job with longest tenure in the service industry, the dummy takes a value of 1. For respondents who had their job with longest tenure in another industry, the dummy takes a value of 0. We also considered to use three binary variables, one for each sector of the economy, but there were very few observations in the primary sector and the retirement behavior of the first two sectors was very similar, so we decided to put them together. Jobs in the service industry are more often part-time jobs, so we expect this variable to be an indicator for the part-time work decision.

Undesirable working conditions. Quinn (1977) considers in his search for determinants of early retirement several working conditions that are generally experienced as undesirable. These conditions are for example extreme heat, hazards and fumes. He concludes that these conditions have a minor influence on the retirement decision. Unfortunately, the HRS does not ask questions about the conditions that are considered by Quinn (1977). However, there are questions about several different undesirable job characteristics and we are interested to see whether these characteristics can also influence the retirement decision. This introduces some endogeneity to this variable, as some of the characteristics are about physical requirements of the job. For instance, respondents with physically demanding jobs likely have a lower BMI than respondents with other jobs. The ten characteristics that we include are about physical effort, lifting heavy weights, stooping or kneeling, good eyesight, intense concentration, people skills, increasing difficulty to perform the job, stress involvement, whether young employees are given preferential treatment in terms of promotion and whether there is pressure to retire. A statement is made about each of these characteristics, for instance:

> "My job requires lots of physical effort"

Then it is asked to what degree the respondent agrees with this statement or not. Similar to the 'difficulty with activities' variable, we count the number of times the respondent answers (strongly) agree to these questions, so we obtain a score between zero and ten. Again, we account for missing questions by scaling the score to the number of questions answered. Then, we take the average score of all years where any of the questions were answered. Similar to for instance the usual retirement age variable, we impute this average score to the years where information was missing. Finally, we make a binary variable which takes a value of 1 if the average score of the respondent is above five and takes a value of 0 if the average score is five or lower.

Ever got a new job. Honig and Hanoch (1985) notes that, for workers of old age, partially retired people have a much shorter tenure at their current job than non-retirees, which supports their claim that retiring partially is often associated with getting a new job. The we create uses answers to a question in the HRS where the respondent is asked for the month and year he started working for his current employer or business:

> "In what month and year did you start working for (this business?/this employer?)"

We calculate the time between this start date and the date of the survey. We then create a dummy that that takes a value of 1 if the tenure at their current job in any of the survey years was less than two years (since there is roughly two years between interviews) and takes a value of 0 if the tenure was larger than two years in all survey years. Respondents with missing observations in all years are assigned a missing value for this variable.

Ever able to reduce hours. Having the ability to reduce the number of working hours may increase the likelihood of a more gradual retirement path, where working full-time transitions into working part-time, before going into full retirement. Americans who work full-time and are not able to reduce their number of working hours have to change jobs before they can take this gradual path to retirement, so we think the ability to reduce hours promotes working part-time. The corresponding question in the HRS interview is the following:

> "(Not counting overtime hours, could/Could) you reduce the number of paid hours in your regular work schedule?"

If the respondent answers 'yes' in at least one of the survey years, the dummy takes a value of 1. If the answer was 'no' in all of the survey years, the dummy takes a value of 0. We should note, however, that this question is not asked to respondents who are self-employed, so we need to account for this in the interpretation of the estimation results of this variable.

Ever self-employed. The HRS asks to the respondents who are employed at the time of the survey:

> "(On the job you plan to go back to,/On your current (main) job,) do you work for someone else, are you self-employed, or what?"

We generate a dummy that takes a value of 1 for respondents who answered 'yes' to this question in at least one of the survey years. The dummy takes a value of 0 for respondents who always answered 'no' to this question.

Self-employed people are more flexible in their working hours (Ekerdt et al., 1996; Kim and DeVaney, 2005), so we expect that self-employed respondents are more likely to work part-time compared to those who are not.

Ever shifted to self-employment. This variable is very similar to the 'Ever self-employed' variable, so we expect it to behave in a similar way. The inclusion of this variable in the models is based on the statement by Honig and Hanoch (1985) that shifting to self-employment is often associated with partial retirement

This variable takes a value of 1 for respondents who reported to be self-employed after at least one observation of being not self-employed. It takes a value of 0 to respondents who were always or never observed to be self-employed.

In Table 3, we present employment rates per category of each dummy variable discussed above, where we distinguish between part-time workers and part-time retirees. This table gives an impression of what we might expect in the regressions. Variables where we can see large changes in the full-time work category, while the employment rates in part-time work and part-time work stay about the same, which we take as an indication that this is an instrument for full-time work. Similarly, we can find clues for instruments for part-time work. Taking the retirement ages of the respondent as an example, we see large changes in the full-time work category, while the changes in the part-time work and retirement categories are much smaller. This means that the retirement eligibility ages of the respondent are strong predictors of the full-time work decision. Similar patterns hold for the retirement ages of the partner, education level, gender, household net of own income, household net worth, labor force status of the spouse, marital status, difficulty with activities, self-rated memory, race, word recall, blue-collar work, health insurance, usual retirement age. For the employer pension coverage variables, we see a change in both the full-time work and the part-time work categories, but the change for full-time work is larger. The economic sector and undesirable working conditions variables seem to not be good predictors for either full-time work or part-time work, as we see change in all categories. On the other hand, retirement windows, union coverage, new job, shift to self-employment, firm size and years of experience seem to be independent sources of exogenous variation for the part-time work decision.

4 Descriptive statistics

In Table 2, we show descriptive statistics of all variables we described in Section 3.1. The average age of the respondents is 62.3. Over all survey years, 40.59% of all respondents is overweight and 29.20% has obesity. However, since 1992, the percentage of obese respondents has almost doubled, while the percentage of overweight respondents has decreased in the same period. 46.5% of all respondents is a works full-time and 16.1% works part-time. 51.3% of all respondents is under the early retirement age and 14.7% are between the early and normal retirement ages during the survey period. The percentage of males in the sample is 51.8%. In total, there are 91,379 observations of 18,449 individuals. There are 8,017 individuals in the first wave and 5,844 in the last wave.

The mean BMI of respondents of age 50 is 28.2 for full-time workers, 27.1 for part-time workers and 30.6 for those retired. So at this relatively young age, there are large differences in BMI across the labor force statuses. This difference gets smaller as the respondents age, as the mean BMI of respondents of age 74 is 26.7 for full-time workers and part-time workers and 27.2 for retired respondents.

To get a better idea of how this difference evolves over the age distribution, we visualize the difference in BMI over age across the three labor force statuses in Figure 1. The graph presents kernel-weighted local polynomials, with their respective 95% confidence intervals. Mainly between the ages 50 and 60, there are large differences in the average BMI across the retirees and the working population. This difference decreases as one ages, but retirees remain as having the highest BMI and part-time workers the lowest BMI across the distribution. The difference in the BMI between part-time workers and retirees is larger than the difference between full-time workers and retirees. An important implication of this pattern is that full-time work instruments need to have strong predictive power, as otherwise identifying the effect of full-time work will be difficult.

5 Results

In this section, we discuss the results of our models and the process for determining the validity of the instruments. This process is as follows. We first discuss the first-stage results, where we address weak identification and relevance. We start with a discussion of the results of the baseline models. There are two baseline models: one has as instruments the retirement eligibility ages of the respondent and the other has as instruments the retirement eligibility ages of the

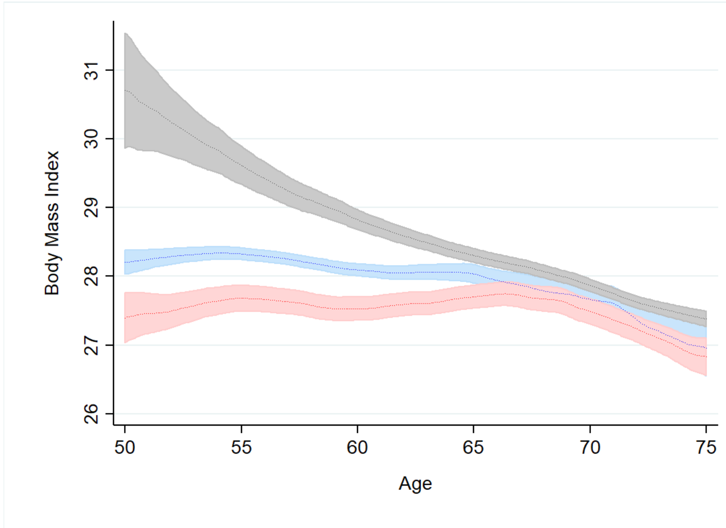

Figure 1: BMI for retirees (grey), part-time workers (red) and full-time workers (blue) by age

partner. We discuss the results of the diagnostic tests, as well as the coefficient estimates of the instrumental variables. We continue with a discussion of the results of the models where we consider the retirement eligibility ages of the respondent, augmented with one by one the other instruments described in Section 3.1. We will again discuss the results of the diagnostic tests and the coefficient estimates. If, for a certain instrument, the diagnostic test results are favorable, the first-stage coefficient estimate is larger for part-time work than for full-time work and the part-time work coefficient estimate is statistically significant, this indicates an instrument for the part-time work decision. In these models, we cannot perform these checks for variables that might be an instrument for the full-time work decision. This is because then there are no instruments for the part-time work decision in the model, since the retirement eligibility ages for the respondent identify only the full-time work decision. Therefore, we estimate models where the retirement eligibility ages of the partner are augmented with the other instruments, and then we check the test results for possible instruments for the full-time work decision. In models that are weakly identified or where the instruments are not relevant, we know that the considered additional instrument is not valid and we will not further consider this as an instrument.

Second, we discuss the second-stage results, where we consider the results in the same order as in the first-stage. For the baseline models, we again check the results of the diagnostic tests and the coefficient estimates of the part-time work and full-time work decisions. To check whether the possible instruments for part-time work found in the first step are valid, we consider the models with these instruments augmented one by one with the retirement eligibility ages of the respondent. If the test results are favorable and the second-stage coefficients are significant, then the instrument set is valid. In models where the possible instruments for full-time work found in the first step are considered, augmented one by one with the retirement eligibility ages of the partner, we perform the same validity checks.

