Light at the End of the Tunnel - Unemployment and Mental Health after Age 50

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Abstract

Recent economics literature reports a U-shape in mental health over the life-cycle, with mental health dipping during prime working ages. However, the U-shape (i) contrasts with the traditional psychology literature of stable mental health over the life-cycle, (ii) is criticized on methodological grounds, and (iii) is not supported by satisfying theoretical explanations – the U-shape therefore remains a mystery that requires further understanding. We find that across countries (USA, UK and continental Europe) the U-shape operates for the unemployed, whereas mental health is stable over the life-cycle for the employed. For unemployed individuals aged 50+ we find that mental health scores improve with age, thereby converging with mental health of the employed. Interestingly, across countries this convergence seems to coincide with the ages at which the fraction of retired individuals increases. We hypothesize that the labor market activity of "relevant others", such as one's peers in age, has a causal effect on mental health of the unemployed. Mechanisms for this effect are (i) the social norm to work and (ii) the value of leisure, which both depend on the fraction of peers working. Specifically, as the retirement fraction increases, the social norm to work decreases and the value of leisure for the unemployed increases, which translates in improved mental health for the unemployed. We investigate this using SHARE data on individuals aged 50+ from 11 European countries. We regress mental health (measured by the EURO-D scale) of the unemployed on the age-, country-, and wave-dependent retirement fraction and find statistically and economically significant effects (also when only exploiting within-individual variation).[1,2]

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[1]This paper uses data from the LISS panel. The LISS panel data were collected by CentERdata (Tilburg University, The Netherlands) through its MESS project funded by the Netherlands Organization for Scientific Research. More information about the LISS panel can be found at: www.lissdata.nl.

[2]This paper uses data from SHARE Waves 1, 2, 4, 5 and 6 (DOIs: 10.6103/SHARE.w1.600, 10.6103/SHARE.w2.600, 10.6103/SHARE.w4.600, 10.6103/SHARE.w5.600, 10.6103/SHARE.w6.600), see Börsch-Supan et al. (2013) for methodological details.

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1 Introduction

Keynes predicted in 1930 that by the early 21st century we might only have to work 15 hours per week. Advances in technology and productivity would allow us to increasingly substitute work hours for leisure hours. However, it seems that for most of us technological progress has not (yet) redefined our working life to the extent envisioned by Keynes. Instead, one may come to believe that over the past decades work has taken a more prominent role in how we humans define ourselves. Politicians across the political spectrum routinely claim to stand up for the rights of "hard-working families" and governments continuously redesign institutions in their attempt to optimize labor markets for economic growth. Their efforts materialize in ever-changing sets of laws and regulations to increase (female) labor market participation and reduce unemployment (e.g., through the earned income tax credit, childcare benefits, job search requirements for the unemployed, etc.). Finding oneself without work, or the prospect thereof, can be a stressful experience in such work-centered societies, with serious mental health and well-being consequences for those unable to (find) work. In this paper we provide a new perspective on how the role of work affects mental health of the unemployed. In particular we investigate how the level of labor market activity of "relevant others" (i.e. one's peers) affects mental health of the unemployed by exploiting variation in the level of labor market activity of relevant others over age, countries, and time.

Mental health problems are widespread among the general population. At any point in time 15-20% of the working age population is affected by a common mental health problem, such as anxiety or depression, and one in two people experiences mental ill-health during life (OECD, 2014). Poor mental health leads to huge direct and indirect economic costs through its negative effects on well-being, productivity, wages and employment. The (OECD, 2014) estimates that, at the country level, the annual costs of mental ill-health exceed 4% of GDP and finds that countries take insufficient measures to improve mental health and reduce the costs of mental ill-health. However, to adequately alleviate the burden of mental health we need a proper understanding of how mental ill-health is distributed among the population and what economically significant mechanisms may be targeted to improve mental health in society.

One quantitatively important pattern reported in the recent economics literature is the U-shape in mental health and well-being over the life-cycle (e.g. Blanchflower & Oswald 2008, 2016). This suggests that mental health dips during prime ages but is better among the young and old. However, this U-shape is insufficiently understood for at least three reasons. First, there are no (theoretical) explanations for such a pattern across academic fields, including economics, psychology and gerontology (Ulloa et al., 2013). Second, it contrasts with the traditional finding in psychology literature, which says that mental health and well-being are stable over the life-cycle (e.g. Lucas 2007).[3] Third, several authors contest the U-shape reported in the economics literature on methodological grounds such as the omission of individual fixed effects (Frijters & Beatton, 2012) or the inclusion of certain problematic control variables that may drive life cycle patterns (Glenn, 2009). All in all, the U-shape remains a mystery that requires further understanding.

In our own recent work (Van de Kraats et al., forthcoming) we only find the U-shape associated with involuntary labor market inactivity, such as unemployment and disability. Interestingly, this is also the socioeconomic dimension along which the largest inequalities in mental health scores appear: labor market status is strongly related to mental health, and much more so than other variables such as educational attainment, household income, or marital status. Figure 1 plots the average MHI-5 score, an index score for depression and anxiety between 0 (worst mental health) and 100 (best mental health), for Dutch men between the ages of 16-70. Mental health is fairly stable for individuals with work, but a clear U-shape is apparent for those without work. Based on this figure alone, one could expect this U-shape for the non-working to be largely driven by selection into and out of work.[4] However, when we broke this non-working

[3] Recently some psychologists have started to look into the U-shape in more detail and report patterns consistent with a U-shape over life, such as increases in positive affect and decreases in perceived stress after age 50 (Stone et al., 2010, 2017). Nevertheless, these authors consider this finding a puzzle or even a "paradox" given the increasing morbidity with advancing age.

[4] For example, at young ages the group of non-working men is large as individuals are still in school or studying, looking for first employment or frequently transitioning between jobs in their early career phase. Hence, the group is large and includes many types of individuals with a variety of mental health scores. Then, as individuals increasingly join the labor force and find (stable) jobs, the group of non-working men quickly decreases. During prime working ages primarily those who cannot work due to health reasons or who are unable to find (re-)employment are included in the non-working group. This much smaller group is prone to select individuals with bad mental health either (i) because they cannot work due to their mental health or (ii) because their mental health deteriorates upon job loss during prime working ages. Eventually, as individuals age

group further down into sub-groups consisting of the unemployed, disabled and "others" (incl. students, homemakers, (early) retirees), we found that much of the U-shape remained present for the unemployed and disabled. This pattern was persistent, especially for the unemployed, to the inclusion of time invariant individual fixed-effects, when we exploited the longitudinal dimension of the data (Van de Kraats et al., forthcoming).

The patterns found in Dutch data do not seem to be unique to The Netherlands. Figure 2 plots the fractions of individuals in the 50+ population with a mental health score indicative of clinical mental ill-health for the employed and unemployed in the USA, the UK and continental Europe next to a similar plot for The Netherlands (the latter is based on the same data as Figure 1). Here we find a similar pattern of improving mental with age for the unemployed as the fraction of depressed individuals goes down, while mental health for the employed is relatively stable. This is consistent with a U-shape in mental health for the unemployed over the life cycle and shows that the patterns found in Figure 1 are not merely driven by country-specific institutions or cohort effects in The Netherlands.

To the best of our knowledge, this U-shape in mental health specifically for the unemployed is a new finding. In the context of the larger academic debate about a U-shape in mental health and well-being, our finding begs for further explanation and analyses, as it may be instrumental in resolving the mystery of the U-shape in the current literature. Moreover, it can be informative in formulating effective labor market policy that deals with both mental health and unemployment. Hence, the question arises what actually happens to the unemployed and disabled that their mental health follows this U-shaped patterns over the life cycle. In this paper we attempt to partially answer this question by looking at the second half of the U-shape: the increases in mental health scores that unemployed individuals experience after approximately age 50.

When we inspect mental health for the 50+ population in Europe by country using data from the Survey for Health, Aging and Retirement (SHARE) we again uncover patterns consistent with the U-shape for the unemployed. Figure 3 plots the EURO-D score, a 12-item survey score on depression symptoms that runs from 0 (best mental health) to 12 (worst mental health) for 11 European countries. The figure gives the average mental health score by age in years both for the unemployed and the "non-unemployed" separately. Furthermore, we present linear fits and 95% confidence intervals of those fits for both groups. Here, we uncover the same pattern of improving mental health for the unemployed with age, while mental health for the non-unemployed is stable. Interestingly, the scores of the two groups converge as the retirement fraction increases. The only countries that deviate from this pattern are southern European countries: Spain and especially Greece and Italy. This may be partly the result of the different labor market conditions, especially during the recent economic crisis, that individuals in these countries are/were exposed to.

Overall, our plots reveal the following three stylized patterns across countries. First, mental health of the employed is stable and shows no U-shape. Second, there is a U-shape for the unemployed. Third, the mental health gap between the employed and unemployed closes after the age of 50 as individuals approach the legal retirement age, which coincides with the gradual start of the (early) retirement process in these countries. The latter is depicted by the plot of the retirement fraction in Figure 3.

