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Short and long-term change in subjective well-being among voluntary and involuntary retirees

Márta Radó[a,b,*], Michaël Boissonneault[c]

[a] MTA CSS Research Center for Educational and Network Studies (RECENS), Hungary
[b] Corvinus University of Budapest, Social Futuring Center and Institute of Sociology and Social Policy, Hungary
[c] Netherlands Interdisciplinary Demographic Institute (NIDI-KNAW)/University of Groningen, 1097 Budapest, Tóth Kálmán u. 4, The Netherlands

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ABSTRACT

This paper investigates the differential change in subjective well-being among Hungarians 0–3 years and 8–11 years following voluntary and involuntary retirement. Controlling for baseline individual characteristics is important to circumvent possible endogeneity problems between retirement and subjective well-being; however, voluntary and involuntary retirees correspond to considerably different sets of observed confounders, and thus regression models may be subject to interpolation and extrapolation bias. Here, we use genetic matching to improve the comparability of these two subgroups and approximate the conditions of a controlled experiment in which voluntary retirement is the treatment variable. The same regression model applied to the matched and the non-matched data leads to different results. However, the results obtained through the matching procedure are superior in terms of subgroups comparability and model performance. These results show that voluntary retirees have a higher level of subjective well-being than involuntary retirees not only in the short but also in the long-term, the latter contradicting our expectation that the two groups would converge over time.

Introduction

Despite having been the topics of numerous papers since at least the 1950s, research on the impact of retirement on subjective well-being is still flourishing. There now seems to be a fair amount of agreement that retirement has at the aggregate level either a neutral or slightly positive effect on subjective well-being (Henning et al., 2016; Luhmann et al., 2012; Wang et al., 2011). However, more recent research identified new questions that still lack unequivocal answers. As a recent review highlighted (Henning et al., 2016), several recent papers found a dynamic effect of retirement on subjective well-being as well as important heterogeneity between individuals. Indeed, it seems that subjective well-being may fluctuate following retirement, and that individuals with different characteristics or experiences may differ considerably concerning how they perceive their well-being following retirement.

This paper concentrates on the differential effect of voluntary and involuntary retirement on subjective well-being 0–3 years and 8–11 years following retirement. In this paper, subjective well-being is conceptualized as someone's assessment of his or her life (Diener et al., 2016). Voluntary retirees are those who prefer retirement over the continuation of their job whereas involuntary retirees are those who retire due to labor market constraints (Dorn and Sousa-Poza, 2010). With the important aging of populations in Europe and other parts of the world, actions are taken to narrow disparities in subjective well-being among older people (Zaidi et al., 2013). If involuntary retirement proves to have long-lasting consequences on subjective well-being, then actions can aim at reducing the incidence of such retirements. These actions can target the context in which the retirement transition takes place as it is thought to influence whether retirement is voluntary or not (Dorn and Sousa-Poza, 2010).

A few papers already studied the impact of involuntary retirement on subjective well-being at more than one point after the retirement transition. Gall et al. (1997) and Reitzes and Mutran (2004) considered subjective well-being at two points after the retirement transition, both finding a significant effect in the short-term and an insignificant one in the long-term. Using a rich longitudinal dataset, Bonsang and Klein (2012) measured yearly change in subjective well-being up to ten years before and ten years after the retirement transition. These authors observe an important drop in subjective well-being among involuntary retirees in the first few years following retirement, but also an almost complete recovery in the subsequent years. Other research aimed at explaining the difference in subjective well-being between voluntary and involuntary retirees. Using similar data and methods as Bonsang and Klein (2012), Albohassani and Alessie (2013) find that the

* Corresponding author at: MTA TK CSS Research Center for Educational and Network Studies (RECENS), Hungary.
E-mail address: Rado.Marta@tk.mta.hu (M. Radó).

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significant difference in subjective well-being between voluntary and involuntary retirees disappears when controlling for those who involuntary retired following unemployment. Dingemans and Henkens (2014) find that bridge employment (employment following a period of retirement) mitigate the negative effect of involuntary retirement on subjective well-being, while Hershey and Henkens (2013) found that a faster rate of decline in health among involuntary retirees explains in part their lower subjective well-being.

The present paper further examines the question of whether involuntary and voluntary retirees converge over time in terms of subjective well-being. The way it does so differs from the previous literature in at least two aspects. First, genetic matching is used on longitudinal data to test the hypotheses at hand. Previous research fitted regression models to longitudinal data controlling for baseline characteristics to avoid any endogeneity bias between subjective well-being and retirement (Bonsang and Klein, 2012; Abolhassani and Alessie, 2013; Fonseca et al., 2014). We identified two shortcomings of such approaches. First, they are subject to extrapolation bias since voluntary and involuntary retirees can differ considerably concerning their observed characteristics. Second, parametric regression models are exposed to interpolation bias, which arise from using the wrong functional form of the control variables (Ho et al., 2006; King and Zeng, 2006). We use matching to avoid these types of biases. Matching allows to increase homogeneity in a set of covariates between members of two groups that differ concerning a characteristic of interest, e.g. between voluntary and involuntary retirees. This in turn allows to approximate as much as possible the conditions of an experiment. Matching on longitudinal data was previously used to study the effect of parenthood on subjective well-being (Baetschmann et al., 2016; Balbo and Arpino, 2016; Sironi and Billari, 2013), but we are unaware of its use to study the effect of retirement on subjective well-being.

This paper further contributes to the literature by examining the case of Hungarian retirees. Traditionally, western European and north American countries have been the countries of interest when studying the effect of retirement on subjective well-being. The transition from a centrally planned state economy to a market economy had serious repercussions on the labor market in Hungary, and the spike in unemployment that followed was to a large extent absorbed by the early retirement system (Szalai, 1991). However, in the last 20 years, various policy measures aiming to extend working careers have entered into force. The official retirement age was raised from age 60 for men and age 55 for women to age 62 for both, effective in 2000 and 2008 respectively (OECD, 2015). Still, the employment rates of Hungarian men aged 60–64 were the lowest of all OECD countries during the 2001–2010 period (Ebbinghaus & Hofäcker, 2013). Although Hungary is in general terms poorer than western European countries, in comparison to the whole society the relative income position of Hungarian elderlies is one of the best in the European Union. The median earner in Hungary makes a pension which amounts to 94% of their previous earning (Szalai, 1991; Zaidi, 2011), which is to a large extent thanks to a generous state pension (OECD, 2015). This in turn means that Hungarian elderly rely comparatively little on own savings or on occupational pensions, and that very few of them work past the retirement age. At the same time, interestingly, the proportion of involuntary retirement is high in this country in comparison to other European countries (Dorn and Sousa-Poza, 2010; Kohli, 2014).

We draw two lessons from our results. First, matching provides an excellent framework for studying the effect of retirement on subjective well-being. This method increases considerably the comparability of the two sub-samples, thus reducing the risk of extrapolation and interpolation bias. Second, contrary to our expectation, the conditions in which retirement takes place does have long lasting effects on subjective well-being. This warrants efforts for either reducing the incidence of involuntary retirement or promote the mechanisms that dampens the negative effects of involuntary retirement on subjective well-being.

The paper is organized as follow. The second section presents the theoretical framework. The third section presents the data, including some descriptive results. The fourth section presents the matching method. The fifth section presents results from the regression model as performed on the whole sample and compares them to results of the regression model performed on the matched sample. The sixth section concludes.