Finally, we discuss second-stage results of models estimated with combinations of instrumental variables that were found to be valid after the checks above. In these estimations, we do not consider the retirement eligibility ages of the respondent or the partner. We then perform the same checks on the estimation results as in step two to determine whether the instruments are also valid in other model specifications.

5.1 First-stage results

In Tables 4a, 4b and 4c, we present the results of the first-stage regressions. Table 4a displays the results for the base instruments: the retirement eligibility ages. The coefficients estimates presented in this table are estimated from Equation 2.5. For both the RE and the FE models, the coefficient estimates of the respondent's retirement eligibility ages are significant and their signs are the same. The coefficients, as well as the results of the diagnostic tests, are very close to each other in the two models, which is an indication that RE and FE are both consistent[3]. These instruments are mainly predictive of the full-time work decision, since the coefficient estimates are much higher (in absolute terms) than those of part-time work. This is consistent with our observations in Table 3.

The Sanderson-Windmeijer statistic is significant at the 1% level for both the part-time and full-time work decisions, meaning that weak identification is rejected and therefore that the instruments provide exogenous sources of variation for both of the endogenous variables.

The table also displays the values for Shea's partial R^2, but the values of this statistic are informative only when compared to the values from the estimation of an alternative model using a different instrument set. Just as in all models across Tables 4a and 4b, the value of the partial R^2 statistic is higher for full-time work than for part-time work. This is a direct result from our observations that the retirement eligibility ages are very predictive for full-time work, which leads to a higher value of the test statistic for full-time work. This is also reflected in the Shea partial R^2 values in Table 4b.

The Cragg-Donald test statistic is quite low, which means that these instruments are not very strong. This can be explained by the fact that the retirement eligibility ages mainly predict full-time work and we lack explanatory power for the part-time work decision.

In all regressions, the coefficient estimates for age and age squared terms are jointly significant. The coefficient estimates for the partner's eligibility ages are plausible, but they are mostly significant for the part-time work decision rather than for the full-time work decision. The number of observations drop by 25%. This is explained by the observations where the respondent is not married or partnered, since in also 25% of observations the respondent is not married or partnered. Coefficient estimates and their statistical significance are similar across the FE and RE models, except that the indicator for being older than 70 is significant for full-time in the RE model, but not in the FE model. Weak identification is again rejected at the 1% level, but in this case, the Cragg-Donald statistic is high, suggesting that these instruments are strong.

In Table 4b we consider the respondent's retirement eligibility ages as the baseline instruments for the full-time work decision, which are augmented one by one with other instruments discussed in Section 3.1. This means that here, we analyze whether the additional instruments we consider are strong determinants of the part-time work decision so that they can be used as instruments for this decision. We can identify an instrument as one for the part-time work decision if it has a larger (in absolute value) and more statistically significant effect for the part-time work variable than the full-time work variable. The following instruments meet this requirement: the partner retirement eligibility ages, marital status, employer pension covered (both variants of this variable),

[3]This can be formally tested by a Hausman test, but that is not relevant in this section. We will discuss the Hausman test in Section 6.1

early retirement window offer, health insurance past age 65, household net of own income, firm size (both variants), union coverage, job in tertiary sector, undesirable working conditions, ever got a new job and ever shifted to self-employment. All of these variables, with the exception of health insurance past age 65, have a lower p-value for the S-W statistic and a higher Shea partial R^2 than the results in Table 4a. This indicates that weak identification is rejected. The variables for marital status, early retirement window offers and health insurance past 65 still have a low C-D statistic, suggesting that these sets of instruments are still not strong enough, although they include predictors for part-time work. This indicates that these variables are not good instruments for the part-time work decision. For the other instruments for the part-time work decision mentioned above, there are no such signs in Table 4b that point to invalidity.

In Table 4c we consider the partner's retirement eligibility ages as the baseline instruments for the full-time work decision. So here we analyze whether the additional instruments we consider are strong determinants of the full-time work decision. We also use the results in this table to verify our conclusions above. For example, the coefficient estimate of marital status is insignificant for both the part-time and full-time work decision, which supports our conclusion that it is not a good instrument. The variables for whether the respondent is past the usual retirement age, spouse retired, health insurance (currently and to 65), race, education, difficulty with activities, self-rated memory, word recall total and years of experience have higher and more significant coefficient estimates for the full-time work decision than for the part-time work decision. All these variables, with the exception of self-rated memory, show favourable p-values for the S-W and the Shea partial R^2 statistics. The C-D statistic values in these regressions are lower than many of those in Table 4a, but they are still highly significant. The exception is the word recall total variable. The reason that the C-D statistic is small for this variable is that its coefficient estimate is small as well.

5.2 Second-stage results

In tables 5a, 5b and 5c, we present the results of the second-stage regressions. We first consider Table 5a. This table displays the results for the base instruments: the retirement eligibility ages. In the models with the respondent's retirement eligibility ages, the significance of the coefficient estimates is higher for full-time work than for part-time work, which supports our conclusion from Section 5.1 that these instrument full-time work. The test results are also favorable, since the endogeneity of hours worked is rejected, suggesting that they are not affected by BMI, and joint validity of the instruments is not rejected, suggesting that the spouse's retirement eligibility ages are valid instruments, in both the FE and RE model.

The conclusions for the partner's retirement eligibility ages are similar. They have more predictive power for the part-time work decision than they have for the full-time work decision, which is reflected in the result that the part-time work variable is highly significant. In the RE model, the full-time work dummy is more significant than in the FE model, which can be explained by the higher coefficient estimate and statistical significance of the variable for being over 70 years old in the first stage results of the RE model in Table 4a. Again, endogeneity of hours worked is rejected and the joint validity of the instruments is not rejected, suggesting that these variables are good instruments. On first sight, it seems that the results of the RE model are better than those of the FE model. This is because the RE model also accounts for variation between respondents, while the FE model only accounts for the within variation.

In the next step, we study the results in Table 5b. This table presents the results where the respondent's retirement eligibility ages are considered as the baseline instrument set for full-time work, augmented one by one with an additional instrumental variable for part-time work. In particular, we study the results of the instruments that we have identified as possible indicators of the part-time work decision in Section 5.1 to find out whether these instruments are valid. These are the following instruments: employer pension covered (both variants of this variable), household net of own income, firm size (both variants), union coverage, job in tertiary sector, undesirable working conditions, ever got a new job and ever shifted to self-employment. Of these instruments, the employer pension covered, firm size, union coverage, undesirable working conditions, ever shifted to self-employment and, to a lesser extent, ever got a new job have significant coefficient estimates for both the part-time and full-time work decisions. In addition, in all these models, endogeneity of hours worked is rejected and joint validity is not rejected. These results indicate that these variables are all plausible instruments for the part-time work decision. A note is that the coefficient estimates of the work decisions in models with employer pensions are very high compared to all other models, which indicates a correlation of the instrument with the error term and therefore invalidity of the instrument, even though test results are favorable.

Next, we consider Table 5c, which presents the results where the partner's eligibility ages are considered as the baseline instrument set for part-time work, augmented one by one with an additional instrumental variable for full-time work.. In particular, we study the results of the instruments that we have identified as possible indicators of the full-time work decision in Section 5.1 to find out whether these instruments are valid. Note that the previously identified possible instruments for full-time work are: usual retirement age, spouse retired, health insurance (currently and until age 65), race, education, difficulty with activities and years of experience. Both of the health insurance variables, education, difficulty with activities and, to a lesser extent, race result in significant coefficient estimates for both endogenous variables.

In contrast to what we would expect, the coefficient estimates of both work decisions in the model with the usual retirement age are insignificant. A possible reason is that this variable is very similar to the baseline instruments, as it tries to capture a similar effect. Another reason can be that it has much less observations than the other variables, leading to insignificant effects. Therefore, we will later consider this variable together with instruments that replace the retirement eligibility ages.

For the health insurance and education variables, endogeneity of hours worked is rejected and joint validity of the instruments is not rejected. This indicates that these are plausible instruments for the full-time work decision, although we do note that the p-value of the overidentification test for the health insurance currently variable is slightly lower compared to that of using the non-orthogonalized version of the same variable. As mentioned in the variable description, we expected to find endogeneity issues with the difficulty with activities variable and they are clearly visible in Table 5c: the joint validity of the instruments is rejected at the 1% significance level. It is surprising that validity of the education variable is not rejected, since we have previously discussed in Section 3.1 that this variable could be endogenous.

Also, note that in models with the employer pension covered as instruments, we reject the joint validity of instruments at the 5% significance level. This supports our earlier remark that the instrument might not be valid.

Finally, we estimate a number of regression models where we use different combinations of instruments that were identified as valid instruments above. Not all combinations of these instruments are jointly valid: some of the instruments are endogenous, other instruments have relatively few observations, and certain instruments are highly correlated with each other. Correlation between instruments is not necessarily an issue, but it does reduce the explanatory power of the given instrument set. For example, in a combination with two correlated instruments, the second instrument does not provide much additional information, as that has already been provided by the first.

In the first step, we test combinations of the full-time work instruments, where we consider two full-time work and one part-time work instruments at a time. After this, we study combinations of the part-time work instruments. Our approach for part-time work instruments is similar to that of full-time instruments, but is more extensive, since there are much more combinations to consider here. Results based on all combinations are presented in Table 6. This table also presents results combining two instruments for the part-time work decision and two instruments for the full-time work decision. All regression models are estimated with the RE method.

The considered instruments for the full-time work decision are the variables for being past the retirement age, having health insurance and education. There is some correlation between the health insurance and usual retirement age variables, but if their idiosyncratic explanatory power is high enough, the combination of the instruments is still valid. To test the validity of the instruments further, we estimate a number of models with two of the full-time work instruments and an additional instrument for part-time work. In our results, we find that in all models where the education variable is included, we reject the joint validity of the instruments. This is an expected result, since education can be endogenous, as discussed in Section 3.1. With few exceptions, the combination of usual retirement age and the health insurance gives favorable results, suggesting that both are valid instruments for the full-time work decision. These exceptional cases can be explained by the large difference in the number of observations available for the health insurance and usual retirement age variables. Compared to all other variables, the usual retirement age has very few observations, which we will explain the cause of in Section 6.2. This can affect the results, as the usual retirement age variables fails to account for professions that have no clear usual retirement age, as mentioned in Section 3.1.