Based on these patterns, we hypothesize that the extent of labor market activity of "relevant others", such as one's peers in age, has a causal effect on mental health of the unemployed. This may explain a significant portion of the U-shaped life cycle pattern of mental health for the unemployed. Probable mechanisms for this effect are: (i) the social norm to work and (ii) the value of leisure, which both depend on the fraction of peers working. Specifically, as the retirement fraction increases, the social norm to work decreases and the value of leisure for the unemployed increases, which can both translate in improved mental health for the unemployed.

In this paper we investigate this hypothesis using data from the Survey for Health, Aging and Retirement (SHARE) on individuals aged 50+ from the 11 European countries in Figure 3. For each unemployed individual we measure labor market activity of "relevant others" using the age-, country-, and wave-dependent retirement fraction. We argue that this is an exogenous measure of labor market activity of relevant others as it represent aggregate information unrelated to the unemployed individual that largely reflects labor market institutions. We regress mental health of the unemployed on the age-, country-, and year-dependent retirement fraction and find statistically and economically significant effects, also when only exploiting within-

further, an increasing number of men will choose to voluntarily leave the labor market to enjoy (early) retirement. The group of non-working individuals grows again and the inflow is likely to increase the average mental health score of this group.

individual variation using the first-difference estimator. When comparing the effect of several thresholds of the retirement fraction and their impact on mental health of the unemployed, we find that the start of the retirement process is most important in improving mental health of the unemployed. In other words, a relatively small increase in the fraction of retired individuals already impacts mental health of the unemployed.

Section 2 discusses literature relevant to our hypothesis. Section 3 incorporates our ideas in a simple model. Section 4 describes the SHARE data. Section 5 outlines the empirical methodology. Section 6 presents the results of our analyses. Section 7 concludes.

2 Literature

2.1 Unemployment and mental health

The negative association between unemployment and mental health and well-being is well-established across various academic disciplines.[5] Paul & Moser (2009) provide a meta-analysis of the effect of unemployment on mental health using 237 cross-sectional and 87 longitudinal studies. They find that the unemployed have worse mental health with a standardized mean difference estimated at $d = 0.5$, implying that unemployment is on average associated with a decrease in mental health of half the variance in the relevant mental health measure. Men are generally found to be more distressed by unemployment than women.

In the economics literature specifically, it is also well-established that the unemployed score worse on a range of mental health and well-being scores than the employed (e.g., see Björklund, 1985; A. E. Clark & Oswald, 1994; Gerlach & Stephan, 1996; Winkelmann & Winkelmann, 1998; Korpi, 1997; Hamilton et al., 1997; Blanchflower & Oswald, 2004; Knabe & Rätzel, 2011; Helliwell & Huang, 2014). Naturally, one of the main empirical challenges consists of uncovering causal mechanisms. Much of the literature - also outside economics - is mostly concerned with estimating the causal effect of unemployment on mental health. Several authors have attempted to estimate this by instrumenting the transition form employment to unemployment using exogenous firm or plant closures. The results in this literature are mixed. For example, Browning et al. (2006) finds no effect of job displacement on mental health in Denmark, Böckerman & Ilmakunnas (2009) find no effect on self-assessed health in Finland, Salm (2009) finds no effect of plant closures on health outcomes in the US, and Schmitz (2011) finds no effect on health satisfaction, mental health and hospital visits in Germany. These findings support the idea that the unemployed have worse (mental) health mainly due to selection of the unhealthy into unemployment. On the other hand, Kassenboehmer & Haisken-DeNew (2009) find negative effects of job loss on life satisfaction for German women and Kuhn et al. (2009) find that job loss increases expenditures on antidepressants and hospitalizations for mental health problems among Australian men.

2.2 Potential mechanisms behind the U-shape

Our descriptive results in Figure 3 show a convergence of mental health scores for the employed and unemployed. This pattern is consistent with to the U-shape in mental health scores that we reported in Van de Kraats et al. (forthcoming). Theoretically there are 3 reasons why a negative association between mental health and unemployment may occur: (i) a mental health deterioration may cause unemployment, (ii) unemployment may cause poor mental health, or (iii) the unemployed may simply be different people, along potentially unobserved dimensions, with worse mental health outcomes. The U-shape in the association between mental health and unemployment and the convergence of scores in Figure 3 over the life cycle then logically imply that at least one of these three relationships changes with age.

We hypothesize that an important driver of these patterns is the changing effect of unemployment on mental health with age. More specifically, we hypothesize that the extent of labor market activity of "relevant others", such as one's peers in age, has a causal negative effect on mental health of the unemployed. Thus, as a higher fraction of relevant others is employed, the larger the mental health burden we expect for the unemployed. With age, an increasing fraction of relevant others will become inactive, mainly due to (early) retirement. Consequently, mental health of the unemployed improves with age, as the retirement fraction goes up. There are (at least) three reasons why we expect this to be the case. First, the fraction of relevant

[5]The social psychology literature is one of the oldest in this respect. For example, see Eisenberg & Lazarsfeld (1938) and Jahoda (1981, 1988) for early work and Feather (1990) for a review.

others who are retired is a proxy for the "social norm to work". With a stronger social norm to work, we expect mental health of the unemployed to be more negatively affected by the social norm. This *social norm effect* is consistent with both existing theory and empirical findings as further explained in section 2.2.1. Second, when the fraction of relevant others who work decreases, there are more peers available for social interactions with unemployed individuals. As such the value of leisure for the unemployed is negatively related to the labor market activity of relevant others. This *value of leisure effect* is further explained in section 2.2.2. [Third, uncertainty around income may decrease as individuals approach legal retirement ages, which can have a positive impact on mental health.]

2.2.1 Social norm effect

According to Elster (1989, p.121) "[t]here is a social norm against living off other people and a corresponding normative pressure to earn one's income from work." Hence, unemployment is generally associated with social stigma and a loss of status as unemployment constitutes a violation of the *social norm to work*. To fully understand what we mean by this, it is useful to use a particular definition of social norms and how this can be applied to the unemployed in the case of mental health outcomes in particular. One useful definition in the economics literature is given by Fehr & Gächter (2000), who define a social norm as:

> "[...] 1) a behavioral regularity; that is 2) based on a socially shared belief of how one ought to behave; which triggers 3) the enforcement of the prescribed behavior by informal social sanction."

In the context of the labor market and mental health the idea is that: 1) individuals generally work, 2) it is commonly believed that this is appropriate behavior for able-bodied adults, and 3) a violation of this behavioral regularity implies that the unemployment suffers from a punishment in terms of mental health and well-being, providing a motivation to (search for) work. This punishment can both be driven by internal beliefs and expectations of the unemployed him-/herself, as well as a social sanction imposed by peers. The stronger the social norm of work, the larger the negative effect of nonconformity of the social norm will be for the unemployed. Or as A. Clark et al. (2010) state: "The social-norm effect suggests that, in a society in which most people work, being unemployed represents a greater deviance from the social norm and is thus harmful for the individual's social status and perceived well-being."[6]

Direct measurement of social norms for empirical analysis is difficult as it requires the ability to measure individuals' beliefs and a method to aggregate these beliefs. However, several authors take the pragmatic approach to consider behavior as a proxy of beliefs and to look at aggregate outcomes of behavior for the proxy of the prevalent social norm. For example, in their theoretical model on social norms and work incentives, Lindbeck et al. (1999) treat the social norm as an endogenously determined variable based on the number of people who receive welfare benefits. Thus they "[...]assume that to live off one's own work is a social norm, and that the larger the population share adhering to this norm, the more intensely it is felt by the individual." A similar approach is taken in empirical work, where authors often proxy the social norm to work by the unemployment rate in the locality of an unemployed individual (e.g., A. E. Clark, 2003; A. Clark et al., 2010; Powdthavee, 2007; Shields et al., 2009). The idea is that by focusing on the region of the unemployed individual, one selects an appropriate group of relevant others, and that the unemployment rate resembles labor market behavior that is a good proxy for the socially shared belief of how one ought to behave. Thus, "[a]s the number of unemployed rises, working gradually loses its normative effect, which attenuates the negative effect of unemployment on the well-being of the unemployed" (A. Clark et al., 2010). Other authors have (also) proxied the social norm in various other ways, such as, employment status of spouses or household members (A. E. Clark, 2003) regional voting results in an election on unemployment benefit (Stutzer & Lalive, 2004), and benefit receipt (Chadi, 2014).

Empirically, the notion that the unemployment rate, as a proxy of the social norm to work, has a negative effect on mental health of the unemployed receives support in psychology and medicine.[7] Cohn (1978) finds that the negative effect of unemployment on satisfaction with self is higher in areas where the

[6] Similarly, in their theoretical work Lindbeck et al. (1999) "[...]assume that to live off one's own work is a social norm, and that the larger the population share adhering to this norm, the more intensely it is felt by the individual."