Theoretical background

The focus of this paper is the differential impact of voluntary and involuntary retirement on short and long-term change in subjective well-being. We are interested in the effect of the retirement transition itself, ruling out the effect of confounding variables. We expect different transition forms (i.e. voluntary and involuntary) to have different impacts on subjective well-being. Also, we suppose that this effect may differ in the shorter and longer term. In this section we make predictions about the differential evolution of subjective well-being among voluntary and involuntary retiree, 0–3 years and 8–10 after the retirement transition.

Retirement is an important transition in someone's life. This transition requires important adjustments from individuals as it affects their income, their allocation of time and their identity (Wang et al., 2011). Preparation to this transition is therefore crucial as to whether it will be successful or not. Individuals who involuntary retired possibly needed more time to adequately prepare for this transition, both financially and psychologically. A feeling of emotional distress may ensue, which in turn may reflect in people's perceived well-being (Solinge and Henkens, 2008; Wang et al., 2011). Accordingly, the majority of research that studied the effect of involuntary retirement on subjective well-being found a negative relationship (Gall et al., 1997; Reitzes and Mutran, 2004; Bonsang and Klein 2012; Dingemans and Henkens, 2014; Hershey and Henkens, 2013).

Analyses that studied change in subjective well-being following different events such as accidents and marital or professional transitions were often framed around one dominant theory, namely the set-point theory (Lucas, 2007). This theory postulates that people have an inborn, average level of subjective well-being. Although this level may vary across individuals, subjective well-being tends to remain rather constant over time for each individual. Life events may have an important short-term impact on the level of subjective well-being although convergence to original levels will occur as people adapt to their new situation.

We formulate our hypotheses based on the considerations reviewed above. First, we expect involuntary retirement to have a detrimental effect on subjective well-being in the short-term. This is in line with the frustration that may ensue following the insufficient preparation before the retirement transition. Also, we consider that after 0–3 years, subjective well-being has not yet returned to its initial level as the set-point theory predicts.

Hypothesis 1: In the short term, retirement induces a more positive change in subjective well-being among voluntary retirees than among involuntary retirees.

Our second hypothesis is based on the prediction of the set-point theory that life events do not induce long term changes in subjective well-being. We consider that 8–11 years is sufficient for people to adapt to the retirement event, and that voluntary and involuntary retirees no longer differ in terms of subjective well-being, controlling for baseline subjective well-being and the other relevant characteristics.

Hypothesis 2: Voluntary and involuntary retirees no longer differ in terms of change in subjective well-being eight to eleven years after the retirement transition.

Data and measurements

Data

The empirical base of the present research is the *Turning Points of Life Course* program (Hungarian GGS), a longitudinal survey carried out by the Hungarian Central Statistical Office. This survey was carried out in 2001, 2004, 2008 and 2012. However, well-being was not measured in 2008 thus information collected in this wave was not used. Participants who made a transition from “not retired” to “retired” between 2001 and 2004 were selected for analyses (n = 353). Out of this number, 47 observations had missing values in one or several control variables and 5 had missing values in the outcome variable. Little’s test provided a P-value of 0.001 thus indicating some problematic pattern. We imputed all the missing values for the control variables based on the given person’s non-missing responses to the other covariates. After including the imputed values for the covariates, Little’s test was rerun and showed a P-value higher than 0.05, indicating successful imputation. The imputation model was run using predictive mean matching by the help of the R package “mice” (van Buuren, 2018; Siddique and Belin, 2008). The analyses below are based on the imputed dataset but other analyses (not shown) run on the dataset without imputation yielded similar results. Those observations which had missing values in the outcome variables were dropped, bringing the effective sample size down to 348 cases.

This survey followed an initial number of 16,663 Hungarian adults born between 1922 and 1983. A limitation of the Hungarian GGS is that the sample used suffered from high sample attrition as it is often the case with longitudinal datasets. In 2012, about half of the initial sample (8103 cases) was still part of the survey. Longitudinal weights were applied to correct for selective attrition (Bartus, 2015). Despite this, there is still a possibility that involuntary retirees are underrepresented in our sample. The implications of this will be discussed in the conclusion.

Treatment variables

Not retired individuals in 2001 and retired individuals in 2004 were identified using the question “Do you receive some kind of pension?”[1]. Whether retirement was voluntary or not was measured based on three questions: (i) whether it was the respondent’s decision to retire, (ii) whether the interviewee is satisfied with the timing of retirement, and (iii) whether fear of unemployment played a role in the decision to retire. Those considered as voluntary retirees are those who (1) made the decision over their own retirement, (2) did not want to retire later and (3) did not make this decision due to fear of unemployment. All the other respondents are considered as involuntary retirees.

Overall, 48.4% of the respondents retired involuntarily. This high proportion of involuntary retirements is in line with what other studies found for this country. Kohli (2014) found that this measure was 48.1% for the years 2010/2011, while Dorn and Sousa-Poza (2010) found that it was 62.1% for the year 1997. This rate is one of the highest in comparison with those found in western but also in eastern European countries (Dorn and Sousa-Poza, 2010; Kohli, 2014). The high incidence of involuntary retirements in Hungary has been attributed to the lack of demand for workers (Dorn and Sousa-Poza, 2010; Szalai, 1991), poor labour market position (Radó, 2012), alternative commitments such as care responsibilities (Kohli, 2014) and health limitations (Kohli, 2014; Radó, 2012).

The dependent variable

Subjective well-being was measured with the question “*On an eleven-point scale, how satisfied are you with the trajectory of your life*?” This variable takes a value of 0 when someone is not satisfied at all, and a value of 10 when the person is completely satisfied. This question was asked in 2001, 2004 and in 2012, but not in 2008. The outcome variable in this paper is not subjective well-being itself, but the change in subjective well-being before and after the exposure the treatment (more about this in the methodology part). More specifically, change in subjective well-being is calculated in terms of the deviation in life satisfaction between the first and the second wave (short-term effect), and between the first and the fourth wave (long-term effect). Subjective well-being is treated as a cardinal variable as other studies have found that it makes little difference to treat it as an ordinal one instead (Ferrer-i-Carbonell and Frijters, 2004). Table 1 shows the mean scores of subjective well-being for voluntary and involuntary retirees, for each period. We see that voluntary retirees have in each wave a systematically higher level of subjective well-being than involuntary retirees. Table 1 further presents change in subjective well-being between the first and the second period, as well as between the first and the third period, for both types of retirees. This table shows that voluntary retirees have a significantly higher level of subjective well-being than involuntary retirees, both before and after retirement. However, the two groups do not differ significantly from each other in terms of change in subjective well-being, neither in the short nor the long run.

Control variables

All the control variables were measured in the first wave, before retirement. Controlling for post-treatment variables can create endogenous selection bias since these variables are often affected by the treatment variable (Elwert and Winship, 2014; Rosenbaum, 1984). For example, health has an influence on the type of retirement, but retirement also was found to affect health (Eibich, 2015). Thus controlling for post-retirement health would explain away the treatment effect. We therefore choose not to include in our models control variables that were measured after the treatment took place. Although it is unlikely, we note that this practice might create selection bias if the post-treatment variables were indeed not influenced by the treatment. To assess this problem, we ran a sensitivity analysis (See this in the Analytical Strategy part) which estimates whether our results are still significant when we take into account that certain information was left on the table (Rosenbaum, 2002a,b).