To find out which part-time work instruments are valid, we will now take a similar approach to the problem, where we use the finding that education is not a valid instrument. Since there are many possible instruments for the part-time work decision, our approach will be more elaborate than our approach of the full-time work instruments. That is, we first investigate the variables where the difference in the number of available observations is large. In this respect, we need to take a look at the variables for ability to reduce hours and firm size. This has two reasons. First, the HRS question on the ability to reduce hours is only asked to respondents who are not self-employed. This does not mean that this instrument is not useful, but it means that we need to be careful in our interpretation of the results of the models which include this variable as an instrument. It can also bias our results, because it does not take into account self-employed people who might have different preferences regarding working hours. We also should not consider these two variables together. We also cannot combine both types of self-employment variables. Second, the variable for firm size also has much less observations than the other part-time work instruments. Although this has a different explanation, which we will discuss in Section 6.2, it can still influence the estimation results. This influence is visible in models where we use both the ability to reduce hours and firm size as instruments, since the joint validity of the instruments is rejected at the 5% significance level. It is also rejected when we combine the firm size variable with the new job variable.

We find that some of the instrumental variables we use are endogenous. This holds for undesirable working conditions, job switch and employer pensions when combined with other instrumental variables. Exceptions are observed when we combine the undesirable working conditions variable with the firm size, self-employment or union membership, when we combine the new job variable with either the ability to reduce hours or the employer pension and when we combine the employer pension variable with union membership.

In its variable description in Section 3.1, we already mentioned that the definition of the variable for undesirable working conditions could be endogenous. Therefore, this result is not unexpected. Regarding the job switch variable, it could be that the reason why people switch jobs could be related to their BMI: people may gain weight enough to make their job harder to perform, making other, less demanding, jobs more attractive. The reason for the endogeneity of the employer pension variable is less obvious, but it may be the case that people with an employer pension feel more pressure to work hard in order to keep their pension, reducing their BMI. Although we have not obtained evidence that these variables are endogenous in Tables 4b and 5b, the current results provide reason to doubt their validity. The other variables however, show again no reason for concern. Therefore, we argue that these are valid instruments. These instruments are the variables for firm size, (shift to) self-employment, union coverage and ability to reduce hours.

We have also considered models with two instruments for part-time work and two instruments for full-time work, of which results of five of these models are presented at the lower panel of Table 6. Results found in this specification can again all be explained using one or more of the reasonings discussed above. This supports our conclusion that we now have two instruments for the full-time work decision and five instruments for the part-time work decision that can be considered as valid instruments across the range of regression models that have been considered.

6 Sensitivity checks

6.1 Random vs. fixed effects

We have used the FE method in regression models where the value of all instruments change over time for a given individual. As mentioned in Section 2.1, the FE estimator exploits the variation in a variable of interest within individuals, while the RE method exploits differences between individuals as well. The RE method is preferred under the null that the individual-specific intercept is independent of the regressors. This is tested by the Hausman test (Hausman, 1978). Unfortunately, this test is not valid in models with robust errors, since such models violate the assumption on the error term that is also required to perform this test. Therefore, we will use this test in models where the error is not robust to possible heteroskedasticity and serial correlation. We acknowledge that this is not an ideal solution, but still the conclusions from the test give an indication toward whether or not the assumption on the individual-specific intercept holds.

The variables which allow us to apply FE method are the following: self-rated memory, word recall total, labor force status of the spouse, difficulty with activities, years of experience, household net worth, usual retirement age and household income net of own income. The first five of these variables have been identified as possible instruments for the part-time work decision in Section 5, while the latter two were possible instruments for the full-time work decision.

Household net worth is a variable that was not previously identified as a predictor for either the part-time work or the full-time work decision, but since its coefficient in the first stage regressions is larger the for full-time work decision than for the part-time work decision, we will consider it as an instrument for the full-time work decision.

For the indicators of part-time work, we use the respondent's retirement eligibility ages as our baseline instrument set, while for the full-time work indicators, we use the partner's retirement eligibility ages, as in Section 5. To perform the Hausman test, we need the coefficient estimates of both the RE and the FE model. Under the null hypothesis, the RE model is efficient. Therefore, if the null hypothesis of the test is rejected, our use of FE is justified. The results show that in all cases, the null hypothesis is indeed rejected, with the following two exceptions. First, with the household net worth variable, the null hypothesis is not rejected. Second, with the usual retirement age variable, the test statistic is negative. Under the null, the test statistic follows a chi-squared distribution, which is only defined for non-negative values. The reason we obtain a negative test statistic is that the model violates one of the assumptions of the Hausman test, as mentioned above. However, a negative test statistic can be interpreted as a small test statistic, which indicates that the null hypothesis is not rejected. This means that the RE method is preferred. Therefore, we have used the RE method in models where we have combined the usual retirement age variable with instruments other than the retirement eligibility ages in Section 5.

6.2 Number of observations

Across all models presented in Tables 4a to 5c, the number of individuals and observations can differ heavily[4]. This main reasons for this are the following. First, the respondent does not meet the necessary requirements for the question to be asked. Second, the respondent chooses not to answer (one of) the question(s) required to create the variable. Third, the respondent does not know the answer to (one of) the question(s).

The third reason is the cause of a loss of a large number of observations in the variable for usual retirement age, as almost 40% of respondents answers that their job does not have a usual retirement age. As a result, this variable has the most missing values out of all possible instruments that we considered. This can explain why the results in several models in Section 5 where we used this variable as an instrument indicated an invalid instrument set. We found similar problems in the variable for firm size, although on a smaller scale. Approximately 15% of respondents did not know the size of the firm at their location. This may influence our conclusions, as we expect that respondents in large companies are more likely to be unaware of the number of employees in their firm than respondents in small companies.

Another issue for the usual retirement age variable is that most respondents answer the question only once. Only 7,900 out of 10,871 respondents answer the question more than once, and only 2,637 answer the question at least four times. This may lead to a bias in our result, as for instance respondents who switch jobs might not answer the question anymore, while their new job can have a very different usual retirement age as their previous job.

6.3 Control variables

In our models so far, we have only controlled for a linear and squared function of the respondent's age, to account for (non-)linear effects of age on both the hours worked by the respondent and his BMI. In this section, we discuss a few other variables that could be used as control variables:

[4]Note that the number of observations stated in Tables 4a to 5c are after values observed in the HRS were imputed to survey years where information was missing. Before imputation, the number of observations is only 29,809. The number of individuals, however, is the same as in the HRS questionnaire.

education, mental health, a binary indicator for high income and gender. We test these variables separately by, for each of these control variables, applying four models. In each model, we include several of the instruments for part-time work and full-time work that that we have identified as valid instruments in Section 5, as well as the retirement eligibility ages. The first model uses the respondent's and their partner's retirement eligibility ages as instruments, the second uses the union membership variable and the respondent's retirement eligibility ages, the third uses the union membership, health insurance and firm size variables and the fourth model uses the usual retirement age, self-employment and firm size.

As we have mentioned before, education and income can affect the respondent's BMI as well as the retirement decision, so therefore it might be useful to include these as control variables. We argue that for mental health the same can be said. Mental problems often include eating disorders, which affect the BMI. In addition, mental health problems may make it necessary for the respondent to retire early, therefore also affecting the retirement decision.

The binary variable for high income takes a value of 1 if the respondent earns more than $50,000 per year and it takes a value of 0 if the respondent ealr at most $50,000 per year. In this definition of income, we include income from wages or salary, bonuses and overtime pay, as well as income from a second job or military reserve.

For the mental health variable, we consider several HRS questions about the feelings of the respondent in the week leading up to the interview. The questions were formulated as:

> "Much of the time during the past week..."

and then followed up by all of the following seven statements, one by one: " you felt depressed", "you felt that everything you did was an effort", "your sleep was restless", "you felt lonely", "you felt sad", "you were happy" and "you enjoyed life". The possible answers to the questions are 'yes' and 'no'. We create a variable that counts the number of times the respondent answers 'yes' to any of the first five questions year and 'no' to any of the latter two questions in a given survey. To obtain our mental health variable, we take the sum of these feelings, where all have an equal weight.

Results show that in all models, the coefficient estimates of working part-time and full-time are very similar to the estimates of the model where we only consider the age variables as control variables. Also, the significance level of the coefficient estimates of the part-time and full-time work decisions remains the same in all models. The validity of the instruments also does not change across the models. We draw the same conclusion if we use all new control variables in each of the four instrument specifications. Since the results show no or very little change, we conclude that our results are not sensitive to these control variables.

7 Heterogeneous treatment effects

In this section, we perform a check of heterogeneity, where we will focus on differences in the effect of working part-time or full-time on BMI between men and women. Figure 2 shows the BMI by age of men compared to women for retirees, part-time workers and full-time workers. After roughly the age of 65, the BMI across the labor force statuses are very close to each other for men. Before the age of 65, the BMI of part-time working and full-time working men is very similar, while that of retired men is higher. For women, there are clear differences between all labor force statuses, though after the age of 73, full-time workers have the lowest BMI. However, this might be due to a small number of full-time working women older than 73, which is also implied by the wide 95% confidence intervals in these ages. In addition, the BMI of part-time working women is lower than that of part-time working men across the whole distribution and the BMI of retired female is higher than that of retired men between the ages of 60 and 70. This indicates that there might be differences in the effects of part-time working and full-time working on the BMI across both genders.