[7] Theoretically the sign of such an effect is not a priori clear. For example in the medical literature, Jackson & Warr (1987) hypothesize that on the one hand higher unemployment may be associated with impoverishment, while on the other hand it may be associated with resilience of the community, e.g., through support networks.

local unemployment rate is low. Jackson & Warr (1987) and Warr et al. (1988) report similar results for mental health in the UK. However, Dooley et al. (1988) find that the prevailing unemployment rate in an unemployed's community increases psychological symptoms. Finally, Glavin & Young (2017) found support in Canadian data for a similar "social norm of insecurity" hypothesis: the mental health penalty of job insecurity is weaker for employed individuals in high-unemployment areas.

Recently, a growing empirical economics literature also recognizes the potential importance of social norm to work and investigates the effect of such a norm on mental health of the unemployed. We distinguish five relevant lines of inquiry in this literature.[8]

First, a series of papers shows a positive relation between the local unemployment rate or various other proxies of the social norm to work and mental health of the unemployed. Using data from the British Household Panel Survey (BHPS), A. E. Clark (2003) finds that in the UK mental health of the unemployed is positively correlated with measures of unemployment among three different types of reference groups: the regional unemployment rate (using 11 UK regions), unemployment of a partner and unemployment among household members.[9] The result are generally only significant for men and robust to the inclusion of individual fixed effects. Quantitatively, A. E. Clark (2003) estimates that (for prime-age men) well-being for the unemployed equates to employment at an unemployment rate of around 20%.[10] Similarly, Powdthavee (2007) finds that in South Africa unemployment hurts life satisfaction less if the local unemployment rate is high and Shields et al. (2009) report the same result for unemployed men in Australia.[11] Stutzer & Lalive (2004) take a slightly different approach as they measure the social norm to work using the regional results of a Swiss referendum on cuts in unemployment benefits. They find that in regions with a stronger norm, the unemployed suffer from a relatively larger reduction in life satisfaction.[12]

Second, A. Clark et al. (2010) build on these findings and claim that instead of distinguishing the employed from the unemployed one should in fact consider the perception of labour market risk or attachment as the "natural dividing line with respect to the social-norm effect of others' unemployment." Using German panel data on life satisfaction scores[13] they find that men with good labor market prospects are negatively affected by the regional unemployment rate, regardless of whether they are employed or unemployed themselves. On the other hand, poor-prospect unemployed men and insecure employed men are less negatively and the former are even positively affected by the regional unemployment rate.

Third, Gathergood (2013) recognizes that previous work, such as that by A. E. Clark (2003) and A. Clark et al. (2010), may suffer from an endogeneity bias: if the social norm effect exists, self-selection into unemployment may be more likely in high unemployment areas. Therefore, Gathergood (2013) investigates the social norm effect using labor market transitions whereby he instruments the transition from employment to unemployment with industry-age-year unemployment rates from the UK Labour Force Survey. Using BHPS data and unemployment rates at the country level, Gathergood (2013) replicates the result that unemployment rates are positively related to mental health of the unemployed. Quantitatively, the results are also similar to that of A. E. Clark (2003): he estimates that the negative effect of a transition to unemployment is fully mitigated at a local unemployment rate of 15%.

Fourth, Chadi (2014) argues that most previous research ignores an important channel that captures a negative effect of higher unemployment rates on the unemployed: as fewer jobs are available the prospects of leaving unemployment worsen. This in itself may have a negative impact on mental health and well-being of the unemployed. Consequently, the sign of the effect of the local unemployment rate on mental health of the unemployed is not a priori clear. Chadi (2014) therefore proposes a distinction between the unemployment rate and the norm violation at the individual level, both of which may affect mental health and well-being of individuals. He defines a norm violation as living of public funds, i.e. receiving any benefits, which may apply to both employed and unemployed individuals in most developed countries. Using German data, Chadi

[8] A related but slightly different type of work is Moffitt's (1983) finding on stigma-related disutility from participation in welfare programs. This may explain why many eligible individuals decide not to enroll in welfare programs.

[9] On the other hand, the well-being of employed individuals is negatively related to unemployment of relevant others.

[10] An alternative quantification is given by the estimation that when the unemployment rate increases from 5% to 10%, the probability of an unemployed individual reporting the maximum mental health score increases from 30.8% to 38.4%.

[11] Related, Shields & Price (2005) use a regional deprivation measure that includes the employment level and find that the unemployed in the UK suffer more in low-deprivation areas.

[12] Moreover, they find that in regions with a stronger norm the unemployed return more quickly to work.

[13] Note, this is an outcome variable that differs from mental health scores that aim to captures mood and anxiety disorders. Stone et al. (2010) show that results in the mental health and well-being literature may be sensitive to the outcome variable used.

(2014) finds result that are in conflict with previous findings: higher regional unemployment further reduces life satisfaction for the unemployed. On the other hand, norm violation "is easier to bear when more people in the reference group also deviate from the norm."

Fifth, Hetschko et al. (2014) estimate the effect of the social norm to work on life satisfaction of German unemployed individuals by investigating transitions from unemployment to retirement. They apply the identity utility framework of Akerlof & Kranton (2000) and argue that upon retirement, previously unemployed individuals switch from the social category working age to that of retirement age and thereby restore norm conformity while there are no substantial changes in their life circumstances. In their analysis they compare (i) transitions from unemployment to retirement to (ii) transitions from employment to retirement. They argue that the latter group experiences a "pure retirement effects", whereas the former experience both a social norm and a retirement effect. Hence, they claim to identify the effect of restoring norm conformity using a difference-in-difference design where they compare mental health effects of both types of labor market transitions. The effect sizes of restored norm conformity that they estimate are in the range of 0.3-0.7 on a 0-10 point life satisfaction scale (where the mean and standard deviation are 6.32 and 1.95 respectively for the unemployed prior to retirement). As in most of the papers in this literature, the significant effects are driven by men only.

We can apply the hypothesis on the social norms to work to our finding of improving mental health scores for the unemployed with age. With age, relevant others - in terms of age - increasingly retire, and thus the social norm of work changes and it becomes more acceptable to be inactive or unemployed. The experience of a change in the social norm by an unemployed individual should then translate in a direct impact on mental health and well-being of the unemployed individual. Theoretically we can capture this in a simple model based on the seminal work on social norms and identity economics by Akerlof & Kranton (2000), which we incorporate in our model in section 3.

2.2.2 Value of leisure effect

The second mechanism by which the labor market activity of relevant others can affect mental health of the unemployed is through its effect on the value of leisure for the unemployed. Leisure time and market goods are inputs in the consumption production function (Becker, 1965). However, most humans spend much of their leisure time by socially interacting with others. Thus, social contacts are arguably another important input in the consumption production function. Social interactions require synchronization of leisure time between individuals. Hence, there can be an externality to leisure time: the more leisure time one individual has, the more another individual will be able to benefit from his/her own leisure time through social interactions, and vice versa. According to this line of reasoning, a higher fraction of inactive peers creates more opportunities for social interactions and contacts with other people for the unemployed. This, in turn, should increase the (marginal) value of leisure for the unemployed, which can have a positive effect on mental health and well-being.

Empirical results support the idea that time inputs of others are important inputs in the consumption production function. For example, Kahneman et al. (2004a,b) report the highest levels of positive affect among employed women during activities that concern intimate relations and socializing with friends or family. Helliwell & Wang (2014) find that individuals experience significantly more happiness, enjoyment, and laughter, and significantly less anxiety, sadness, and anger on weekends and public holidays than on weekdays. According to these authors a large part in of this so-called "weekend effect" can be explained by the increased amount of time (on average an extra 1.7 hours per day) spent with friends or family. The sociologists Young & Lim (2014) argue that time is a "network good," as its value depends on an individual's ability to coordinate time with others. They compare social time and emotional well-being of workers and the unemployed in the US. For both groups they find that well-being increases in the weekend and drops during the workweek. Moreover, "[t]he unemployed look forward to weekends much the same as workers" and they do not gain as much from their extra free time during the workweek.

Also in the comparison of employed and unemployed individuals we find evidence for the importance of aligning leisure time. Krueger & Mueller (2012) study time use of employed and unemployed individuals in 14 countries. They observe that the amount of time that the unemployed spend socializing is 10% higher in the weekend, "possibly because it is easier to coordinate social activities with employed individuals on the weekend." Knabe et al. (2010) compare the subjective assessment of emotional affects of the employed

and unemployed in Germany. They apply the Day Reconstruction Method (Kahneman et al., 2004a,b), which allows them to consider hedonic well-being by type and duration of different activities throughout the day. They find that although the unemployed report lower life satisfaction and lower hedonic well-being in the activities they undertake, average experienced utility does not differ from the employed because the unemployed can compensate by spending more time on enjoyable activities as they don't have spend time working. For example, the unemployed spend more time socializing, which they find to be one of the highest-valued activities.