The control variables comprise individual basic characteristics (such as education, residence, sex, age, equivalent household income, satisfaction with housing, and subjective health status), pre-retirement job-related characteristics (such as labor market status, type of work, whether the respondent works in the private or state sector, whether the respondent has ever experienced unemployment, and how much the respondent enjoys working in general) and family-related characteristics (such as marital status, satisfaction with the partner, partner labor market status and the number of female children, male children and grandchildren). Subjective indicators are controlled for (including perceived standard of living and trust in the future). Subjective well-being as measured in the first wave is also included as a control variable (see further details in the methodology section). Table 2 presents the means or proportions of respondents for each value of each control variable and the corresponding standard deviations[2]. We see that involuntary retirees are less satisfied before retirement. They are also less educated and have lower pre-retirement income. Our selected sample is quite young (given the official retirement ages of 62 for men and 58 for women that were in force at the time), with the involuntary retirees being younger than the voluntary ones. Involuntary retirees unsurprisingly have poorer baseline health, have experienced unemployment more frequently and are more often blue collars.

[1] Excluding temporary pension for being a widow(er) or orphan.

[2] These values are weighten using the longitudinal sample weight.

Table 1
Difference in subjective well-being between voluntary retired and involuntary retired people (mean, standard deviation, and level of significance).

	Voluntary Retirees		Involuntary Retirees		ANOVA P-value
	Mean	SD	Mean	SD	
Subjective well-being measured in 2001 (0–3 years before retirement)	6.79	1.96	5.93	2.08	0.00
Subjective well-being measured in 2004 (0–3 years after retirement)	6.81	1.86	6.27	1.91	0.01
Subjective well-being measured in 2012 (8–11 years after retirement)	7.31	2.14	6.45	2.29	0.00
Change in subjective well-being between 2001 and 2004	0.02	2.05	0.34	2.35	0.17
Change in subjective well-being between 2001 and 2012	0.52	2.41	0.52	2.49	0.97

Analytical strategy

The present study intends to approximate as closely as possible the average treatment effect (ATE) of voluntariness of retirement on change in subjective well-being. For that, we rely on the potential outcome framework (Neyman, 1923; Fisher, 1925; Rubin 1974, 1978) and use a matching procedure to estimate causality. First, we present a discussion of the advantages of using matching over more standard approaches. Second, the matching procedure is presented in detail. The third subsection describes the estimation of the causal effects. The Sections 4–6 present some further methodological choices inherent to the present study.

Motivation

Let J denote a binary treatment variable which would take 0 if the individual retired involuntarily (control individual) between the first and the second wave and 1 if the individual retired voluntarily (treated individual) in the same period. Further, let Y_{ji}^{t} denote the potential outcome (i.e. subjective well-being) that individual i would have under j treatment at time t. The inference of such a causal relation is particularly challenging. As seen in the previous section, voluntary and involuntary retirees systematically differ from each other. Thus, any difference in subjective well-being between these two groups may also stem from other factors than the form of retirement. Previous papers applied regression models to longitudinal data including, for example, fixed or random effects to account for observed and unobserved time-invariant confounders (Abolhassani and Alessie, 2013; Bonsang and Klein, 2012; Fonseca et al., 2014).

Here, we use the regressor variable method (Allison, 1990), which is similar to fixed effects model in the sense that both estimate causality by ruling out not only the observed time variant confounders, but also the time-invariant confounding variables. This method involves a Y_i^1 lagged outcome variable as predictor and the $Y_i^2 - Y_i^1$ difference between the first and second wave as an outcome. More specifically:

$$Y_i^2 - Y_i^1 = \alpha + \beta_1 \times J + \beta_2 \times Y_i^1 + \beta_3 \times X_i^1 \quad (1)$$

where X_i^1 denotes the observable properties of individual i at time 1 and β_1 is the estimated causal effect of voluntary retirement on subjective well-being.

Using such an approach to draw causal inference may; however, lead to biased estimators (Ho et al., 2006; King and Zeng, 2006). First, interpolation bias can arise from using the wrong functional form in a parametric regression model. Second, extrapolation bias can also appear as a result of an improper overlap between the treatment and control groups (here voluntary and involuntary retirees). To avoid these biases, we use matching to select from the original dataset a more homogenous subset in terms of the control variables.

Matching procedure

The essence of matching is to assign to each ($j = 1$) voluntary retiree one or several ($j = 0$) involuntary retiree(s) who are (is) as similar as possible to the given voluntary individual in every observed control variable, except for the treatment itself (Cochran and Rubin, 1973; Ho et al., 2006; Rosenbaum and Rubin 1983, 1985; Rubin 1973, 1974). By doing this, the method aims at replicating as much as possible the conditions of an experimental design. In other words, matching aims to fit the *unconfoundedness* assumption, which states that treatment (J) is conditionally independent from the potential outcomes (Y_{1i}, Y_{0i}) given the covariates (X_i):

$$J_i \perp (Y_{1i}, Y_{0i}) | X_i \quad (2)$$

Matching may be performed using one of several procedures. The present study employed genetic matching. This method generalizes propensity score matching and the Mahalanobis distance matching. The former applies an $e_i(X_i)$ one-dimensional distance metric[3] which is the probability $P(J = 1)_i$ of treatment assignment based on the subject's X_i observable properties:

$$e_i(X_i) = P(J_i = 1| X_i) \quad (3)$$

The latter measures multivariate distance, which can be defined the following way:

$$D^{Mahalanobis}(k, l) = \sqrt{(X_k - X_l)^T \times S^{-1} \times (X_k - X_l)} \quad (4)$$

where S is the sample covariance matrix of X, and X^T is the transposition of matrix X. Although both propensity score matching and the Mahalanobis distance matching methods are widely used, in certain cases they fail to produce unbiased estimates. Therefore, it is advisable to apply these methods together; for example, in the case of genetic matching (Diamond and Sekhon, 2013; King and Nielsen, 2016; Rosenbaum and Rubin, 1985) as in this paper.

Genetic matching uses a $D^{Genetic}(k, l)$ distance measure, which is given as a transformation of the Mahalanobis metric by using the Cholesky decomposition[4] and by adding a weight parameter to each covariate:

$$D^{Genetic}(k, l) = \sqrt{(X_k - X_l)^T \times (S^{-1/2})^T \times W \times S^{-1/2} \times (X_k - X_l)} \quad (5)$$

where $S^{-1/2}$ is the Cholesky decomposition of the S covariance matrix and W is a positive definite weight matrix which contains a set of weights for each X covariate and the propensity score. Based on this $D^{Genetic}(k, l)$ distance, a genetic search algorithm[5] is used to find the matched pairs. More specifically, this algorithm relies on a loss function, which in this paper minimizes the difference between the units

[3] Although this metric is unknown in the sample, it can be estimated by logistic regression

[4] That is, $S = S^{-1/2}\left(S^{-1/2}\right)^T$, in which $S^{-1/2}$ is a lower triangular matrix with positive diagonal elements

[5] The genetic search algorithm is a strategy to run multiple *local search algorithms* in parallel. Local search algorithms initially select a starting point randomly, keeps track of the current states only and move on to the neighbouring states (i.e. local modification). Thus, these strategies optimize the solution by considering the local modifications only. By running multiple local searches at the same time, the genetic algorithm is not only able to conduct local modifications, but it can also use the combinations of the states of different local searches, which provides a better starting point for new local searches (Holland 1992; Selman & Gomes 2006).

Table 2
Control variables among voluntary and involuntary retirees.