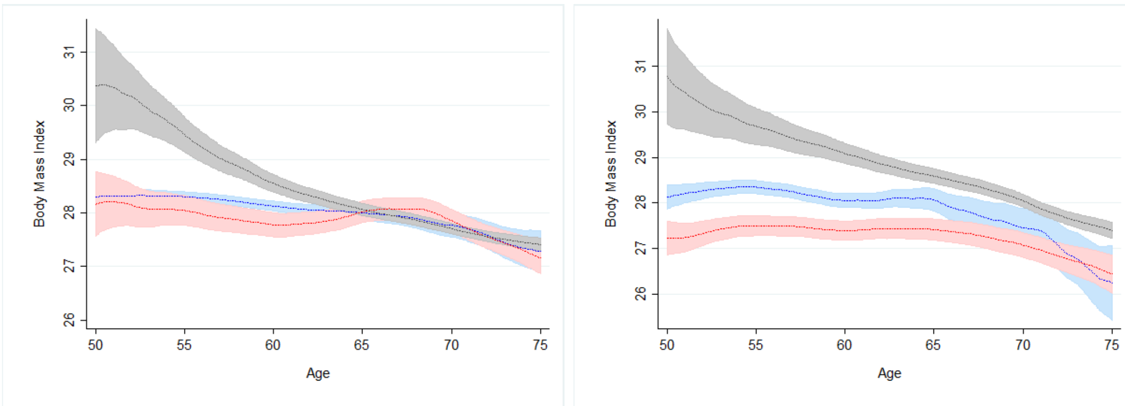

Figure 2: BMI of men (left) and women (right) for retirees (grey), part-time workers (red) and full-time workers (blue) by age

In this check we use the same four models that we have used in our sensitivity check for the control variables. The results are displayed in Table 7. This table shows results for models with men and women combined, as well as results when we consider them separately.

From these tables, we conclude that the effects of both working part-time and working full-time are much larger for females in all models. The effects for women are also more statistically significant in general. In the first model, where the instruments are the respondent's and their partner's retirement eligibility ages, the effects for men are not significant. Also worth noting is that the age effect for women is larger than for men.

8 Conclusion

We have considered the endogeneity of working part-time and full-time in the study of their effects on the BMI. This endogeneity is caused by simultaneity, as BMI and the number of hours worked can be codetermined. We take an instrumental variable approach to infer a causal relationship between working part- and full-time and the BMI. To find independent sources of exogenous variation to separately identify both effects, we consider a rich set of instrumental variables, which includes several pension, socio-demographic and employment-related characteristics. After considering each instrument in this set together with a baseline instrument set consisting of the retirement eligibility ages, and together with multiple different combinations of the other instrumental variables, we have found valid instruments for both the full-time work decision and the part-time work decision. The valid instruments for the full-time work decision are the orthogonalized health insurance and the usual retirement age variables. The valid instruments for the part-time work decision are the firm size, union membership, ability to reduce hours and (shift to) self-employment variables.

These instruments all pass the formal hypothesis diagnostic tests which we have performed on all instrument sets. However, for the usual retirement age and firm size variable, we presume that the missing observations may influence the estimation results.

Most of the previous literature has used the retirement eligibility ages as the main instruments for retirement, which has the notable disadvantage that self-employed people are not subject to these retirement ages. The effect estimated with instrumental variable analysis is a local average treatment effect, which means that the estimation results only apply to those affected by the instrument set. Therefore, the results of the models with just the retirement eligibility ages as the instrument set do not apply to the large American population of the respondents in the HRS. To account for this, we consider instruments we consider that affect a larger population of respondents. The exceptions to this are the usual retirement age and ability to reduce hours variables. The former applies only to professions where a usual retirement age can be attributed, and the latter applies only to those who are not self-employed. However, the results of the remaining instrumental variables are applicable to large populations of workers between the ages 50 and 75.

We conclude that both part-time and full-time workers have a lower BMI than retirees. The effect for part-time workers is much larger than that for full-time workers, suggesting that it might be beneficial for US citizens to go into partial retirement, where they gradually decrease their working hours to 'get used to' retirement and take their time to replace their working activities by other social or recreative activities.

A possible direction for future research is the following. In this study, we have only considered the BMI as a health outcome, but there are other important health outcomes that are important to investigate. For example, one can take self-reported health as a dependent variable, or the probability of getting several types of diseases. However, the instruments that are valid with the BMI as the outcome variable may not be valid with another outcome variable, so this would require a reconsideration of the instrument set.

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9 Appendix

Table 1: Normal retirement eligibility age and changes to benefits based on moment of retiring, compared to benefits obtained when retiring at the normal retirement age

Year of birth	Normal retirement age	Benefit changes (%)	
		Retire at 62	Retire at 70
1937 or earlier	65	-20.00	$\leq$ 32.50
1938	65 and 2 months	-20.83	31.42
1939	65 and 4 months	-21.67	32.67
1940	65 and 6 months	-22.50	31.50
1941	65 and 8 months	-23.33	32.50
1942	65 and 10 months	-24.17	31.25
1943-1954	66	-25.00	32.00
1955	66 and 2 months	-25.83	30.67
1956	66 and 4 months	-26.67	29.33
1957	66 and 6 months	-27.50	28.00
1958	66 and 8 months	-28.33	26.67
1959	66 and 10 months	-29.17	25.33
1960 or later	67	-30.00	24.00

Notes: 1. Source: The United States Social Security Administration. 2. People born on January 1 of any year can refer to the previous year benefits. 3. For delayed retirement, increased benefits only apply up to age 70. 4. Respondents born before 1917 get no increased benefits. Those born between 1917 and 1924 get a 3.0% increase per year. After that, benefits increase by 0.5 percent point per two years until 1943.

Table 2: Descriptive statistics (%)

	All waves	1992	2014
Age (50-75) (mean)	62.30	57.04	63.01
Overweight	40.59	43.04	37.55
Obese	29.20	20.40	37.91
Full-time worker	46.49	69.08	42.95
Part-timer	16.09	15.50	16.05
Retired	37.42	15.42	41.00
Male	51.76	60.25	46.36
Retirement ages of the respondent			
Under early ret. age	51.33	87.68	47.62
Between early and normal ret. age	14.74	6.66	21.12
Between normal ret. age and age 70	16.17	4.57	13.61
Over age 70	17.76	1.10	17.65
Prob. work past 62 > 50%	45.44	42.95	47.43
Prob. work past 65 > 10%	58.35	49.80	66.02
Avg. usual retirement age (mean)	63.87	63.08	65.01
Retirement ages of the partner			
Under early ret. age	55.50	89.67	51.30
Between early and normal ret. age	13.64	5.79	17.62
Between normal ret. age and age 70	14.45	3.23	12.60
Over age 70	16.41	1.31	18.48
Spouse retired	39.23	20.08	41.36
Married or partnered	74.65	81.02	69.82
Ever employer pension covered	63.66	41.60	78.45
Always employer pension covered	38.63	18.49	57.49
Ever offered a retirement window	11.89	13.15	9.16
Has health insurance	49.65	57.78*	41.72
Has health insurance up to 65	23.81	40.56*	16.87
Has health insurance past 65	7.02	6.13**	8.39
Household minus own income	42.37	49.91	41.70
Household net worth	43.38	43.34	46.05
Black or white	94.89	96.99	90.55
Education at college level or above	49.34	41.31	57.70
Difficulty with activities score > 1	36.14	19.44	42.61
Self-rated memory good or better	78.47	89.20	73.60
Word recall total score > 10	53.00	35.59*	52.15
Average firm size > 50	47.56	43.59	50.51
Average firm size all locations > 50	53.10	44.43	61.58
More than 30 years of experience	72.23	70.16	64.31
Ever covered by union	26.64	26.88	25.97
Had a blue-collar job	39.43	42.66	38.62
Worked in tertiary sector	69.30	67.44	72.51
Undesirable working conditions score > 5	39.79	36.27	45.22
New job	42.43	38.29	41.94
Ever able to reduce hours	59.09	56.94	55.41
Ever self-employed	24.79	25.53	22.42
Ever shifted to self-employment	9.15	8.88	7.47

Notes: 1. Percentages might not add up to 100 due to rounding errors. 2. *, ** indicate that data from respectively 1994 or 2000 has been used due to no available data in earlier waves.

Table 3: Employment rates by categories of the new dummy variables as instruments (%)

	Full-time worker	Part-time worker	Part-time retiree	Full-time retiree
Pension characteristics				
Retirement ages of the respondent				
Under early ret. age	71.24	11.72	4.29	12.75
Between early and normal ret. age	37.48	6.55	11.68	44.29
Between normal ret. age and age 70	18.35	4.35	12.78	64.52
Over age 70	8.04	3.84	9.77	78.35
Avg. prob. work past 62				
Larger than 50%	69.86	7.88	5.88	16.38
At most 50%	37.64	9.93	8.97	43.46
Avg. prob. work past 65				
Larger than 10%	64.66	9.98	7.34	18.03
At most 10%	32.14	6.96	7.99	52.90
Avg. usual retirement age				
Not past retirement age	76.90	11.40	5.52	6.18
Past retirement age	25.16	4.91	14.84	55.09
Retirement ages of the partner				
Under early ret. age	66.12	9.87	5.96	18.05
Between early and normal ret. age	38.64	8.20	10.32	42.84
Between normal ret. age and age 70	24.48	6.04	11.56	57.92
Over age 70	13.33	5.53	9.42	71.72
Labor force status of spouse				
Working	61.77	11.16	8.28	18.78
Retired	22.73	4.73	8.29	64.25
Marital status				
Married/Partnered	47.68	8.38	7.93	36.01
Otherwise	42.97	8.33	7.14	41.57
Employer pension covered				
Has never had a private pension	44.51	14.97	17.68	22.83
Has ever had a private pension	67.56	8.02	7.00	17.41
Employer pension covered				
Has not always had a private pension	51.98	13.01	15.45	19.56
Has always had a private pension	70.63	6.64	3.63	19.10
Retirement windows				
Has never been offered window(s)	55.44	10.20	9.22	25.15
Has ever been offered window(s)	54.85	4.42	7.63	33.10
Health insurance				
From current or previous job	65.11	5.25	5.40	24.24
No or other health insurance	26.73	10.73	10.44	52.10
Health insurance up to 65				
From current or previous job	66.97	4.25	5.68	23.09
No or other health insurance	40.36	9.87	8.48	41.29
Health insurance past 65				
From current or previous job	54.18	3.95	8.19	33.69
No or other health insurance	43.94	9.07	8.01	38.98
Socio-demographic characteristics				
Household minus own income				
Below median	42.39	6.69	6.22	44.68

Table 3 ctd.