In Figure 3 we observe that improving mental health scores of the unemployed coincide with an increasing retirement rate among peers in age. As more peers retire, the number of individuals who are available for social interactions during the work week increases. Hence, the unemployed can make more effective use of their time; in other words, the marginal value of leisure time goes up. This can have a positive impact on scores of mental health and well-being.

2.2.3 Effect of social norm to work on value of leisure effect

There can also be an effect of the social norm to work on the value of leisure effect. The prevailing social norm to work may influence the extent to which the unemployed can enjoy social interactions with employed peers. It may, for example, be that employed individuals do not want to spend time with the unemployed due to their non-compliance with the social norm to work: "[i]f individuals choose to undertake less social activities with people who violate their belief on how one ought to behave, unemployed people will not enjoy leisure to the same extent in strong norm communities as in weak norm communities" (Stutzer & Lalive, 2004).

3 Theoretical model

We incorporate the two ideas from the previous section, the existence of a social norm effect and a value of leisure effect, in a simple economic model. In our set-up we let utility proxy our main outcome of interest: mental health. Although economists traditionally do not measure utility, this psychology approach has in recent years become mainstream in the growing economics literature on life satisfaction, well-being and mental health (e.g., see A. E. Clark, 2003; Kahneman et al., 2004b; Blanchflower & Oswald, 2004, 2008; Ulloa et al., 2013).

3.1 Set-up

Our model is a direct application of the theory by Akerlof & Kranton (2000) to unemployment of older workers. The theory by Akerlof & Kranton (2000) allows for a tractable analysis of social norms via identity utility. To do so, we require, in addition to the standard economic framework, three ingredients to analyze identity: social categories, norms and ideals, and identity utility.

- *Social Categories:* We begin by classifying adult individuals into two types: (i) working age individuals and (ii) retirement age individuals. We indicate social categories with $\boldsymbol{C}$. Each person j has an assignment of all individuals to the social categories $\boldsymbol{c}_j$, so that each person has a conception of her own social category and that of all other people.

- *Norms and Ideals:* We suppose that working age individuals *should* be employed. In contrast, retirement age individuals do not have to be employed but can enjoy leisure time during retirement or may choose to continue working, depending on individual preferences and the constraints of the institutional environment (e.g., enforced retirement exists in some countries). We indicate the behavior that is appropriate for people in different social categories (in different situations) with $\boldsymbol{P}$. Hence, $\boldsymbol{P}$ represents what is commonly referred to as the "social norm," i.e. the socially shared belief.

- *Gains and Losses in Identity Utility:* We suppose individuals lose utility when they fail to comply with the social norm $\boldsymbol{P}$ that corresponds to their assigned social category $\boldsymbol{c}_j$. Applied to our setting, a working age individual loses utility when he/she is not employed. A retirement age individual, on the other hand, does not lose utility from not working.

We can further formalize this using the following utility function

$$U_j = U_j(\boldsymbol{a}_j, \boldsymbol{a}_{-j}, I_j), \tag{1}$$

where $\boldsymbol{a}_j$ represent an individual's actions and $\boldsymbol{a}_{-j}$ the actions of all other individuals.[14] $U(\cdot)$ is increasing in identity I_j, which captures the individual's identity or self-image as described by the following function:

$$I_j = I_j(\boldsymbol{a}_j, \boldsymbol{a}_{-j}; \boldsymbol{c}_j, \varepsilon_j, \boldsymbol{P}). \tag{2}$$

Here ε_j represents j's own given characteristics and identity depends on these characteristics to the extent that they match the ideal of j's assigned category, indicated by $\boldsymbol{P}$. An individual j chooses actions to maximize utility, taking as given $\boldsymbol{c}_j$, ε_j, $\boldsymbol{P}$ and $\boldsymbol{a}_{-j}$.

3.2 Identity losses for the unemployed

Next, we argue that the actions of unemployed (older) individuals are themselves also constrained in an important way. In its simplest form, the individual faces the choice set for labor market activity $\boldsymbol{a}_j$ = {to work, not to work}. Thus an individual of working age would prefer to work as this increases his/her identity. However, in most/many cases unemployed older individuals are unable to find suitable work such that the choice set simply consists of $\boldsymbol{a}_j$ = {not to work}, and increasingly so as individuals age. This implies that the actions of a working age individual will not conform to the prescribed social norm and consequently the individual suffers a loss in identity utility.

3.2.1 Social norms to work and age

In reality the social norm to work (or not to work) is often not as black and white as described above. The actions of individuals ($\boldsymbol{a}_j$ and $\boldsymbol{a}_{-j}$) are likely to directly feed into the commonly held believes of what appropriate behavior constitutes. Then, the decisions of individuals to engage in work determines, to an important extent, the social norm of who is expected to work in which situation, captured by $\boldsymbol{P}$. One important dimension along which this norm is likely to vary is age; the expectation of an individual working is especially strong during prime-age.

Hence, it seems intuitive that the social norm to work changes gradually as individuals approach the retirement phase of life and the fraction of age-peers choosing (early) retirement increases. This retirement behavior, which from the unemployed individual's perspective is the behavior of others $\boldsymbol{a}_{-j}$, is likely to affect the social norm $\boldsymbol{P}$, so that with age it becomes increasingly accepted that individuals are no longer working. Hence, we can distinguish a more finally grained number of social categories $\boldsymbol{C}$ and corresponding social norms $\boldsymbol{P}$. With increasing age, individuals may gradually move from the social category "working age" to that of "retirement age", and as they do so the social norm to work is gradually reduced. Consequently, the deviation from the norm and the corresponding loss in identity utility are reduced when an unemployed individual shifts his/her own assigned social category with age. This may have a direct impact on mental health.

Besides the mentioned punishment in identity utility driven by own internal beliefs of what constitutes socially appropriate behavior, an unemployed individual may also suffer a loss in identity utility through "direct sanctions" imposed by peers. For example, being confronted with one's unemployment in social interactions and the inability to comply with the social norm can negatively affect identity. In most western societies it is common to ask someone what he/she does for a living when getting first acquainted. The inability to give a socially desirable answer[15] to a question of another individual ($\boldsymbol{a}_{-j}$) may negatively impact identity (I_j) and thereby reduce identity utility for the unemployed: $\frac{\delta U_j}{\delta I_j}\frac{\delta I_j}{\delta \boldsymbol{a}_{-j}} < 0$.

3.3 Marginal value of leisure

By incorporating actions of all other individuals $\boldsymbol{a}_{-j}$ in the utility function we also capture the idea that the marginal value of leisure time depends on social interactions. This externality can be an important driver of

[14] "Since $\boldsymbol{a}_j$ and $\boldsymbol{a}_{-j}$ determine j's consumption of goods and services, these arguments in $U(\cdot)$ are sufficient to capture the standard economics of own actions and externalities" (Akerlof & Kranton, 2000).

[15] Or perhaps even an urge to lie about one's labor market status.

improved mental health and well-being for the unemployed as their peers start to retire. The utility derived from leisure activities increases as leisure time can increasingly be spent with others: $\frac{\delta U_j}{\delta \boldsymbol{a}_{-j} \delta \boldsymbol{a}_j} < 0$.

4 Data

We use data from the Survey for Health, Aging and Retirement (SHARE) (Börsch-Supan et al., 2013). SHARE is a panel survey that was modeled after the Health and Retirement Survey in the US and is designed to gather data on a wide range of subjects as individuals age, including work and retirement, assets, income and consumption, health and health care utilization, family life and social networks. Currently there are 6 waves of data available for SHARE. However, the third survey wave consists of life history interviews and as such does not include mental health measures. Hence, we use waves 1, 2, 4, 5, and 6 of SHARE in this paper. We use a "harmonized" version of the SHARE data, prepared by Gateway to Global Aging Data (2017) in an effort to increase comparability of aging data-sets across the world.

The first wave of data in SHARE was collected in 2004/2005 and subsequent follow ups have been timed at approximately 2 year intervals. Data for the latest wave, wave 6, was gathered in 2015. The exact timing of a survey wave differs slightly across countries.[16]

SHARE includes a range of European countries, as well as Israel. Several, mostly Eastern European, countries have been added over the course of time so that data is not available for all countries for all waves. In this paper we limit ourselves to the set of European countries that have been included since the start of SHARE: Austria, Belgium, Denmark, France, Germany, Greece, Italy, The Netherlands, Spain Sweden, and Switzerland. This ensures that we have a sufficient number of observations in consecutive waves for each country so that we can exploit the panel dimension of the survey. Moreover, the institutions in this set of countries is more comparable to each other than to the - mostly Eastern European - countries that have been added later.

4.1 Sample restrictions and definitions

We restrict our main analyses to individuals 50-68 years old. This is the age bracket in which the retirement fraction gradually increases with age. Our cut-off of 68 is just above the maximum normal retirement age in the set of countries (see Table 4). Table 3 provides an overview of the total number of individuals interviewed by country and wave in the 50-68 age interval.