		Voluntary retirees		Involuntary retirees	
		Mean	SD	Mean	SD
Subjective well-being		6.79	1.96	5.93	2.08
Recent perceived well-being		5.94	1.75	5.26	1.98
Sex	Male	0.51	0.51	0.47	0.5
	Female	0.49	0.51	0.53	0.50
Education	Primary	0.2	0.4	0.31	0.46
	Vocational secondary school	0.23	0.43	0.36	0.48
	General secondary school	0.33	0.47	0.26	0.44
	Tertiary	0.24	0.43	0.07	0.25
Satisfaction with housing		7.55	2.19	6.95	2.37
Age		55.18	4.92	50.73	7.19
Residence	Capital city	0.22	0.42	0.09	0.29
	Bigger city	0.24	0.43	0.15	0.35
	Smaller city	0.27	0.45	0.35	0.48
	Village	0.27	0.44	0.41	0.49
Subjective health status		7.14	2.01	5.75	2.25
Equivalent household income		75.41	87.4	51.25	67.35
Labour market status	Employed	0.77	0.43	0.66	0.48
	Entrepreneur/self-employed owner	0.13	0.34	0.09	0.28
	Unemployed	0.02	0.14	0.14	0.34
	Other non-working	0.08	0.27	0.11	0.32
Has ever experienced unemployment		0.28	0.45	0.47	0.5
Workplace	Owned by the state	0.37	0.48	0.32	0.47
	Private	0.51	0.5	0.42	0.5
	Non respond	0.12	0.33	0.26	0.44
Last (most important) work	Blue collar	0.54	0.5	0.75	0.43
	White collar	0.43	0.5	0.24	0.43
	Never had, no respond	0.03	0.16	0.01	0.09
Marital status	Single	0.05	0.22	0.05	0.22
	Married living together	0.72	0.45	0.68	0.47
	Married living apart	0.01	0.11	0.02	0.14
	Widow	0.1	0.3	0.09	0.29
	Divorced	0.12	0.32	0.16	0.37
Partner labour market status	Does not have partner	0.2	0.4	0.25	0.43
	Employed	0.32	0.47	0.34	0.48
	Entrepreneur/self-employed	0.07	0.26	0.04	0.21
	Retired	0.31	0.46	0.21	0.41
	Unemployed	0.04	0.2	0.05	0.22
	Other non-working	0.04	0.17	0.1	0.28
	Do not answer	0.02	0.14	0.01	0.1
Satisfaction with the partner	Does not have partner	0.2	0.4	0.25	0.43
	Dissatisfied	0.05	0.22	0.06	0.24
	Neutral	0.07	0.25	0.06	0.26
	Rather satisfied	0.31	0.46	0.22	0.42
	Very satisfied	0.35	0.48	0.37	0.48
	Does not answer	0.02	0.14	0.04	0.18
Number of female children		0.9	0.94	0.88	0.94
Number of male children		1.05	1.01	1.13	1.1
Number of grandchildren		0.13	0.34	0.09	0.28
Does not enjoy working	Completely disagree	0.68	0.47	0.48	0.50
	Disagree	0.13	0.34	0.25	0.44
	Rather agree	0.1	0.3	0.21	0.41
	Completely agree	0.09	0.28	0.06	0.24
Trust in the future	Completely disagree	0.06	0.24	0.08	0.27
	Disagree	0.1	0.3	0.12	0.33
	Rather agree	0.48	0.50	0.53	0.50
	Completely agree	0.36	0.48	0.27	0.44

based on the P-values from paired *t*-tests (for dichotomous variables) and Kolmogorov-Smirnov test (for multinomial and continuous variables). This research uses the default setting, which allows only one control for each treated unit. Further, by default, we allow replacement, which means that a controlled individual can be matched to more than one treated individual. After the pairs are selected, each observation receives a weight. Control units that were not matched receive a weight of zero (i.e. they are "dropped"). Further, the weights are proportional to the number of times that a unit was matched. We verify that no control unit receives too high weights by visually inspecting the distribution of matching weights in the treatment and control groups as shown in Fig. 4 in the Appendix.

A successful matching procedure demands that good balance is reached between the treatment and control groups in the sense that the treatment and control groups must randomly differ from each other in all of the covariates (Stuart, 2010)[6]. We assess whether a good balance was reached by visually comparing the propensity score distributions (See in Figs. 1–3) and descriptive statistics (Table 5) between the treated and control groups, before and after matching.

Estimation of the causal effects

Once a satisfying balance is achieved, one needs to obtain causal estimates of the effect of the treatment variable (voluntary or involuntary retirement) on the treated variable (change in subjective well-being). These estimates are obtained using the linear model described in Eq. (1). This choice may seem contradictory at first sight, since we argued above that Eq. (1) leads to biased estimators. This is indeed the case when the data set is not well-balanced, i.e. the values of the control variables corresponding to the two groups of interest have distributions that differ too much. Matching, when successful; however, significantly improves this balance and the regression model no longer needs to rely on extrapolation to obtain causal inferences. Furthermore, the parametric assumption will not create interpolation bias anymore since in the matched dataset, the treatment variable will be independent from the confounding variables (Ho et al., 2006; King and Zeng, 2006).

The model described by Eq. (1) further includes the same control variables as in the matching procedure. This may seem unnecessary as the goal of the matching procedure is to create two groups that are similar in all points except for the treatment variable (i.e. voluntary retirement). However, the matching procedure rarely succeeds in producing two perfectly similar groups. Previous research (DuGoff et al., 2014) showed that including the control variables in the model used to estimate the causal effects helps to further improve the balance between the two groups, thus making the estimation of the causal effect even less biased.

Extending matching to a longitudinal design

The matching method was originally developed for data with cross-sectional design. It is here extended to a longitudinal design, which enables us to not only control for the observed variables, but also to rule out time invariant unobserved variables (Athey and Imbens, 2006; Arpino and Aassve, 2013). This is done in two steps. First, we conduct matching on the X_i^1 and Y_i^1 covariates (measured in the first wave) only. These are measured before the exposure to the treatment; therefore, these covariates are less likely to be affected by the treatment. Second, we run the regression model (See in Eq. (1)) with regressing the difference between the pre-retirement and post-retirement outcomes ($Y_i^2 - Y_i^1$ for the short-term effect and $Y_i^4 - Y_i^1$ for the long term effect) on the same X_i^1 and Y_i^1 covariates, which were used in the matching procedure. By using longitudinal data, the unconfoundedness assumption can be extended to a longitudinal design, as follows:

$$J_i \perp (Y_{1i}^2, Y_{o1}^2) \mid X_i^1, Y_i^1 \tag{6}$$

This means in the present study that people who retired voluntarily between 2001 and 2004 are matched with individuals who retired involuntarily in the same period, but who had similar properties in 2001 (including subjective well-being). The outcome variable is the difference between the level of subjective well-being measured in 2001 and in 2004 for the short-term effect and between 2001 and 2012 for the long-term effect. Although matching was already applied to data with longitudinal designs for estimating the effect of some life events (e.g. parenthood) on subjective well-being, we are not aware of its use in the context of estimating the effect of retirement on subjective well-being. Matching was conducted using the *MatchIt* package in the R environment (Ho et al., 2006).

Use of sample weights

Sample weights play an important role in longitudinal data analysis, especially when there is significant attrition as in the sample used here. DuGoff et al. (2014) suggested that the original sampling weights should also be involved in the matching procedure if one desires to reach conclusions pertaining to the entire population[7]. They also advised the creation of a new weight variable for the regression estimation, generated as the product of the sampling weight and the matching weight. Consequently, this analysis applied the calibrated longitudinal weight calculated by the Hungarian Statistical Office (Bartus, 2015) as a sample weight.