	Full-time worker	Part-time worker	Part-time retiree	Full-time retiree
Above median	49.49	9.60	8.84	32.07
Household net worth				
Below median	48.98	9.02	6.12	35.87
Above median	44.57	7.87	8.96	38.60
Race				
White/black	45.84	8.21	7.89	38.05
Other	57.92	11.02	4.80	26.26
Education level				
Up to high school	41.47	8.57	6.64	43.32
College and above	51.64	8.15	8.85	31.36
Difficulty with activities				
Score below 2	53.93	9.02	7.76	29.29
Score 2 or higher	33.32	7.22	7.67	51.79
Self-rated memory				
Good or better	49.18	8.69	8.21	33.92
Fair or worse	34.78	7.37	7.38	50.46
Word recall total				
Score 10 or less	36.98	6.81	7.80	48.41
Score higher than 10	49.39	9.27	8.94	32.40
Employment characteristics				
Average firm size				
50 employees or less	53.05	13.25	12.32	21.38
More than 50 employees	61.68	6.49	6.56	25.28
Average firm size all Locations				
50 employees or less	50.44	13.60	13.08	22.87
More than 50 employees	63.16	6.76	6.61	23.47
Years of experience				
Up to 30	47.29	12.77	4.13	35.82
31 or more	46.19	6.76	9.04	38.00
Covered by union				
Was ever covered by a union	54.19	7.00	6.03	32.78
Was never covered by a union	54.78	10.21	10.08	24.93
Blue-collar work (Job Longest Tenure)				
Is/was a blue-collar worker	44.83	8.65	6.73	39.79
Is/was not a blue-collar worker	49.88	8.16	8.54	33.43
Industry sectors				
Tertiary Sector	48.71	9.83	8.56	32.91
Other Sector	46.04	5.04	6.23	42.70
Undesirable working conditions				
Average score 5 or higher	59.58	8.45	5.76	26.20
Average score below 5	55.09	11.13	12.00	21.78
New job				
Has ever gotten a new job	54.69	11.45	14.08	19.77
Has never gotten a new job	54.54	8.60	5.36	31.49
Ability to reduce hours				
Was ever able to reduce hours	56.48	11.63	12.14	19.75
Was never able to reduce hours	58.33	5.79	3.35	32.53
Self-employment				

Table 3 ctd.

	Full-time worker	Part-time worker	Part-time retiree	Full-time retiree
Was ever self-employed	52.10	14.26	16.95	16.69
Was never self-employed	55.41	8.36	6.48	29.75
Shift to self-employment				
Has ever shifted to self-empl	52.55	12.67	20.49	14.29
Has never shifted to self-empl	54.80	9.54	7.92	27.74

Notes: 1. Percentages might not add up to 100 due to rounding errors.

Table 4a: First-stage estimates for the respondent's or the partner's retirement eligibility ages as instruments

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	S-W stat.	S-W p-value	Partial R^2	C-D stat.		
Respondent										
Early to normal age	Part-time work	FE	0.035***	0.005	5.812***	$2.998e{-}03$	0.000	4.557	91379	18449
Normal age to 70			0.036***	0.007						
Older than 70			0.023**	0.010						
Early to normal age	Full-time work		−0.165***	0.006	6.524***	$1.471e{-}03$	0.005			
Normal age to 70			−0.249***	0.008						
Older than 70			−0.217***	0.010						
Early to normal age	Part-time work	RE	0.035***	0.005	5.963***	$2.577e{-}03$	0.000	5.545	91379	18449
Normal age to 70			0.036***	0.007						
Older than 70			0.022**	0.010						
Early to normal age	Full-time work		−0.166***	0.005	6.706***	$1.227e{-}03$	0.005			
Normal age to 70			−0.250***	0.008						
Older than 70			−0.218***	0.010						
Partner										
Early to normal age	Part-time work	FE	−0.005	0.005	28.137***	$6.409e{-}13$	0.003	38.158**	68151	14556
Normal age to 70			−0.033***	0.008						
Older than 70			−0.079***	0.012						
Early to normal age	Full-time work		−0.056***	0.006	70.998***	$2.153e{-}31$	0.006			
Normal age to 70			−0.062***	0.009						
Older than 70			−0.019	0.013						
Early to normal age	Part-time work	RE	−0.001	0.005	26.275***	$4.070e{-}12$	0.003	41.624**	68151	14556
Normal age to 70			−0.026***	0.008						
Older than 70			−0.069***	0.011						
Early to normal age	Full-time work		−0.061***	0.006	78.923***	$8.114e{-}35$	0.007			
Normal age to 70			−0.069***	0.009						
Older than 70			−0.031**	0.012						

Notes: 1. Standard errors and Sanderson-Windmeijer test statistics are robust to heteroskedasticity and serial correlation within individuals. 2. The base outcome for the binaries part-time and full-time working is retirement. 3. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement. 4. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. For the Cragg-Donald test statistic, **, * indicate a value higher than the critical values for 10% maximal IV size and 15% maximal IV size, respectively.

Table 4b: First-stage estimates for all instruments, considered one by one with the respondent's retirement eligibility ages as base instruments

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	S-W stat.	S-W p-value	Partial R^2	C-D stat.		
Past avg. usual ret. age	Part-time work	FE	0.021***	0.007	5.446**	$9.713e{-04}$	0.001	5.874	63054	11073
for respondent's job	Full-time work		−0.183***	0.008	6.013**	$4.349e{-04}$	0.010			
Prob. work past 62	Part-time work	RE	−0.000***	0.000	3.785***	$9.979e{-03}$	0.000	3.989	74556	13034
	Full-time work		0.003***	0.000	4.714***	$2.725e{-03}$	0.005			
Prob. work past 65	Part-time work	RE	−0.000***	0.000	13.808***	$5.475e{-09}$	0.000	4.375	77469	13668
	Full-time work		0.003***	0.000	21.308***	$9.157e{-14}$	0.006			
Spouse retirement ages										
Early to normal age	Part-time work	FE	−0.011**	0.006	12.682***	$2.570e{-12}$	0.003	23.199**	68151	14556
Normal age to 70			−0.040***	0.008						
Older than 70			−0.084***	0.012						
Early to normal age	Full-time work		−0.027***	0.006	37.223***	$5.007e{-38}$	0.026			
Normal age to 70			−0.021**	0.009						
Older than 70			0.012	0.013						
Spouse retired	Part-time work	FE	−0.013**	0.006	12.631***	$3.070e{-08}$	0.002	15.291**	56430	13206
	Full-time work		−0.120***	0.007	33.677***	$1.165e{-21}$	0.041			
Married	Part-time work	RE	0.016**	0.006	5.920***	$4.952e{-04}$	0.000	7.281	91327	18449
	Full-time work		−0.010	0.007	7.316***	$6.724e{-05}$	0.008			
Ever emp. pension covered	Part-time work	RE	−0.222***	0.006	411.408***	$4.140e{-256}$	0.005	83.997**	76492	13957
	Full-time work		0.140***	0.007	358.719***	$1.948e{-224}$	0.026			
Always emp. pension covered	Part-time work	RE	−0.194***	0.006	416.886***	$4.933e{-256}$	0.004	57.820**	58998	10638
	Full-time work		0.087***	0.006	336.659***	$7.701e{-209}$	0.011			
Ret. window ever	Part-time work	RE	−0.092***	0.007	64.084***	$4.069e{-41}$	0.001	7.951	71552	12720
	Full-time work		0.033***	0.008	64.178***	$3.542e{-41}$	0.008			
Health insurance	Part-time work	RE	−0.064***	0.004	9.121***	$4.993e{-06}$	0.001	12.064**	82644	17684
current/previous job	Full-time work		0.203***	0.005	10.022***	$1.354e{-06}$	0.007			
Health insurance to 65	Part-time work	RE	−0.044***	0.004	23.485***	$3.679e{-15}$	0.002	26.391**	69590	16919
current/previous job	Full-time work		0.070***	0.006	31.548***	$2.524e{-20}$	0.019			
Health insurance past 65	Part-time work	RE	0.004	0.006	3.778**	$1.007e{-02}$	0.000	4.252	69590	16919
current/previous job	Full-time work		−0.059***	0.008	4.426***	$4.081e{-03}$	0.008			
Household minus own income	Part-time work	FE	−0.022***	0.004	20.987***	$1.442e{-13}$	0.001	23.366**	91379	18449
(lower than median)	Full-time work		−0.006	0.004	37.059***	$7.215e{-24}$	0.019			
Household net worth	Part-time work	FE	−0.009**	0.004	4.654***	$2.966e{-03}$	0.000	4.078	91379	18449

Table 4b ctd.