In this paper we restrict our sample to men. It is important to analyze men and women separately as it is well-established that mental health differs between men and women.[17] Moreover, the recent literature on the social norm effect generally only finds significant effects for men (A. E. Clark, 2003; A. Clark et al., 2010; Gathergood, 2013; Hetschko et al., 2014). Intuitively this makes sense, as men generally still have a stronger labor market attachment than women and as such we can expect that the social norm to work is stronger for men. A similar point applies to the value of leisure effect: during prime working ages relatively few men are at home so that the effect of an increase in the retirement fraction will be felt stronger by unemployment men than by women. This will especially be the case among the older cohorts that we focus on in this paper, who have a more traditional task division according to gender-roles.

4.1.1 Labor market definitions

For our analyses we need to classify individuals' labor market status. We use this both to select our sample of interest, the unemployed, as well as to calculate our main regressor of interest, the age-, country- and year-specific retirement rate.

It is well-established that people misreport their labour market status. This may apply especially to the unemployed, who misreport due to the social stigma surrounding unemployment. Therefore, we do not

[16] Wave 1 roughly corresponds to 2004/5, Wave 2 to 2006/7, Wave 4 to 2011/12, Wave 5 to 2013 and Wave 6 to 2015. See http://www.share-project.org/data-documentation/waves-overview.html for a precise overview of the timing of survey waves by country.

[17] For example, see the review on cross-country epidemiological data by Kessler & Bromet (2013), who report that women consistently have lifetime risk of depression roughly twice that of men.

depend on self-reported labour market status[18] but use information reported on income sources (over the past year) and hours worked per week to classify an individual as retired, employed or unemployed. We use this information to categorize individuals in the following way:

- **Retired:** retirement income $> 0 \cap$ weekly work hours < 10
- **Employed:** retirement income $= 0 \cap$ weekly work hours $\geq 10 \cap$ earnings *or* self-employment income > 0
- **Unemployed:** retirement income $= 0 \cap$ weekly work hours < 10
- **Undefined:** all others

Table 1 cross-tabulates our labor market status definition with the self-reported labor market status for men aged 50-68. Our total sample of interest for the regression analysis consists of 6,425 unemployed individuals.

4.2 Mental health score: EURO-D scale

We measure mental health using the EURO-D scale, a measure of symptoms of depression. The EURO-D scale has been developed specifically for older individuals to derive a common depression symptoms scale to compare risk profiles across European countries and health care centers (Prince et al., 1999). It is a simple 12-item screening instrument that can be easily administered in surveys such as SHARE. The 12 items consist of yes/no answers to survey questions on items related to: depression, pessimism, suicidality, guilt, sleep, interest, irritability, appetite, fatigue, concentration, enjoyment, tearfulness. A score of 1 is allocated to an item if the answer is indicative of depression (see appendix A.1 for the full description of EURO-D items and the way they are scored). The total EURO-D score is then calculated by summing over the individual items so that it ranges from 0 (best mental health) to 12 (worst mental health).

The EURO-D scale has been validated as a useful scale to screen for diagnostic criteria for depression using SHARE data (Castro-Costa et al., 2008) but also in other contexts, such as developing nations (Guerra et al., 2015). The optimal cut-off point for the prediction of depression has generally been determined at a score of 4 or higher (Prince et al., 1999; Castro-Costa et al., 2007; Fonseca et al., 2014).

Figure 4 shows the distribution of EURO-D scores for unemployed men in the pooled sample. A substantial fraction of individuals has a score of 4 or higher, indicating that they are likely to suffer from a mood disorder such as depression. Moreover, Figure 5 shows that there is substantial wave-to-wave variation in EURO-D scores.

4.3 Descriptive statistics

Table 2 provides descriptive statistics for the sample. The average age is 58.6, and 36% and 10% of unemployed men are above the early retirement and the normal retirement age, respectively. Household income is measured in Euros as the sum of all income, after any taxes and contributions, at the couple-level economic unit, i.e. the respondent and the spouse, if there is a spouse.[19]

In our analyses we control for physical health using variables that measure the number of limitations in activities of daily living (ADL) and instrumental activities of daily living (IADL). Both measures range from 0-5 and measure the number of activities that an individual reports to have "some difficultly" with. The activities of daily living consist of bathing, dressing, eating, getting in/out of bed and walking across a room. The instrumental activities of daily living consist of using the phone, taking medications, managing money, shopping for groceries, and preparing meals. Table 2 shows that men in our sample score, on average, higher on the ADL scale than on the IADL scale.

We measure educational attainment using the 1997 International Standard Classification of Education (ISCED-97) codes. Respondents reported their highest obtained degree which were mapped by educational experts to educational achievements according to the ISCED-97 codes. This results in seven categories of educational attainment, with most individuals having obtained upper-secondary education.

[18] In SHARE this is elicited using the question: "In general, how would you describe your current situation?" Individuals can then select from the following six categories: employed or self-employed, unemployed, retired, permanently sick or disabled, home maker, don't know or refuse to answer.

[19] However, for the first wave it gives income before taxes, but this measures is not available for wave 6.

Finally, we consider marital status. Marital status is after gender the most consistent and strongest correlate of mental disorder, with a higher prevalence rate of disorders for those who are divorced, separated or widowed (Kessler & Bromet, 2013; Rai et al., 2013; Weissman et al., 1996). We distinguish several categories of marital status: being married, partnered, separated, divorced, widowed and never having been married. As expected, the majority of individuals in our samples is married.

5 Methodology

The goal of our analysis is to estimate the effect of the level of labor market activity of "relevant others" on mental health of the unemployed. To that end we investigate how age-(a), country-(c) and wave-(w) related variation in the retirement fraction Ret_{it} affects mental health of the unemployed MH^U_{it}. This means that we define "relevant others" as peers in age from the same country during a particular wave of the SHARE survey. We argue that the retirement fraction is exogenous to the mental health of an unemployed individual as it depends on (i) the labor market behavior of other individuals and (ii) represents aggregate information which is arguably unrelated to a single unemployed individual.

Hence, the retirement fraction Ret_{it} is our proxy of the social norm to work. Although it is also based on aggregate labor market behavior, this measure differs from the unemployment rate as a proxy of the social norm, which is used in much of the related literature (A. E. Clark, 2003; Powdthavee, 2007; Shields et al., 2009; A. Clark et al., 2010; Gathergood, 2013). We believe that our proxy is preferred for three reasons. First, it is not dependent on the labor market status of the population of interest, the unemployed themselves, which reduces the threat of simultaneity issues. Second, since the proxy does not contain the unemployment rate nor directly relates to beliefs on the (un)desirability of unemployment or benefit receipt (as in e.g., Stutzer & Lalive, 2004; Chadi, 2014), it does not suffer from the reverse causation issue that in regions or countries with structurally high unemployment rates a weaker social norm to work may have developed.[20] Third, we expect it is a more accurate proxy of the social norm to work as it is likely to be less sensitive to business cycles than the unemployment rate. Changes in the unemployment rate are likely to influence the social norm to work with a lag as individuals need time to update their beliefs on the social norm to work. Business cycle fluctuations in the unemployment rate are therefore likely to be too quick to accurately reflect the social norm to work.

We perform two different types of analyses that use the retirement fraction as the regressor of interest: first, using a linear relationship with mental health (described in section 5.1) and second, using a step-wise function to characterize the relation between the retirement fraction and mental health (described in section 5.2).

5.1 Linear relationship

In a simple regression framework we want to estimate:

$$MH^U_{it} = \alpha + \gamma Ret_{it} + \beta X_{it} + \varepsilon_{it}, \tag{3}$$

where Ret_{it} gives the relevant age-(a_{it}), country-(c_{it}) and wave-(w_{it}) dependent retirement fraction for unemployed individual i at time t. The total SHARE survey contains $j = 1, ..., N$ individuals, out of which $i = 1, ..., M$ individuals are unemployed and thus in our sample for regression analyses. However, we use information on all j individuals to construct the retirement fraction Ret_{it}, the regressor of interest.

The retirement fraction Ret_{it} varies along three dimensions: age, country and wave. Its exact construction depends on our definition of "relevant others" along these three dimensions. In our main specification we define "relevant others" in terms of age a_{it} as those who are up to one year younger or older than the

[20] Such reverse causality is only present if we assume that for some reason mental health of the unemployed affects the retirement fraction. We cannot think of any reason why this may be the case. One may be concerned that endogeneity may occur due to omitted variables. For example, an age-specific aggregate mental health shock that affects the population of an entire country may lead to a mental health change for the unemployed and an increase in the retirement fraction. However, we do not believe this to be a serious issue, especially since the retirement fraction is increasing with age and it is reasonable to assume that a negative aggregate mental health shock leads to an increase in the retirement fraction and a worsening of mental health of the unemployed. Hence, if we find effects in the expected direction, our estimates suffer at most from a downward bias due to this issue.

unemployed subject of interest; i.e. individual j is considered to be a relevant other for unemployed individual i if $a_{it}-1 \leq a_{jt} \leq a_{it}+1$, where we measure age in years. This means we have a three year moving age band along the age dimension in the definition of the retirement fraction.[21] Furthermore, we consider "relevant others" to be individuals j who are from the same country ($c_{jt} = c_{it}$) and survey wave ($w_{jt} = w_{it}$) as individual i.[22] We let R_{jt} be an indicator variable for retirement. We construct the retirement fraction Ret_{it} by selecting "relevant others" in terms of age, country and wave, and then taking the fraction of retired individuals from that group, i.e.:

$$Ret_{it} = \frac{\sum_{j=1}^{N} \mathbb{1}(R_{jt} = 1 \cap a_{it} - 1 \leq a_{jt} \leq a_{it} + 1 \cap c_{jt} = c_{it} \cap w_{jt} = w_{it})}{\sum_{j=1}^{N} \mathbb{1}(a_{it} - 1 \leq a_{jt} \leq a_{it} + 1 \cap c_{jt} = c_{it} \cap w_{jt} = w_{it})} \tag{4}$$

Figure 8 plots the retirement fraction for each country and wave over the relevant age range. The estimated coefficient γ in equation 3 is our parameter of interest. It captures both relevant channels: (i) the social norm effect and (ii) the value of leisure effect.