Testing the sensitivity of the unconfoundedness assumption

Given that the estimation of causality depends on the validity of the unconfoundedness assumption (Eqs. (2) and (6)), capturing the sensitivity of this assumption is clearly important. This research employed the Rosenbaum (2002a,b) sensitivity analysis to assess to what degree our results are sensitive to unobserved factors. Rosenbaum's test relies on the parameter Γ that assumes a certain degree of departure from the unconfoundedness assumption; that is, from the random assignment of the treatment given the controlled covariates. If $\Gamma = 1$, then for every k treated individual and l control individual with the same covariates $X_k = X_l$ would have an equal chance of receiving the treatment $P(J = 1)_k = P(J = 1)_l$. If $\Gamma = 2$, then given k treated individual and l control individual with the same covariates $X_k = X_l$, the two individuals could differ in terms of the odds of receiving the treatment by as much as a factor of two (one could be twice as likely as the other to receive the treatment). The test observes how much the results are sensitive to a given quantifiable increase in uncertainty. If the results remain significant even for a high value of the Γ parameter, then there is a robust treatment effect even if the unconfoundedness assumption (Eqs. (2) and (6)) did not stand entirely and some confounders were not controlled for. This paper reports the critical value of the Γ parameter using a 90% confidence level. There is no straightforward and reliable critical Γ value which should be considered statistically valid, but DiPrete and Gangl (2004) suggest that a value of approximately 1.5 or more should be considered as robust in the field of social sciences. Sensitivity analysis was conducted using the *rbound* package, which runs in the R environment (Keele, 2010).

Results

The descriptive results presented in the data section showed similar change in subjective well-being among voluntary and involuntary retirees. In this section, we assess whether this relation holds when accounting for the different compositions of the two groups and the possible presence of endogeneity in the association between retirement and subjective well-being. First, results from the regression model are presented for the raw dataset (i.e. dataset before matching). Then, we show how matching modifies the composition of the sample used. To finish, we present the results of the regression model as performed on the matched dataset.

[6] Although a *t*-test or some other hypothesis test may seem an obvious option for testing this, it has been strongly advised against (Austin 2007; Imai King & Stuart 2008; Stuart 2010). The reasons why can be summarized the following way. First, balance is about the sample and not about the population. Second, hypothesis tests measure not only balance, but often statistical power as well.

[7] As a results, the values in the balanced improvement table (Table 5) are not weightened, but sample weight is involved as a matching variable.

Table 3
Regression coefficients for the effect of voluntary retirement (compared to involuntary retirement) on change in subjective well-being as estimated on the raw dataset (number of voluntary retirees: 177, number of involuntary retires: 171).

	Estimated coefficient	P-value
Early post-retirement period (0–3 years after retirement)	0.26	0.23
Late post-retirement period (8–11 years after retirement)	−0.04	0.86

Note: This table contains only the treatment variable; the entire analysis can be seen in Tables 6 and 7.

Raw dataset

Table 3 shows the estimated coefficients associated with the effect of voluntary retirement (reference: involuntary retirement) on subjective well-being 0–3 years and 8–11 after retirement as estimated by Eq. (1). The detailed results of these models, including the coefficients of all the control variables, are presented in the appendix (See Tables 6 and 7). The coefficients associated with both the early and the late post-retirement periods are insignificant. This suggests that voluntary and involuntary retirees experience similar change in well-being following retirement This result is at odds with the majority of the previous research which applied similar methods (Gall et al., 1997; Reitzes and Mutran, 2004; Bonsang and Klein, 2012; Dingemans and Henkens, 2014; Hershey and Henkens, 2013).

Fig. 1 shows the distribution of the propensity scores among the voluntary and the involuntary retirees in the whole dataset. The propensity scores correspond to the predicted probability that a given individual receives the treatment based on his or her characteristics (See Eq. (3)). Regarding this study, someone's propensity score is the probability that he or she retires voluntarily given this person's pre-retirement characteristics. Fig. 1 shows the poor balance between voluntary and involuntary retirees. As it was argued in the Analytical Strategy part, such poor balance increases the risk of biased regression coefficients. Although they used different samples, previous studies might have been subject to such bias by omitting to improve the balance between the two subgroups (Abolhassani and Alessie, 2013; Barrett and Kecmanovic, 2013; Bonsang and Klein, 2012).

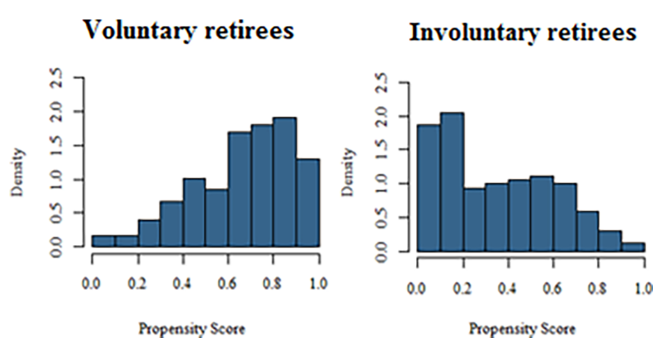

Fig. 1. The distribution of propensity scores for voluntary retires and involuntary retires on the raw dataset. The propensity scores here refer to the probability of retiring voluntarily based on the subject's observable properties (See Eq. (3)).

Matched data

As argued above, matching was performed to improve the balance in propensity scores between voluntary and involuntary retirees. The matching procedure identified a total of 246 retirees (177 voluntary) who satisfied the matching criteria. Thus, matching significantly reduced the sample size compared to the pre-matching state (348 observations). However, in case of matching, only the initial dataset needs to be sufficiently large. Unbiased estimates can also be obtained using an even smaller set of matched data provided that it is well balanced. Fig. 2 shows how matching modified the balance in propensity scores between involuntary and voluntary retirees. It shows a significant improvement in balance compared to the initial dataset (shown in Fig. 1), thus reducing the exposition to extrapolation bias. The improvement in balance in all covariates is to be seen in Table 5 and Fig. 3 of the Appendix.

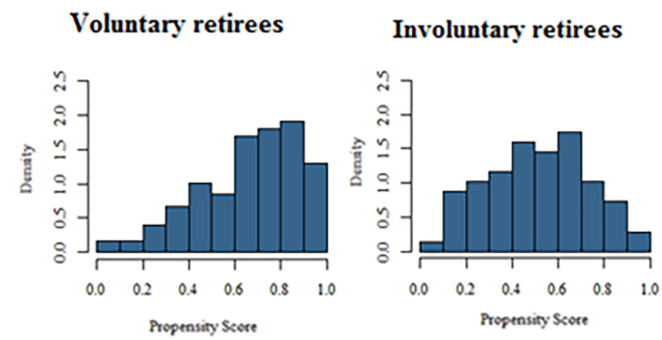

Fig. 2. The distribution of propensity scores for voluntary retires and involuntary retires on the matched dataset. The propensity scores here refer to the probability of retiring voluntarily based on the subject's observable properties (See Eq. (3)).