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	S-W stat.	S-W p-value	Partial R^2	C-D stat.		
(lower than median)	Full-time work		0.018***	0.005	5.246***	$3.094e{-01}$	0.006			
Black or white	Part-time work	RE	−0.002	0.009	4.148***	$6.019e{-03}$	0.000	4.207	91286	18416
	Full-time work		−0.019*	0.011	4.685***	$2.837e{-03}$	0.005			
Education	Part-time work	RE	0.012***	0.004	14.131***	$3.388e{-09}$	0.000	4.867	91377	18448
	Full-time work		0.053***	0.005	16.263***	$1.492e{-10}$	0.006			
Difficulty with activities	Part-time work	FE	−0.002	0.003	6.009***	$4.360e{-04}$	0.000	5.559	91370	18449
(score higher than 1)	Full-time work		−0.033***	0.004	7.348***	$6.427e{-05}$	0.008			
Self-rated memory	Part-time work	FE	0.001	0.004	4.725***	$2.683e{-03}$	0.000	4.130	86163	18022
	Full-time work		0.025***	0.004	5.586***	$7.957e{-04}$	0.007			
Score word recall total	Part-time work	FE	0.008**	0.003	6.951***	$1.137e{-04}$	0.001	6.033	74390	17410
(score higher than 10)	Full-time work		0.009***	0.003	8.930***	$6.587e{-06}$	0.009			
Avg. firm size	Part-time work	RE	−0.146***	0.005	267.081***	$4.550e{-168}$	0.003	37.492**	70420	12640
(larger than 50 empl.)	Full-time work		0.074***	0.006	264.264***	$2.409e{-166}$	0.016			
Avg. firm size all locations	Part-time work	RE	−0.163***	0.006	296.520***	$7.443e{-186}$	0.003	42.885**	70420	12640
(larger than 50 empl.)	Full-time work		0.084***	0.006	292.574***	$1.849e{-183}$	0.018			
Years of experience	Part-time work	FE	0.021**	0.009	8.208***	$1.866e{-05}$	0.001	9.911	91379	18449
(more than 30 years)	Full-time work		0.038***	0.009	12.329***	$4.720e{-08}$	0.013			
Ever union covered	Part-time work	RE	−0.088***	0.005	117.364***	$5.314e{-75}$	0.001	15.026*	74556	13118
	Full-time work		−0.001	0.006	131.845***	$3.791e{-84}$	0.014			
Blue-collar worker	Part-time work	RE	−0.009	0.011	4.574***	$3.315e{-03}$	0.000	5.287	88085	17248
	Full-time work		−0.028**	0.011	5.322***	$1.155e{-03}$	0.006			
Job in tertiary sector	Part-time work	RE	0.027***	0.008	9.659***	$2.289e{-06}$	0.001	12.450*	87881	17258
	Full-time work		−0.015	0.009	14.085***	$3.630e{-09}$	0.012			
Undesirable work cond.	Part-time work	RE	−0.090***	0.005	127.610***	$1.888e{-81}$	0.001	18.326**	71684	12849
(score higher than 4)	Full-time work		0.005	0.006	144.692***	$3.294e{-92}$	0.013			
Ever got a new job	Part-time work	RE	0.107***	0.005	156.329***	$1.132e{-99}$	0.002	27.729**	77676	14096
	Full-time work		−0.030***	0.005	184.512***	$2.364e{-117}$	0.018			
Ever able to reduce hours	Part-time work	RE	0.147***	0.005	335.064***	$1.543e{-208}$	0.003	41.127**	64550	11454
	Full-time work		−0.020***	0.006	408.468	$4.606e{-252}$	0.023			
Ever self-employed	Part-time work	RE	0.175***	0.006	309.317***	$1.667e{-194}$	0.004	54.656**	77809	14144
	Full-time work		−0.026***	0.007	412.178***	$1.108e{-256}$	0.026			
Ever shifted to self-empl.	Part-time work	RE	0.150***	0.010	98.979***	$2.116e{-63}$	0.001	17.362**	77809	14144
	Full-time work		−0.023**	0.010	112.612***	$4.648e{-72}$	0.014			

Table 4b ctd.

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	S-W stat.	S-W p-value	Partial R^2	C-D stat.		

Notes: 1. Standard errors and Sanderson-Windmeijer test statistics are robust to heteroskedasticity and serial correlation within individuals. 2. The base outcome for the binaries part-time and full-time working is retirement. 3. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement. 4. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. For the Cragg-Donald test statistic, **, * indicate a value higher than the critical values for 10% maximal IV size and 15% maximal IV size, respectively.

Table 4c: First-stage estimates for all instruments, considered one by one with the partner's retirement eligibility ages as base instruments

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	S-W stat.	S-W p-value	Partial R^2	C-D stat.		
Past avg. usual ret. age	Part-time work	FE	0.041***	0.007	13.579***	$7.787e{-}09$	0.003	24.279**	47803	9035
for respondent's job	Full-time work		−0.238***	0.008	41.496***	$1.302e{-}26$	0.037			
Prob. work past 62	Part-time work	RE	−0.001***	0.000	18.069***	$1.084e{-}11$	0.003	36.472**	55230	10380
	Full-time work		0.003***	0.000	441.123***	$9.410e{-}270$	0.013			
Prob. work past 65	Part-time work	RE	−0.000***	0.000	23.187***	$5.902e{-}15$	0.003	35.373**	57546	10904
	Full-time work		0.003***	0.000	562.893***	0.000	0.011			
Spouse retired	Part-time work	FE	−0.007	0.006	20.737***	$2.154e{-}13$	0.006	27.976**	56430	13206
	Full-time work		−0.126***	0.007	47.297***	$2.295e{-}30$	0.021			
Married	Part-time work	RE	−0.030	0.058	17.721***	$1.773e{-}11$	0.003	31.218**	68151	14556
	Full-time work		−0.075	0.080	53.049***	$4.293e{-}34$	0.007			
Ever emp. pension covered	Part-time work	RE	−0.220***	0.007	296.910***	$1.588e{-}185$	0.007	88.591**	57412	11277
	Full-time work		0.134***	0.008	57.437***	$7.687e{-}37$	0.008			
Always emp. pension covered	Part-time work	RE	−0.192***	0.007	289.565***	$4.682e{-}179$	0.006	51.403**	44317	8599
	Full-time work		0.089***	0.007	36.320***	$2.571e{-}23$	0.005			
Ret. window ever	Part-time work	RE	−0.094***	0.008	69.823***	$1.089e{-}44$	0.003	33.996**	53236	10199
	Full-time work		0.033***	0.009	50.919***	$1.174e{-}32$	0.007			
Health insurance	Part-time work	RE	−0.063***	0.005	15.098***	$8.312e{-}10$	0.002	29.653**	57234	13145
current/previous job	Full-time work		0.199***	0.006	21.452***	$6.837e{-}14$	0.016			
Health insurance to 65	Part-time work	RE	−0.044***	0.005	19.702***	$9.766e{-}13$	0.003	37.870**	48133	12562
current/previous job	Full-time work		0.075***	0.006	33.991***	$7.167e{-}22$	0.008			
Health insurance past 65	Part-time work	RE	0.007	0.007	13.577***	$7.694e{-}09$	0.003	23.788**	48133	12562
current/previous job	Full-time work		−0.057***	0.009	49.699***	$6.373e{-}32$	0.008			
Household minus own income	Part-time work	FE	−0.022***	0.004	30.767***	$8.097e{-}20$	0.004	36.870**	68151	14556
(lower than median)	Full-time work		−0.015***	0.005	57.917***	$3.282e{-}37$	0.007			
Household net worth	Part-time work	FE	−0.003	0.005	18.784***	$3.748e{-}12$	0.003	28.811**	68151	14556
(lower than median)	Full-time work		0.010	0.006	48.064***	$6.976e{-}31$	0.006			
Black or white	Part-time work	RE	0.007	0.010	17.436***	$2.695e{-}11$	0.003	30.964**	68076	14528
	Full-time work		−0.032**	0.013	55.673***	$8.979e{-}36$	0.007			
Education	Part-time work	RE	0.018***	0.005	26.935***	$2.300e{-}17$	0.003	31.889**	68149	14555
	Full-time work		0.048***	0.006	92.830***	$1.663e{-}59$	0.007			
Difficulty with activities	Part-time work	FE	−0.002	0.004	19.088***	$2.399e{-}12$	0.003	28.639**	68144	14556
(score higher than 1)	Full-time work		−0.029***	0.004	69.739***	$9.811e{-}45$	0.008			

Table 4c ctd.

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	S-W stat.	S-W p-value	Partial R^2	C-D stat.		
Self-rated memory	Part-time work	FE	0.001	0.004	18.036***	$1.126e{-11}$	0.003	26.953**	63225	14101
	Full-time work		0.021***	0.005	54.878***	$3.135e{-35}$	0.007			
Score word recall total	Part-time work	FE	0.006*	0.004	10.388***	$8.008e{-17}$	0.002	13.500*	54011	13414
(score higher than 10)	Full-time work		0.011***	0.004	40.749***	$3.497e{-26}$	0.007			
Avg. firm size	Part-time work	RE	−0.142***	0.006	220.987***	$6.563e{-139}$	0.005	52.359**	53160	10248
(larger than 50 empl.)	Full-time work		0.067***	0.007	45.898***	$1.868e{-29}$	0.007			
Avg. firm size all locations	Part-time work	RE	−0.136***	0.007	146.512***	$1.540e{-92}$	0.005	47.201**	46601	8400
(larger than 50 empl.)	Full-time work		0.075***	0.007	41.564***	$1.182e{-26}$	0.007			
Years of experience	Part-time work	FE	0.010	0.010	19.669***	$1.022e{-12}$	0.003	28.630**	68151	14556
(more than 30 years)	Full-time work		0.060***	0.010	65.310***	$6.586e{-42}$	0.008			
Ever union covered	Part-time work	RE	−0.088***	0.006	103.918***	$2.678e{-66}$	0.004	38.344**	55811	10591
	Full-time work		−0.003	0.007	79.229***	$1.112e{-50}$	0.008			
Blue-collar worker	Part-time work	RE	−0.021	0.013	21.504***	$6.869e{-14}$	0.003	37.005**	65777	13683
	Full-time work		−0.010	0.014	47.698***	$1.175e{-30}$	0.006			
Job in tertiary sector	Part-time work	RE	0.040***	0.009	27.962***	$5.101e{-18}$	0.004	40.225**	65687	13703
	Full-time work		0.006	0.010	50.302***	$2.527e{-32}$	0.006			
Undesirable work cond.	Part-time work	RE	−0.088***	0.006	106.280***	$9.277e{-68}$	0.005	39.460**	53263	10294
(score higher than 4)	Full-time work		0.011*	0.007	59.162***	$6.518e{-38}$	0.007			
Ever got a new job	Part-time work	RE	0.105***	0.006	129.431***	$1.928e{-82}$	0.004	43.831**	58236	11376
	Full-time work		−0.033***	0.006	63.566***	$9.450e{-41}$	0.008			
Ever able to reduce hours	Part-time work	RE	0.0151***	0.006	297.100***	$4.785e{-184}$	0.006	53.666**	47807	9171
	Full-time work		−0.029***	0.007	70.244***	$6.620e{-45}$	0.008			
Ever self-employed	Part-time work	RE	0.168***	0.007	255.289***	$2.406e{-160}$	0.006	54.585**	58342	11415
	Full-time work		−0.024***	0.008	73.199***	$6.920e{-47}$	0.008			
Ever shifted to self-empl.	Part-time work	RE	0.140***	0.011	84.740***	$3.204e{-54}$	0.004	36.826***	58342	11415
	Full-time work		−0.016	0.012	72.695***	$1.448e{-46}$	0.008			

Notes: 1. Standard errors and Sanderson-Windmeijer test statistics are robust to heteroskedasticity and serial correlation within individuals. 2. The base outcome for the binaries part-time and full-time working is retirement. 3. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement. 4. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. For the Cragg-Donald test statistic, **, * indicate a value higher than the critical values for 10% maximal IV size and 15% maximal IV size, respectively.