One may be worried that the composition of the sample biases the obtained estimates for several reasons. First, selective mortality or attrition can influence the results. For example, one may expect that unemployed individuals with the worst mental health are likely to die first or leave the sample for other reasons. We checked this by regressing mental health scores on future attrition from the sample and found no evidence for this. Moreover, we attempt to deal with this by estimating equation 3 in first-differences, so that we can control for individual fixed effects.

Second, since we estimate equation 3 on the sample of the *unemployed only*, one may be concerned that nonrandom selection of data biases the results (Heckman, 1979).[23,24] However, since we find no reason for a relation between the retirement fraction Ret_{it} and mental health of individuals who are not unemployed, we argue that our population of interest consists of the unemployed. If this is the case, in principle we do not

[21] We prefer this definition over defining "relevant others" as those of exactly the same age in years for two reasons. First, we believe that it is reasonable that one's peers are not only individuals of the same age in years but contain individuals who are somewhat younger and older as well. Nevertheless, the existence age-dependent policies means that we should not make the age band too wide. Second, since we construct the retirement fraction Ret_{it} using SHARE survey data we should be careful not to increase the number of cells too much as this will create too much noise in our regressor of interest. Nevertheless, we test variations of our age-definition in section **??**, where we perform sensitivity analyses.

[22] We think it is reasonable to consider waves separately as countries have actively tried to changes retirement policies over the past years, mainly to increase the retirement age. As such the age-dependent retirement fraction Ret_{it} will vary across waves. This can also be seen from Figure 8, where the curves of the retirement fraction Ret_{it} generally seem to shift to the right for later waves, indicating that people retire later. Thus, by considering waves separately we can exploit the variation along this dimension. However, here there is also a clear trade-off between variation and precision: on the one hand, we want to exploit the maximum possible amount of variation in our regressor, on the other hand we need to take into account the curse of dimensionality since as we increase cells, the available data from the SHARE survey to construct the retirement fraction becomes sparse and thus less precise.

[23] The relevant literature on social norm effects on mental health and well-being (e.g. see A. E. Clark 2003; A. Clark et al. 2010; Chadi 2014) frequently includes all labor market status groups in the analyses. In these regressions mental health is, for example, regressed on an indicator variable of unemployment, the unemployment rate and an interaction term of the former two regressors. However, as pointed out by Gathergood (2013) this does not take into account endogeneity of mental health and unemployment, which can bias the estimates. Instead, we select only the unemployed for our regressions.

[24] Our population of interest consist of the unemployed. Therefore, we only select unemployed individuals in our analysis. However, this implies that our data is nonrandomly selected. We have the selection equation:

$$U_{it}^{*} = \delta_0 + Z_{it}\delta_1 + \eta_{it},$$

which indicates if the individual is unemployed or not: indicator U_{it} takes value 1 if $U_{it}^{*} > 0$ and 0 if $U_{it}^{*} \leq 0$. Hence, we only estimate our regression on the sample of unemployed individuals:

$$(MH_{it}|U_{it} = 1) = \alpha_{it} + \gamma Ret_{it} + \beta X_{it} + \varepsilon_{it}.$$

Now, unless the error terms from the two equation (η_{it} and ε_{it}) are independent or $E(\varepsilon_{it}|U_{it} = 1)$, the obtained estimates from the main regression are biased (Heckman, 1979), as we obtain:

$$\begin{aligned}(MH_{it}|U_{it} = 1) &= \alpha_{it} + \gamma Ret_{it} + \beta X_{it} + E[\varepsilon_{it}|U_{it} = 1] \\ &= \alpha_{it} + \gamma Ret_{it} + \beta X_{it} + E[\varepsilon_{it}|\eta_{it} > -\delta_0 - Z_{it}\delta_1] \\ &= \alpha_{it} + \gamma Ret_{it} + \beta X_{it} + +\rho\sigma \frac{\phi(-\delta_0 - Z_{it}\delta_1)}{\Phi(-\delta_0 - Z_{it}\delta_1)},\end{aligned}$$

where the term $\phi(-\delta_0 - Z_{it}\delta_1)/\Phi(-\delta_0 - Z_{it}\delta_1)$ is the Inverse Mills Ratio.

have a nonrandom sample and data selection induced bias is only a concern to the extent that individuals are able to self-select into labor market status groups such as unemployment. A particular concern may then be that the regressor of interest, the retirement fraction Ret_{it}, is found to be statistically significant in equation 3, while in reality it is only a determinant of selection into unemployment but not of mental health (i.e. it should only belong in the selection equation, not in the main regression). For example, this can be the case if institutions are such that entering unemployment becomes relatively easier simultaneously with easier entry into retirement. However, we consider it reasonable that the probability of unemployment goes down when retirement incentives kick in. Moreover, we attempt to control for such selection issues as much as possible by exploiting the longitudinal dimension of our data using the first-differences estimator.

Third, one may be concerned that labor market institutions and conditions vary across countries in the sample. Hence, the type of unemployed individuals may differ across countries. We try to control for by including country dummies in cross-sectional OLS estimations and individual fixed-effects when we exploit the longitudinal dimension of the data. In this way the time invariant differences between countries are controlled for. Moreover, this allows us to control for fixed differences in mental health outcomes and/or survey response between countries.

5.2 Step-wise relationship

Equation 3 assumes a linear relationship between the retirement fraction and mental health. Although this a is a conventional microeconometric approach, this is an arbitrary assumption. In our setting one can imagine that increases in the retirement fraction Ret_{it} are especially important for mental health of the unemployed at relatively low levels of the retirement fraction Ret_{it}. For example, the value of leisure effect can already be noticed when some peers retire. Alternatively, one can imagine that the social norm to work changes more quickly when the retirement process begins than when almost all individuals have retired from the labor force. Also, individuals may only be able to observe crude variation in the retirement fraction among peers so that they update their beliefs on the social norm to work only at thresholds values of the retirement fraction.

To incorporate these ideas, we define an alternative specification of our regression function. We approach the retirement fraction using a step-wise age function. We take threshold values for the retirement fraction and for each country we determine the ages at which the threshold values are crossed for the first time. For example, we start by taking the threshold values at 33%, 67% and 90%. We indicate the corresponding ages with Age_{33}, Age_{67} and Age_{90}. Next, we create indicator variables for each of the thresholds. For example, the indicator variable $\mathbb{1}(\text{Age}_{33} \leq \text{Age}_{it} < \text{Age}_{67})$ is set to 1 if an individual's age is equal to or greater than Age_{33} and smaller than Age_{67} and 0 otherwise. We can then estimate the following regression:

$$\begin{aligned} MH_{it}^{U} = \alpha + \gamma_1 \mathbb{1}(\text{Age}_{33} \leq \text{Age}_{it} < \text{Age}_{67}) + \gamma_2 \mathbb{1}(\text{Age}_{67} \leq \text{Age}_{it} < \text{Age}_{90}) \\ + \gamma_3 \mathbb{1}(\text{Age}_{it} \geq \text{Age}_{90}) + \beta X + \varepsilon_{it} \end{aligned} \tag{5}$$

The choice of threshold values for the retirement fraction Ret_{it} remains arbitrary. However, this approach does provide a method to gain a more refined insight into how mental health of the unemployed varies with the retirement fraction. Hence, in our analysis we will vary the number of threshold values and their levels.

6 Results

6.1 Descriptive results

Descriptively, we already started the analysis with Figure 3, which we discussed in the introduction. Here we observe that in most countries, except the three southern European countries, there is a clear pattern of improving mental health among the unemployed with age. Moreover, the figure shows that the improvements in mental health take place over the age range that coincides with the age range for the retirement process in these European countries. The figure presents above each of the country graphs the correlation between mental heath scores of the unemployed and the retirement fraction at a particular age. There is a clear negative correlation for each of the countries except in southern Europe (Italy, Greece and Spain).