Table 4 shows the results of the regression model as performed on the matched dataset. The coefficients associated with the control variables are to be found in the Appendix (see Tables 6 and 7). These; however, do not have the same meaning as in a regular regression model and there is a little interest in analyzing them. Concentrating on the effect of voluntary retirement on change in subjective well-being, the results show a significantly positive effect for both periods (See the treatment effects in Table 4). Voluntarily retirement (compared to involuntary retirement) increases the level of subjective well-being by 0.66 units in the short-run and by 0.56 unit in the long-run. The short-term effect is similar or higher than previous research suggested[8], whereas the long-term effect found here is higher than what was found in previous studies. The positive, significant effect associated with voluntary retirement was expected concerning the early post-retirement period. Contrary to our expectation; however, this effect remains significant 8 to 11 years after retirement thus contradicting the set-point theory. However, this long-term effect is less than it is 0–3 years after retirement, thus some adaptation to retirement might indeed occur.

Rosenbaum (2002a,b) sensitivity analysis was used for bounding the estimates of the treatment effect. The Γ parameter is 1.5 concerning the short-term effect and 1.1 concerning the long-term effect. In case of a robust result, this parameter should be around 1.5 or even higher (DiPrete and Gangl, 2004). Thus, concerning the short-term effect, the value suggests that it is unlikely that an unobserved difference in covariates would change the inference. In the case of the long-term effect; however, the Γ parameter suggests that the results are more sensitive to

[8] Albohassani and Alessie (2013) found a very small and insignificant effect for voluntary retirement (-0.038) and involuntary retirement (-0.145), whereas Bonsang and Klein (2012) found that voluntary retirement increases subjective well-being by 0.147 units and involuntary retirement significantly decreases it by -0.526 units.

Table 4
Regression coefficients for the effect of voluntary retirement (compared to involuntary retirement) on change in subjective well-being as estimated on the matched dataset (number of voluntary retires: 177, number of involuntary retires: 69).

	Estimated coefficient	P-value	Γ
Early post-retirement period (0–3 years after retirement)	0.66	0.01	1.5
Late post-retirement period (8–11 years after retirement)	0.56	0.03	1.1

Note: This table contains only the treatment variable; the entire analysis can be seen in Tables 6 and 7.

unobserved confounders as its value is below 1.5.

Conclusion

This study investigated the differential effect of voluntary and involuntary retirement on change in subjective well-being 0–3 and 8–11 years following retirement. Two hypotheses were tested: first, that change in well-being would be more positive among voluntary retirees than among involuntary retirees in the short term; second, that change in well-being would be similar again between the two groups in the long-term. Although previous papers that tested such hypotheses proposed regression models that usually controlled for selection bias and unobserved time-invariant heterogeneity, their results were exposed to interpolation and extrapolation bias. To rule out such bias, we tested the hypotheses at hand by applying matching and compared our results to results obtained from a more conventional approach. The results obtained from the conventional approach did not provide any significant difference in well-being between voluntary and involuntary retirees in neither the short nor the long term. However, the results obtained from the matching approach showed a significant difference in subjective well-being in both the short and the long-term.

Our results add up to the extant body of research that tested the set-point theory following different life events. The set-point theory previously received support concerning events such as parenthood and widowhood (Lucas et al., 2003; Clark et al., 2008). Lack of support was found concerning other events such as unemployment (Lucas et al., 2004). Authors such as Lucas et al. (2004) and Clark et al. (2008) have suggested that although set-point theory seems to make correct predictions in many cases, there are some events – like unemployment – that seem to permanently alter the level for the set point. At the hand of our results, it seems that involuntary retirement belongs to this category of events. In fact, as formulated in the theory section, we expected that subjective well-being would be lower immediately following involuntary retirement because of a lack of preparation in front of this involuntary transition. This explanation would; however, also mean that as time passes, people would eventually entirely adapt to their new situation. Clearly, the empirical evidence found in this paper does not support this claim. However, adaptation does seem to occur to a certain extent as the difference in change in subjective well-being between voluntary and involuntary retirees declines over time. But adaptation alone does not explain change in subjective well-being following involuntary retirement. More research will be needed to examine through which mechanisms the levels of subjective well-being is altered among involuntary retirees.

This paper is the first one in our knowledge to apply a matching method to study the impact of retirement on subjective well-being in a longitudinal setting (see Nikolova and Graham, 2014 for a similar study using cross-sectional data). This method is considered superior to more traditional regression approaches in that it mimics the conditions of a controlled experiment. As we argued above, voluntary and involuntary retirees differ considerably in terms of their observed characteristics. Estimators obtained from models performed on an unbalanced dataset are therefore subject to interpolation and extrapolation bias. The result section showed not only that matching improves considerably the comparability of voluntary and involuntary retirees in terms of their observed characteristics, but also that different results can be arrived at when using the two methods. This can have important implications for how to approach the problem. Indeed, previous papers concluded that voluntary and involuntary retirees converged over time in terms of change in subjective well-being (Bonsang and Klein, 2012; Gall et al., 1997; Reitzes and Mutran, 2004). Using matching, we showed that this was not necessarily the case, although we used data from a different context. Future research should therefore consider using matching to verify to which extent these different results are due to the different methods used or to the different contexts in which the studies took place.

Our results further raised some substantive implications for the Hungarian pension system. We found that voluntary retirees fare better in the short-term and that their advantage seems to persist even after 8 years or more of retirement. Therefore, our results suggest that the retirement transition, when negative, can have long-lasting consequences for subjective well-being in old age. Policies that aim at improving subjective well-being among older people should address the determinants of involuntary retirement. Considering the Hungarian context – including a higher rate of involuntary retirements than in most western European countries (Dorn and Sousa-Poza, 2010; Kohli, 2014) –, the fact of providing more flexibility in terms of when people may choose to retire could diminish the proportion of involuntary retirements. However, such measure should not be taken at the expense of higher unemployment rates among older people, which are also known to be high in Hungary (Micheel et al., 2011). Furthermore, providing retirees with supplementary government benefits or possibilities for bridge-work could dampen the negative effect of involuntary retirement (Dingemans and Henkens, 2014).

There were; however, some limitations to our approach. Although matching aims at reproducing as closely as possible the conditions of a controlled experiment, the validity of the results still depend on whether the model is sufficiently robust against unobserved confounders. The tests that we provided showed that although the short-term treatment effect was robust against unobserved variables, the long-term effect was more sensitive. Future studies should be in state of obtaining less sensitive results by using datasets that contain more observations than the one used here. Also, although a wide range of variables was available for controls when performing the matching procedure, some potentially important covariates such as the work-life balance could not be included. Furthermore, data at more points in time could have provided a more complete picture of change in subjective well-being following voluntary and involuntary retirement.

Another limitation of this research is that the sample used suffered from high sample attrition as is often the case with longitudinal datasets. This may have introduced some bias in our estimations. In order to mitigate this effect, we applied longitudinal weights, which is partially able to remove the bias caused by sample attrition. The main source of sample attrition was nonresponse. Based on previous research (Bartus, 2015), nonresponse was lower in case of elderlies (which is our target population in this study) compared to the whole population. However, our analyses may have suffered from higher than average attrition due to death. We know that those who have a lower social status and lower subjective well-being tend to die earlier. Therefore, inequalities could be underestimated over time due to sample attrition. As a result, although we may have underestimated the treatment effect, our conclusion that involuntary retirement lastingly worsens subjective well-being should still stand.

Acknowledgment

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Appendix A

See Figs. 3 and 4 and Tables 5–7.