Table 5a: Second-stage estimates for the respondent's or the partner's retirement eligibility ages as instruments

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	End. test	p-value	Ove. test	p-value		
Retirement ages respondent	Part-time work	FE	−4.177*	2.378	4.587**	0.010	0.737	0.391	91379	18449
	Full-time work		−1.112**	0.489						
Retirement ages respondent	Part-time work	RE	−3.890*	2.310	10.510***	0.005	0.438	0.508	91379	18449
	Full-time work		−1.185**	0.470						
Retirement ages partner	Part-time work	FE	−3.015***‡	1.037	5.081***	0.006	0.502	0.479	68151	14556
	Full-time work		−0.450	0.573						
Retirement ages partner	Part-time work	RE	−3.422***‡	1.101	12.545***	0.002	0.124	0.725	68151	14556
	Full-time work		−1.035*	0.552						

Notes: 1. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 2. ‡ indicates that equality of the coefficients for part-time work and full-time work is rejected at the 0.05 level. 3. Results are robust to heteroskedasticity and correlation within individuals. 4. The base outcome for the binaries part-time and full-time working is retirement. 5. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement.

Table 5b: Second-stage estimates for all instruments, considered one by one with the respondent's retirement eligibility ages as base instruments

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	End. test	p-value	Ove. test	p-value		
Past avg. usual ret. age	Part-time work	FE	−0.941	1.610	1.017	0.362	1.974	0.373	63054	11073
for respondent's job	Full-time work		−0.311	0.364						
Prob. work past 62	Part-time work	FE	−4.437*	2.416	5.568*	0.062	7.300**	0.026	74556	13034
	Full-time work		−0.871*	0.509						
Prob. work past 65	Part-time work	FE	−0.084	1.865	1.392	0.499	9.621***	0.008	77469	13668
	Full-time work		−0.079	0.370						
Spouse retirement ages	Part-time work	FE	−3.021***‡	0.662	5.118***	0.006	1.394	0.845	68151	14556
	Full-time work		−0.846***	0.209						
Spouse retired	Part-time work	FE	0.400	1.075	1.726	0.178	4.713*	0.095	56430	13206
	Full-time work		−0.167	0.215						
Married	Part-time work	RE	5.660**‡	2.393	6.889**	0.032	21.329***	0.000	91327	18449
	Full-time work		0.604	0.490						
Ever emp. pension covered	Part-time work	RE	−3.591***‡	0.514	47.764***	0.000	0.137	0.934	76492	13957
	Full-time work		−1.065***	0.224						
Always emp. pension covered	Part-time work	RE	−8.100***‡	0.714	148.101***	0.000	0.392	0.822	58998	10638
	Full-time work		−3.835***	0.514						
Ret. window ever	Part-time work	RE	−0.254	1.453	4.522	0.104	2.603	0.272	71552	12720
	Full-time work		−0.349	0.379						
Health insurance	Part-time work	RE	−5.368***‡	1.802	11.136***	0.004	0.493	0.781	82644	17684
current/previous job	Full-time work		−1.517***	0.500						
Health insurance to 65	Part-time work	RE	−2.274**	1.016	5.815*	0.055	2.727	0.256	69590	16919
current/previous job	Full-time work		−0.898***	0.300						
Health insurance past 65	Part-time work	RE	−6.744**‡	2.919	12.496***	0.002	1.574	0.455	52354	14381
current/previous job	Full-time work		−1.729***	0.571						
Household minus own income	Part-time work	FE	1.812*‡	0.991	10.945***	0.004	9.870***	0.007	91379	18449
(lower than median)	Full-time work		−0.072	0.241						
Household net worth	Part-time work	FE	−4.795**	2.321	5.250***	0.005	0.979	0.613	91379	18449
(lower than median)	Full-time work		−1.220**	0.487						
Black or white	Part-time work	RE	−3.388	2.234	10.194***	0.006	9.080**	0.011	91286	18416
	Full-time work		−1.076**	0.456						
Education	Part-time work	RE	−4.441**	2.145	12.777***	0.002	0.922	0.631	91377	18448
	Full-time work		−1.213***	0.442						

Table 5b ctd.

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	End. test	p-value	Ove. test	p-value		
Difficulty with activities	Part-time work	FE	−12.103***‡	3.302	36.857***	0.000	8.815**	0.012	91370	18449
(score higher than 1)	Full-time work		−2.727***	0.662						
Self-rated memory	Part-time work	FE	−3.070	2.035	2.777*	0.062	0.561	0.756	86163	18022
	Full-time work		−0.863**	0.407						
Score word recall total	Part-time work	FE	−0.303	1.613	3.153**	0.043	6.663**	0.036	74390	17410
(score higher than 10)	Full-time work		−0.526	0.382						
Avg. firm size	Part-time work	RE	−6.751***‡	0.780	78.803***	0.000	1.983	0.371	70420	12640
(larger than 50 empl.)	Full-time work		−2.149***	0.345						
Avg. firm size all locations	Part-time work	RE	−7.511***‡	0.721	113.196***	0.000	3.106	0.212	69469	12307
(larger than 50 empl.)	Full-time work		−2.352***	0.348						
Years of experience	Part-time work	FE	1.787	1.539	4.350**	0.013	9.962***	0.007	91379	18449
(more than 30 years)	Full-time work		0.042	0.324						
Ever union covered	Part-time work	RE	−4.853***‡	1.129	21.067***	0.000	1.547	0.461	74556	13118
	Full-time work		−1.283***	0.305						
Blue-collar worker	Part-time work	RE	−6.504**‡	2.597	12.895***	0.002	5.155*	0.076	88085	17248
	Full-time work		−1.614***	0.543						
Job in tertiary sector	Part-time work	RE	−0.635	1.526	4.886*	0.087	1.761	0.415	87881	17258
	Full-time work		−0.470	0.331						
Undesirable work cond.	Part-time work	RE	−6.480***‡	1.069	44.921***	0.000	2.984	0.225	71684	12849
(score higher than 4)	Full-time work		−1.957***	0.361						
Ever got a new job	Part-time work	RE	−1.468*	0.875	7.123**	0.028	1.003	0.606	77676	14096
	Full-time work		−0.651***	0.252						
Ever able to reduce hours	Part-time work	RE	−3.249***‡	0.701	24.625***	0.000	0.743	0.690	64550	11454
	Full-time work		−1.108***	0.250						
Ever self-employed	Part-time work	RE	−5.721***‡	0.592	98.972***	0.000	0.541	0.763	77809	14144
	Full-time work		−1.549***	0.244						
Ever shifted to self-empl.	Part-time work	RE	−4.253***‡	1.064	19.952***	0.000	0.282	0.869	77809	14144
	Full-time work		−1.237***	0.296						

Notes: 1. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 2. ‡ indicates that equality of the coefficients for part-time work and full-time work is rejected at the 0.05 level. 3. Results are robust to heteroskedasticity and correlation within individuals. 4. The base outcome for the binaries part-time and full-time working is retirement. 5. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement.

Table 5c: Second-stage estimates for all instruments, considered one by one with the partner's retirement eligibility ages as base instruments

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	End. test	p-value	Ove. test	p-value		
Past avg. usual ret. age	Part-time work	FE	−2.546**‡	1.176	0.949	0.387	1.166	0.558	47803	9035
for respondent's job	Full-time work		−0.426	0.276						
Prob. work past 62	Part-time work	FE	−3.112***‡	1.080	9.847***	0.007	3.433	0.180	55230	10380
	Full-time work		−0.247	0.400						
Prob. work past 65	Part-time work	FE	−2.852***‡	1.047	8.802**	0.012	7.423**	0.024	57546	10904
	Full-time work		−0.140	0.399						
Spouse retired	Part-time work	FE	−2.923***	0.977	1.740	0.176	1.593	0.451	56430	13206
	Full-time work		0.090	0.304						
Married	Part-time work	RE	−3.435***‡	1.099	12.426***	0.002	0.221	0.895	68151	14556
	Full-time work		−1.047*	0.550						
Ever emp. pension covered	Part-time work	RE	−5.435***‡	0.899	40.047***	0.000	0.186	0.911	44317	8599
	Full-time work		−1.337	0.949						
Always emp. pension covered	Part-time work	RE	−3.126***‡	0.578	112.828***	0.000	7.660**	0.022	57412	11277
	Full-time work		−0.676	0.520						
Ret. window ever	Part-time work	RE	−2.591***	0.980	8.128**	0.017	2.872	0.238	53236	10199
	Full-time work		−0.924*	0.549						
Health insurance	Part-time work	RE	−3.910***‡	1.296	16.296***	0.000	1.422	0.491	57234	13145
current/previous job	Full-time work		−0.918**	0.423						
Health insurance to 65	Part-time work	RE	−3.342***‡	1.091	11.275***	0.004	0.178	0.915	48133	12562
current/previous job	Full-time work		−1.627***	0.600						
Health insurance past 65	Part-time work	RE	−3.140**	1.263	13.388***	0.001	0.260	0.878	48133	12562
current/previous job	Full-time work		−1.771***	0.558						
Household minus own income	Part-time work	FE	−1.883**	0.831	9.780***	0.008	12.046***	0.002	68151	14556
(lower than median)	Full-time work		−0.518	0.478						
Household net worth	Part-time work	FE	−3.036***‡	1.039	5.892***	0.003	1.672	0.434	68151	14556
(lower than median)	Full-time work		−0.386	0.570						
Black or white	Part-time work	RE	−3.455***‡	1.108	12.404***	0.002	4.651*	0.098	68076	14528
	Full-time work		−1.005*	0.552						
Education	Part-time work	RE	−3.620***‡	1.074	15.264***	0.000	3.649	0.161	68149	14555
	Full-time work		−1.162**	0.536						
Difficulty with activities	Part-time work	FE	−3.815***‡	1.047	23.889***	0.000	25.539***	0.000	68144	14556
(score higher than 1)	Full-time work		−1.719***	0.512						

Table 5c ctd.