However, in Figure 3 mental health scores and the retirement fraction are both averaged across survey waves for a better graphical representation. A more direct visual test of the relation between the retirement

fraction and mental health of the unemployed is provided by the scatter plots in Figures 9, 10 and 11. Figure 9 plots the relation between EURO-D score and the retirement fraction by taking the average EURO-D score and the corresponding retirement fraction (as in equation 4) for each age (in years between the ages of 50-68), country and wave (Figure 12 does the same averaged over the survey waves). The figure shows the hypothesized negative relation, but at higher levels of the retirement fraction the EURO-D scores seem to fan out. However, the points at high levels of the retirement fraction correspond with higher ages, when the number of unemployed individuals decreases and thus the average EURO-D score becomes less precise. Figure 10 plots the same points but this time only for retirement fractions below 0.4. The negative relation becomes a lot more pronounced as can be seen from the increase in the coefficient for the linear fit (from -0.84 in Figure 9 to -2.30 in Figure 10). Figure 11 excludes the southern European countries (Greece, Italy and Spain) from the plot. This strengthens the negative relationship and slightly improves the fit of the linear regression line as indicated by the R^2-value which improves from 15.2% in Figure 9 to 17.1% in Figure 11. Overall, the raw data enables us to visualize the negative relation between the retirement fraction and mental health of the unemployed that we aim to uncover in our regression analysis.

6.2 Regression analysis

6.2.1 Linear relationship

Next, we perform the main econometric analysis based on individual-level data. Table 5 gives the results from a cross-sectional OLS estimation of the regression in equation 3. Columns (1) indicates that when we only control for country and year fixed-effects, we obtain a highly significant estimate of -0.84 for the effect of the retirement fraction on mental health of the unemployed. Hence, a 10%-point increase in the retirement fraction is associated with a drop of approximately 0.08 on the EURO-D scale.

However, columns (2) and (3) show that once we control for either a linear or quadratic age function our estimate for the retirement fraction is no longer significant. Instead, the effect seems to be absorbed by the age function itself, which is highly significant. Figure 8 shows how the retirement fraction is increasing with age. We can see from the figure that age and the retirement fraction are highly collinear. Moreover, Figure 17 shows that most of the variation in the retirement fraction Ret_{it} is along the age dimension and not along the country or wave dimension. Consequently, the age functions dominate any effect that we want to isolate using our regressor of interest. However, we believe there are three arguments as to why we should not control for an age function in our regression. First, traditional psychology literature generally finds life-cycle profiles of mental health with stable mental health scores. Second, both in this paper and in our previous work, (Van de Kraats et al., forthcoming) data shows that on average mental health scores remain stable with age. For example, Figure 15 gives the average life-cycle pattern of mental health for men in the SHARE survey from a fixed-effects regression of the EURO-D score on a full set of age dummies. Here we see that none of the coefficient estimates for ages 51-68 significantly differ from 0, thus there is no differences in mental health compared to the reference group of 50 years old individuals. When we differentiate in the regression between the unemployed and "non-unemployed", we find the same pattern flat pattern for the latter group, as can be seen from Figure 13 (the reference group consists of 50 year old "non-unemployed" men). On the other hand, for unemployed men we find a age pattern of improving mental health with age, as can be seen from Figure 14. [Note: Figure 16 gives the average fixed-effect by age for unemployed men. Here we also see a pattern of improving mental health.] Third, across academic disciplines no compelling theoretical argument has been put forward as to why mental health should follow a particular life cycle pattern (Ulloa et al., 2013).

When we drop the age function and add a set of standard controls such as education attainment and marital status dummies (column (4)) and (instrumental) activities of daily living and household income (column (5)), we find estimates for the retirement fraction that are again highly significant. Again, controlling for age makes the coefficient insignificant (column (6)). Columns (4) and (5) give estimates for the retirement fraction of -0.81, which are similar in size to the coefficient that we found in column (1). Given the average score EURO-D score of 2.58 (standard deviation 2.43), this implies that the level of labor market activity of "relevant others" has a large impact on mental health. Comparing it to one of the most important correlates of mental health, marital status, we see that the estimate for the retirement fraction (going from 0% to 100% of retired individuals) is even larger than that of divorce.

Table 6 repeats the steps of Table 5 while estimating equation 3 using the first-difference estimator with clustered standard errors. Across the columns we observe the same pattern: coefficient estimates for the retirement fraction Ret_{it} are highly significant as long as we do not control for an age pattern. Compared to Table 5 the estimated effect size increases in absolute terms up to -1.2 in column (5). Moreover, when we do control for age, we observe that all estimates for the retirement fraction Ret_{it} are in the expected direction even though they are imprecisely estimated.

6.2.2 Step-wise relationship

Next, we turn to the results of our estimation where the retirement fraction Ret_{it} is specified as a step-wise function in age, as in equation 5. Table 7 give the the threshold ages for men that correspond to a retirement fraction of 33%, 67% and 90% (i.e. Age_{33}, Age_{67} and Age_{90}) for each of the waves.

Table 8 presents the results from a cross-sectional OLS estimation of equation 5. Again, we only find significant estimates for the regressors of interest in specifications where we do not control for an age function. In columns (1), (4) and (5), the estimates for the indicator variables for being between Age_{33} and Age_{67} ($\mathbb{1}(\text{Age}_{33} \leq \text{Age}_{it} < \text{Age}_{67})$) and being between age Age_{67} and Age_{90} ($\mathbb{1}(\text{Age}_{67} \leq \text{Age}_{it} < \text{Age}_{90})$) are significant and roughly similar in size. This indicates that much of the effect of the labor market activity of "relevant others" on mental health of the unemployed occurs already at the bottom of the retirement curve. In other words, a relatively small increase in the fraction of retired individuals already impacts mental health of the unemployed. However, the coefficient for the indicator variable $\mathbb{1}(\text{Age}_{it} \geq \text{Age}_{90})$ is not significant, but still in the hypothesized direction. This imprecision may be due to the relatively low number of observations left in our sample after Age_{90}.

The results from a first-difference estimation in Table 9 further corrobarote the findings from Table 8. When we exploit within individual variation we find significant negative estimates for the coefficient for $\mathbb{1}(\text{Age}_{33} \leq \text{Age}_{it} < \text{Age}_{67})$ across all 6 specifications. The coefficient for $\mathbb{1}(\text{Age}_{67} \leq \text{Age}_{it} < \text{Age}_{90})$ is only significant in the specifications that do not control for age.

6.3 Robustness

[Sensitivity tests and robustness analysis to be incorporated here.]

7 Conclusion

In this paper we investigate how the level of labor market activity of "relevant others" (i.e. one's peers) - measured by the retirement fraction - affects mental health of the unemployed by exploiting variation in the level of labor market activity of relevant others over age, countries, and time. Mechanisms for this effect are (i) the social norm to work and (ii) the value of leisure, which both depend on the fraction of peers working. Specifically, as the retirement fraction increases, the social norm to work decreases and the value of leisure for the unemployed increases, which in theory translates in improved mental health for the unemployed.

We find statistically and economically significant effects in the hypothesized direction, also when only exploiting within-individual variation using the first-difference estimator. When comparing the effect of several thresholds of the retirement fraction and their impact on mental health of the unemployed, we find that the start of the retirement process is most important in improving mental health of the unemployed. In other words, a relatively small increase in the fraction of retired individuals already impacts mental health of the unemployed.

References

Akerlof, G. A., & Kranton, R. E. (2000). Economics and identity. *The Quarterly Journal of Economics*, *115*(3), 715–753.

Becker, G. S. (1965). A theory of the allocation of time. *The economic journal*, 493–517.

Björklund, A. (1985). Unemployment and mental health: some evidence from panel data. *Journal of Human Resources*, 469–483.

Blanchflower, D. G., & Oswald, A. J. (2004). Well-being over time in britain and the usa. *Journal of public economics*, *88*(7), 1359–1386.

Blanchflower, D. G., & Oswald, A. J. (2008). Is well-being u-shaped over the life cycle? *Social science & medicine*, *66*(8), 1733–1749.

Blanchflower, D. G., & Oswald, A. J. (2016). Antidepressants and age: A new form of evidence for u-shaped well-being through life. *Journal of Economic Behavior & Organization*, *127*, 46–58.

Böckerman, P., & Ilmakunnas, P. (2009). Unemployment and self-assessed health: evidence from panel data. *Health economics*, *18*(2), 161–179.

Börsch-Supan, A., Brandt, M., Hunkler, C., Kneip, T., Korbmacher, J., Malter, F., ... Zuber, S. (2013). Data resource profile: the survey of health, ageing and retirement in europe (share). *International journal of epidemiology*, *42*(4), 992–1001.

Browning, M., Moller Dano, A., & Heinesen, E. (2006). Job displacement and stress-related health outcomes. *Health economics*, *15*(10), 1061–1075.