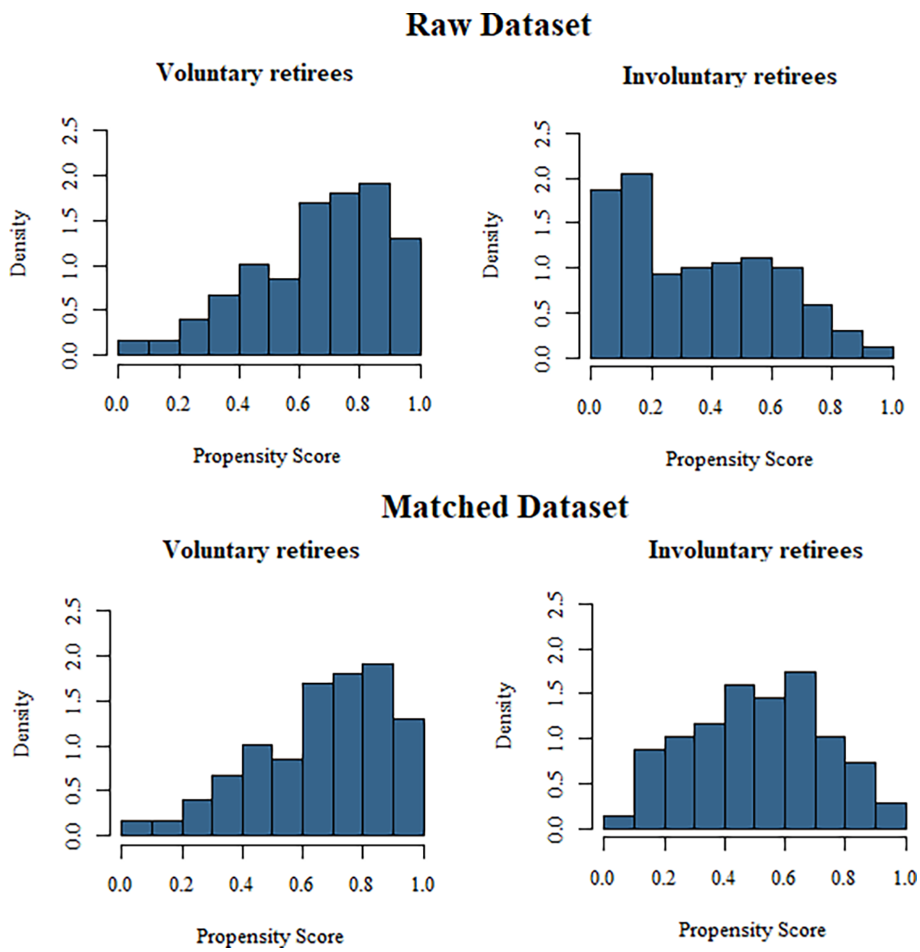

Fig. 3. The distribution of propensity scores for voluntary retires and involuntary retires on the raw and matched datasets. The propensity scores here refer to the probability of retiring voluntarily based on the subject's observable properties (See Eq. (3)).

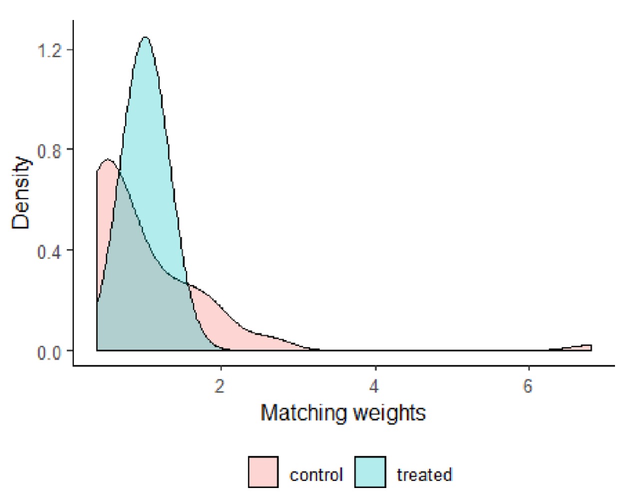

Fig. 4. Histogram for the matching weights in the control (involuntary retirees) and treatment (voluntary retirees) group. Surfaces show that weights do not take very extreme values, thus the results are based on a sufficient number of observation.

Table 5
Balance improvement in matching involuntary retirees to voluntary retirees.

		Raw Data				Matched data	
		Treatment		Control		Control	
		Mean	SD	Mean	SD	Mean	SD
Distance		0.67	0.22	0.35	0.25	0.63	0.23
Satisfaction with life		6.78	1.95	6.03	2.08	6.66	1.69
Recent perceived well-being		6.00	1.76	5.27	1.99	6.16	1.54
Sex	Male	(R)	(R)	(R)	(R)	(R)	(R)
	Female	0.50	0.50	0.53	0.50	0.54	0.50
Education	Primary school	(R)	(R)	(R)	(R)	(R)	(R)
	Vocational secondary school	0.23	0.42	0.35	0.48	0.25	0.44
	General secondary school	0.32	0.47	0.27	0.44	0.34	0.48
	Tertiary school	0.26	0.44	0.08	0.27	0.23	0.42
Satisfaction with housing		7.54	2.21	6.96	2.40	7.58	2.15
Age		55.28	4.82	50.94	7.05	54.47	3.78
Residence	Capital city	(R)	(R)	(R)	(R)	(R)	(R)
	Bigger city	0.25	0.43	0.16	0.37	0.20	0.41
	Smaller city	0.28	0.45	0.35	0.48	0.24	0.43
	Village	0.25	0.43	0.41	0.49	0.31	0.46
Subjective health status		7.12	2.00	5.74	2.30	7.18	1.68
Equivalent household income		79.33	97.06	50.54	60.15	62.67	33.52
Labour market status	Employed	(R)	(R)	(R)	(R)	(R)	(R)
	Self-employed	0.14	0.34	0.09	0.29	0.07	0.25
	Unemployed	0.02	0.13	0.13	0.34	0.01	0.08
	Other non-working	0.08	0.27	0.11	0.31	0.06	0.24
Has ever experienced unemployment		0.27	0.44	0.46	0.50	0.25	0.44
Workplace	Owned by the state	(R)	(R)	(R)	(R)	(R)	(R)
	Private	0.50	0.50	0.43	0.50	0.56	0.50
	Non respond	0.11	0.32	0.25	0.43	0.07	0.26
Last (most important) work	Blue collar	(R)	(R)	(R)	(R)	(R)	(R)
	White collar	0.45	0.50	0.24	0.43	0.46	0.50
	Never had. no respond	0.02	0.15	0.01	0.11	0.02	0.13
Marital status	Single	(R)	(R)	(R)	(R)	(R)	(R)
	Married living together	0.75	0.44	0.71	0.46	0.77	0.43
	Married living apart	0.01	0.11	0.02	0.13	0.01	0.11
	Widow	0.11	0.32	0.09	0.29	0.11	0.32
	Divorced	0.10	0.30	0.14	0.35	0.09	0.29
Partner labour market status	Does not have partner	(R)	(R)	(R)	(R)	(R)	(R)
	Employed	0.33	0.47	0.36	0.21	0.33	0.47
	Self-employed	0.07	0.26	0.05	0.11	0.05	0.21
	Retired	0.31	0.46	0.22	0.41	0.37	0.49
	Unemployed	0.04	0.20	0.05	0.22	0.02	0.13
	Other non-working	0.03	0.17	0.09	0.28	0.02	0.15
	Do not answer	0.03	0.13	0.02	0.11	0.02	0.13
Satisfaction with the partner	Does not have partner	(R)	(R)	(R)	(R)	(R)	(R)
	Dissatisfied	0.05	0.22	0.06	0.24	0.03	0.17
	Neutral	0.07	0.25	0.08	0.27	0.03	0.18
	Rather satisfied	0.31	0.46	0.23	0.42	0.41	0.49
	Very satisfied	0.36	0.48	0.38	0.49	0.32	0.47
	Does not answer	0.02	0.13	0.04	0.18	0.02	0.13
Number of female children		0.92	0.95	0.89	0.94	0.80	0.72
Number of male children		1.08	1.01	1.15	1.10	0.93	0.81
Number of grandchildren		0.13	0.34	0.09	0.29	0.12	0.33
Does not enjoy working	Completely disagree	(R)	(R)	(R)	(R)	(R)	(R)
	Disagree	0.14	0.34	0.24	0.43	0.12	0.33
	Rather agree	0.10	0.30	0.21	0.41	0.07	0.26
	Completely agree	0.08	0.28	0.06	0.24	0.06	0.23
Trust in the future	Completely disagree	(R)	(R)	(R)	(R)	(R)	(R)
	Disagree	0.10	0.30	0.12	0.33	0.06	0.23
	Rather agree	0.49	0.50	0.51	0.50	0.04	0.20
	Completely agree	0.36	0.48	0.28	0.45	0.47	0.50
Sample weights		0.98	0.17	1.04	0.21	0.95	0.18