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	End. test	p-value	Ove. test	p-value		
Self-rated memory	Part-time work	FE	−3.113*** ‡	1.034	3.716**	0.024	1.267	0.531	63225	14101
	Full-time work		−0.542	0.532						
Score word recall total	Part-time work	FE	−3.023** ‡	1.334	2.821*	0.060	3.364	0.186	54011	13414
(score higher than 10)	Full-time work		−0.711	0.623						
Avg. firm size	Part-time work	RE	−4.208** ‡	0.775	46.124***	0.000	3.228	0.199	53160	10248
(larger than 50 empl.)	Full-time work		−1.162*	0.640						
Avg. firm size all locations	Part-time work	RE	−5.029*** ‡	0.917	44.113***	0.000	8.898**	0.012	46601	8400
(larger than 50 empl.)	Full-time work		−1.334*	0.700						
Years of experience	Part-time work	FE	−2.597***	0.979	5.580***	0.004	3.516	0.172	68151	14556
(more than 30 years)	Full-time work		0.058	0.502						
Ever union covered	Part-time work	RE	−3.196*** ‡	0.892	16.803***	0.000	0.817	0.665	55811	10591
	Full-time work		−0.773	0.514						
Blue-collar worker	Part-time work	RE	−3.469*** ‡	1.006	20.923***	0.000	6.418**	0.040	65777	13683
	Full-time work		−0.857	0.582						
Job in tertiary sector	Part-time work	RE	−3.153*** ‡	0.902	14.286***	0.001	0.195	0.907	65687	13703
	Full-time work		−0.965*	0.545						
Undesirable work cond.	Part-time work	RE	−3.976*** ‡	0.889	35.941***	0.000	4.740*	0.093	53263	10294
(score higher than 4)	Full-time work		−1.111*	0.601						
Ever got a new job	Part-time work	RE	−2.206*** ‡	0.781	7.159**	0.028	2.622	0.270	58236	11376
	Full-time work		0.633	0.495						
Ever able to reduce hours	Part-time work	RE	−3.103*** ‡	0.710	21.650***	0.000	0.101	0.951	47807	9171
	Full-time work		−1.386**	0.572						
Ever self-employed	Part-time work	RE	−4.054*** ‡	0.650	65.312***	0.000	2.246	0.325	58342	11415
	Full-time work		−0.887*	0.538						
Ever shifted to self-empl.	Part-time work	RE	−3.083*** ‡	0.903	15.458***	0.000	0.162	0.922	58342	11415
	Full-time work		−0.739	0.513						

Notes: 1. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 2. ‡ indicates that equality of the coefficients for part-time work and full-time work is rejected at the 0.05 level. 3. Results are robust to heteroskedasticity and correlation within individuals. 4. The base outcome for the binaries part-time and full-time working is retirement. 5. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement.

Table 6: Second-stage results of models with various combinations of the instruments

Instrumental variable	Endo. var.	Estimation results		Test results			
		Coef	SE	End. test	p-value	Ove. test	p-value
Health ins., usual ret. age, empl. pension	Part-time work	−2.524***	0.661	6.198**	0.045	0.015	0.903
	Full-time work	−0.672***	0.210				
Health ins., usual ret. age, new job	Part-time work	−2.249***	0.809	4.680**	0.097	0.027	0.870
	Full-time work	−0.603***	0.233				
Health ins., usual ret. age, shift to self-empl.	Part-time work	−3.535***	0.929	5.438*	0.066	1.867	0.172
	Full-time work	−0.925***	0.263				
Health ins., usual ret. age, able to reduce hours	Part-time work	−2.699***	0.719	5.007*	0.082	1.195	0.274
	Full-time work	−0.766***	0.223				
Health ins., usual ret. age, self-empl.	Part-time work	−4.406***	0.696	10.860***	0.004	3.151	0.076
	Full-time work	−1.147***	0.220				
Health ins., firm size, union	Part-time work	−7.173***	0.864	75.548***	0.000	0.494	0.482
	Full-time work	−2.180***	0.367				
Health ins., shift to self-empl., union	Part-time work	−4.748***	0.849	33.830***	0.000	1.040	0.308
	Full-time work	−1.292***	0.216				
Health ins., undes. work cond., union	Part-time work	−6.983***	0.966	55.331***	0.000	0.330	0.565
	Full-time work	−2.082***	0.370				
Health ins., self-empl., undes. work cond.	Part-time work	−6.297***	0.582	122.151***	0.000	1.840	0.175
	Full-time work	−1.900***	0.270				
Health ins., self-empl., union	Part-time work	−6.308***	0.630	107.479***	0.000	0.203	0.652
	Full-time work	−1.787***	0.269				
Usual ret. age, firm size, undes. work cond.	Part-time work	−7.303***	0.859	78.317***	0.000	0.692	0.405
	Full-time work	−1.515***	0.305				
Usual ret. age, firm size, union	Part-time work	−7.040***	0.998	53.627***	0.000	1.003	0.317
	Full-time work	−1.425***	0.311				
Usual ret. age, shift to self-empl., union	Part-time work	−4.872***	0.987	26.299***	0.000	0.015	0.903
	Full-time work	−0.936***	0.251				
Usual ret. age, undes. work cond., union	Part-time work	−7.032***	1.241	35.530***	0.000	0.754	0.385
	Full-time work	−1.274***	0.305				
Usual ret. age, self-empl., union	Part-time work	−6.307***	0.734	81.425***	0.000	0.513	0.474
	Full-time work	−1.151***	0.246				
Health ins., usual ret. age, empl. pension, shift to self-empl.	Part-time work	−2.993***	0.595	9.714***	0.000	3.486	0.175
	Full-time work	−0.791***	0.199				
Health ins., usual ret. age, empl. pension, union	Part-time work	−2.901***	0.688	6.359**	0.042	2.018	0.364

Table 6 ctd.

Instrumental variable	Endo. var.	Estimation results		Test results			
		Coef	SE	End. test	p-value	Ove. test	p-value
	Full-time work	-0.755^{***}	0.216				
Health ins., usual ret. age, firm size, union	Part-time work	-5.520^{***}	0.969	7.923^{**}	0.019	4.601	0.100
	Full-time work	-1.452^{***}	0.297				
Health ins., usual ret. age, shift to self-empl., union	Part-time work	-3.840^{***}	0.866	5.945^{*}	0.051	2.169	0.338
	Full-time work	-0.987^{***}	0.250				
Health ins., usual ret. age, self-empl., union	Part-time work	-4.893^{***}	0.708	11.099^{***}	0.004	4.144	0.126
	Full-time work	-1.253^{***}	0.223				

Table 7: Second-stage results of both males and females

Instrumental variable	Endo. var.	Estimation results			Test results				N obs	N ind
		Model	Coef	SE	End. test	p-value	Ove. test	p-value		
Males & females										
Model 1	Part-time work	FE	−3.460***	1.076	12.910***	0.002	0.107	0.999	67382	14518
	Full-time work		−1.106***	0.282						
Model 2	Part-time work	RE	−4.853***	1.130	21.067***	0.000	1.547	0.461	73641	13083
	Full-time work		−1.283***	0.305						
Model 3	Part-time work	FE	−7.173***	0.864	75.548***	0.000	0.494	0.482	58111	11130
	Full-time work		−2.180***	0.367						
Model 4	Part-time work	RE	−6.163***	0.678	87.952***	0.000	1.109	0.292	59360	10495
	Full-time work		−1.287***	0.264						
Females only										
Model 1	Part-time work	FE	−4.243**	1.963	14.297***	0.001	1.207	0.877	27655	6157
	Full-time work		−1.392***	0.381						
Model 2	Part-time work	RE	−7.933***	2.069	15.495***	0.000	0.442	0.802	36044	6466
	Full-time work		−1.787***	0.508						
Model 3	Part-time work	FE	−9.031***	1.414	52.153***	0.000	0.402	0.526	29022	5517
	Full-time work		−2.840***	0.642						
Model 4	Part-time work	RE	−7.485***	1.003	63.066***	0.000	0.153	0.696	27802	4991
	Full-time work		−1.123**	0.489						
Males only										
Model 1	Part-time work	FE	−0.486	1.952	1.810	0.404	2.162	0.706	39727	8361
	Full-time work		−0.280	0.517						
Model 2	Part-time work	RE	−2.714**	1.206	6.783**	0.034	2.955	0.228	37597	6617
	Full-time work		−0.726**	0.356						
Model 3	Part-time work	FE	−5.111***	1.041	24.100***	0.000	1.706	0.192	29089	5613
	Full-time work		−1.515***	0.396						
Model 4	Part-time work	RE	−3.947***	0.799	25.584***	0.000	1.077	0.299	31558	5504
	Full-time work		−0.871***	0.293						

Notes: 1. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 2. ‡ indicates that equality of the coefficients for part-time work and full-time work is rejected at the 0.05 level. 3. Results are robust to heteroskedasticity and correlation within individuals. 4. The base outcome for the binaries part-time and full-time working is retirement. 5. The retirement ages are 62 for early retirement, between 65 and 67 for normal retirement (depending on cohort) and 70 for late retirement.