Table 6
Regression models about the effect of voluntariness retirement on change in life satisfaction between 2001/2002 and 2004/2005 (coefficients and significances[9]).

		Raw data correlation		Raw data regression adjustment		Matched data regression adjustment	
(Intercept)		4.50	***	4.04	**	1.95	
Voluntariness of retirement		**0.21**		0.26		0.66	**
Satisfaction with life		−0.73	***	−0.86	***	−0.74	***
Recent perceived well-being		0.15	**	0.14	**	0.05	
Sex	Male			(R)		(R)	
	Female			−0.11		−0.01	*
Education	Primary school			(R)		(R)	
	Vocational secondary			−0.08		−0.58	
	General secondary			0.21		−0.06	
	Tertiary school			0.39		−0.11	
Satisfaction with housing				0.06		0.14	**
Age				−0.01		0.04	*
Residence	Capital city			(R)		(R)	
	Bigger city			0.57	*	0.76	**
	Smaller city			0.14		0.24	
	Village			−0.10		−0.13	
Subjective health status				−0.02		−0.14	**
Equivalent household income				0.00		0.00	
Labour market status	Employed			(R)		(R)	
	Self-employed			−0.42		−0.77	**
	Unemployed			−0.25		−1.16	
	Other non-working			0.18		−0.11	
Has ever experienced unemployment				−0.68	***	−0.42	
Workplace	Owned by the state			(R)		(R)	
	Private			−0.32		−0.21	
	Non respond			−0.05		−0.22	
Last (most important) work	Blue collar			(R)		(R)	
	White collar			−0.15		−0.48	
	Never had. no respond			−0.81		−0.54	
Marital status	Single			(R)		(R)	
	Married living together			0.72		0.51	
	Married living apart			0.67		0.79	
	Widow			0.40		0.39	
	Divorced			0.77		1.09	
Partner labour market status	Does not have partner			(R)		(R)	
	Employed			0.07		0.78	
	Self-employed			0.09		0.77	
	Retired			0.16		0.95	
	Unemployed			0.47		1.75	
	Other non-working			0.42		1.38	
	Does not answer			1.15		−0.22	
Satisfaction with the partner	Does not have partner			(R)		(R)	
	Dissatisfied			−0.35		−0.83	
	Neutral			−0.41		−0.82	
	Rather satisfied			0.13		−0.10	
	Very satisfied			0.40		0.07	
	Does not answer			−0.39		2.34	
Number of female children				0.23	*	0.15	
Number of male children				0.01		0.13	
Number of grandchildren				0.26		0.32	
Does not enjoy working	Completely disagree			(R)		(R)	
	Disagree			0.69	***	0.27	
	Rather agree			0.45		−0.16	
	Completely agree			−0.25		−0.09	
Trust in the future	Completely disagree			(R)		(R)	
	Disagree			−0.44		−0.36	
	Rather agree			−0.58		−0.23	
	Completely agree			−0.21		0.04	
Sample weights				0.80		−0.40	

[9] The level of significance: *** < 0.001, ** < 0.05, * < 0.1

Table 7
Regression models about the effect of voluntariness retirement on change in life satisfaction between 2001/2002 and 2012/2013 (coefficients and significances[10]).

		Raw data correlation		Raw data regression adjustment		Matched data regression adjustment	
(Intercept)		5.05	***	3.52	**	−0.21	
Voluntariness of retirement		**0.38**	*	−0.04		0.56	**
Satisfaction with life		−0.67	***	−0.85	***	−0.78	***
Recent perceived well-being		0.03	*	−0.08		−0.04	
Sex	Male			(R)		(R)	
	Female			0.11		0.06	
Education	Primary school			(R)		(R)	
	Vocational secondary			0.37		−0.25	
	General secondary			0.99	**	0.77	
	Tertiary school			1.30	**	0.49	
Satisfaction with housing				0.09		0.08	
Age				0.02		0.04	
Residence	Capital city			(R)		(R)	
	Bigger city			0.56		0.44	
	Smaller city			0.54		−0.15	
	Village			0.46		−0.24	
Subjective health status				0.13	**	0.04	
Equivalent household income				0.01	*	0.00	
Labour market status	Employed			(R)		(R)	
	Self-employed			0.33		0.24	
	Unemployed			−0.92		−1.79	
	Other non-working			−1.73	*	−0.01	
Has ever experienced unemployment				−0.83	**	−1.04	***
Workplace	Owned by the state			(R)		(R)	
	Private			0.45		0.56	*
	Non respond			1.87	**	0.13	
Last (most important) work	Blue collar			(R)		(R)	
	White collar			0.07		0.05	
	Never had. no respond			0.12		0.56	
Marital status	Single			(R)		(R)	
	Married living together			1.04		2.63	**
	Married living apart			1.06		3.36	**
	Widow			0.24		0.56	
	Divorced			0.35		1.18	
Partner labour market status	Does not have partner			(R)		(R)	
	Employed			−0.72		−4.85	**
	Self-employed			−0.86		−4.75	**
	Retired			−1.09		−5.07	**
	Unemployed			−1.07		−5.84	**
	Other non-working			0.08		−3.36	
	Does not answer			−4.66	*	−4.66	*
Satisfaction with the partner	Does not have partner			(R)		(R)	
	Dissatisfied			0.67		3.32	
	Neutral			1.07		3.72	*
	Rather satisfied			1.06		3.70	*
	Very satisfied			0.04		4.16	*
Number of female children				0.01		0.04	
Number of male children				−0.16		0.08	
Number of grandchildren				−0.24		0.05	
Does not enjoy working	Completely disagree			(R)		(R)	
	Disagree			−0.05		0.02	
	Rather agree			0.46		−0.41	
	Completely agree			0.07		0.08	
Trust in the future	Completely disagree			(R)		(R)	
	Disagree			−0.68		−0.88	
	Rather agree			−0.10		0.38	
	Completely agree			0.15		0.41	
Sample weights				−0.97		1.53	

[10] The level of significance: *** < 0.001, ** < 0.05, * < 0.1.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeoa.2018.11.003.

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