Castro-Costa, E., Dewey, M., Stewart, R., Banerjee, S., Huppert, F., Mendonca-Lima, C., ... others (2007). Prevalence of depressive symptoms and syndromes in later life in ten european countries. *The British Journal of Psychiatry*, *191*(5), 393–401.

Castro-Costa, E., Dewey, M., Stewart, R., Banerjee, S., Huppert, F., Mendonca-Lima, C., ... others (2008). Ascertaining late-life depressive symptoms in europe: an evaluation of the survey version of the euro-d scale in 10 nations. the share project. *International journal of methods in psychiatric research*, *17*(1), 12–29.

Chadi, A. (2014). Regional unemployment and norm-induced effects on life satisfaction. *Empirical Economics*, *46*(3), 1111–1141.

Clark, A., Knabe, A., & Rätzel, S. (2010). Boon or bane? others' unemployment, well-being and job insecurity. *Labour Economics*, *17*(1), 52–61.

Clark, A. E. (2003). Unemployment as a social norm: Psychological evidence from panel data. *Journal of labor economics*, *21*(2), 323–351.

Clark, A. E., & Oswald, A. J. (1994). Unhappiness and unemployment. *The Economic Journal*, *104*(424), 648–659.

Cohn, R. M. (1978). The effect of employment status change on self-attitudes. *Social Psychology*, 81–93.

Dooley, D., Catalano, R., & Rook, K. S. (1988). Personal and aggregate unemployment and psychological symptoms. *Journal of Social Issues*, *44*(4), 107–123.

Eisenberg, P., & Lazarsfeld, P. F. (1938). The psychological effects of unemployment. *Psychological bulletin*, *35*(6), 358.

Elster, J. (1989). *The cement of society: A survey of social order*. Cambridge University Press.

Feather, N. T. (1990). *The psychological impact of unemployment*. Springer Science & Business Media.

Fehr, E., & Gächter, S. (2000). Fairness and retaliation: The economics of reciprocity. *The journal of economic perspectives*, *14*(3), 159–181.

Fonseca, R., Kapteyn, A., Lee, J., Zamarro, G., & Feeney, K. (2014). A longitudinal study of well-being of older europeans: does retirement matter? *Journal of population ageing*, *7*(1), 21–41.

Frijters, P., & Beatton, T. (2012). The mystery of the u-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization*, *82*(2), 525–542.

Gateway to Global Aging Data. (2017). *Produced by the usc program on global aging, health & policy, with funding from the national institute on aging (r01 ag030153).* Retrieved from https://g2aging.org/ (Retrieved 14 September 2017)

Gathergood, J. (2013). An instrumental variable approach to unemployment, psychological health and social norm effects. *Health economics*, *22*(6), 643–654.

Gerlach, K., & Stephan, G. (1996). A paper on unhappiness and unemployment in germany. *Economics Letters*, *52*(3), 325–330.

Glavin, P., & Young, M. (2017). Insecure people in insecure places: The influence of regional unemployment on workers' reactions to the threat of job loss. *Journal of Health and Social Behavior*, *58*(2), 232–251.

Glenn, N. (2009). Is the apparent u-shape of well-being over the life course a result of inappropriate use of control variables? a commentary on blanchflower and oswald (66: 8, 2008, 1733–1749). *Social Science & Medicine*, *69*(4), 481–485.

Guerra, M., Ferri, C., Llibre, J., Prina, A. M., & Prince, M. (2015). Psychometric properties of euro-d, a geriatric depression scale: a cross-cultural validation study. *BMC psychiatry*, *15*(1), 12.

Hamilton, V. H., Merrigan, P., & Dufresne, É. (1997). Down and out: estimating the relationship between mental health and unemployment. *Health economics*, *6*(4), 397–406.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153-161.

Helliwell, J. F., & Huang, H. (2014). New measures of the costs of unemployment: Evidence from the subjective well-being of 3.3 million americans. *Economic Inquiry*, *52*(4), 1485–1502.

Helliwell, J. F., & Wang, S. (2014). Weekends and subjective well-being. *Social indicators research*, *116*(2), 389–407.

Hetschko, C., Knabe, A., & Schöb, R. (2014). Changing identity: Retiring from unemployment. *The Economic Journal*, *124*(575), 149–166.

Jackson, P. R., & Warr, P. (1987). Mental health of unemployed men in different parts of england and wales. *Br Med J (Clin Res Ed)*, *295*(6597), 525–525.

Jahoda, M. (1981). Work, employment, and unemployment: Values, theories, and approaches in social research. *American psychologist*, *36*(2), 184.

Jahoda, M. (1988). Economic recession and mental health: Some conceptual issues. *Journal of Social Issues*, *44*(4), 13–23.

Kahneman, D., Krueger, A. B., Schkade, D., Schwarz, N., & Stone, A. (2004b). Toward national well-being accounts. *The American Economic Review*, *94*(2), 429–434.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004a). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), 1776–1780.

Kassenboehmer, S. C., & Haisken-DeNew, J. P. (2009). You're fired! the causal negative effect of entry unemployment on life satisfaction. *The Economic Journal*, *119*(536), 448–462.

Kessler, R. C., & Bromet, E. J. (2013). The epidemiology of depression across cultures. *Annual review of public health*, *34*, 119.

Keynes, J. M. (1930). Economic possibilities for our grandchildren. In *Essays in persuasion* (pp. 321–332). Palgrave Macmillan, London, 2010 (Reprint).

Knabe, A., & Rätzel, S. (2011). Quantifying the psychological costs of unemployment: the role of permanent income. *Applied Economics*, *43*(21), 2751–2763.

Knabe, A., Rätzel, S., Schöb, R., & Weimann, J. (2010). Dissatisfied with life but having a good day: Time-use and well-being of the unemployed. *The Economic Journal*, *120*(547), 867–889.

Korpi, T. (1997). Is utility related to employment status? employment, unemployment, labor market policies and subjective well-being among swedish youth. *Labour economics*, *4*(2), 125–147.

Krueger, A. B., & Mueller, A. I. (2012). The lot of the unemployed: a time use perspective. *Journal of the European Economic Association*, *10*(4), 765–794.

Kuhn, A., Lalive, R., & Zweimüller, J. (2009). The public health costs of job loss. *Journal of health economics*, *28*(6), 1099–1115.

Lindbeck, A., Nyberg, S., & Weibull, J. W. (1999). Social norms and economic incentives in the welfare state. *The Quarterly Journal of Economics*, *114*(1), 1–35.

Lucas, R. E. (2007). Adaptation and the set-point model of subjective well-being does happiness change after major life events? *Current Directions in Psychological Science*, *16*(2), 75–79.

MISSOC. (2017). *Missoc comparative tables database.* Retrieved from http://www.missoc.org/MISSOC/INFORMATIONBASE/COMPARATIVETABLES/MISSOCDATABASE/comparativeTableSearch.jsp (Retrieved 28 September 2017)

Moffitt, R. (1983). An economic model of welfare stigma. *The American Economic Review*, *73*(5), 1023–1035.

OECD. (2005). *Pensions at a glance 2005: Public policies across oecd countries.* Organisation for Economic Co-operation and Development.

OECD. (2007). *Pensions at a glance 2007: Public policies across oecd countries.* Organisation for Economic Co-operation and Development.

OECD. (2009). *Pensions at a glance 2009: Retirement-income systems in oecd countries.* Organisation for Economic Co-operation and Development.

OECD. (2011). *Pensions at a glance 2011: Retirement-income systems in oecd and g20 countries.* Organisation for Economic Co-operation and Development.

OECD. (2013). *Pensions at a glance 2013: Oecd and g20 indicators.* Organisation for Economic Co-operation and Development.

OECD. (2014, July). Focus on health: Making mental health count. Retrieved from http://www.oecd.org/els/health-systems/Focus-on-Health-Making-Mental-Health-Count.pdf (Retrieved 10 September 2014)

OECD. (2015). *Pensions at a glance 2015: Oecd and g20 indicators.* Organisation for Economic Co-operation and Development.

Paul, K. I., & Moser, K. (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational behavior*, *74*(3), 264–282.

Powdthavee, N. (2007). Are there geographical variations in the psychological cost of unemployment in south africa? *Social Indicators Research*, *80*(3), 629–652.

Prince, M. J., Reischies, F., Beekman, A., Fuhrer, R., Jonker, C., Kivela, S.-L., ... others (1999). Development of the euro-d scale–a european, union initiative to compare symptoms of depression in 14 european centres. *The British Journal of Psychiatry*, *174*(4), 330–338.

Rai, D., Zitko, P., Jones, K., Lynch, J., & Araya, R. (2013). Country-and individual-level socioeconomic determinants of depression: multilevel cross-national comparison. *The British Journal of Psychiatry*, *202*(3), 195–203.

Salm, M. (2009). Does job loss cause ill health? *Health Economics*, *18*(9), 1075–1089.

Schmitz, H. (2011). Why are the unemployed in worse health? the causal effect of unemployment on health. *Labour Economics*, *18*(1), 71–78.

Shields, M. A., & Price, S. W. (2005). Exploring the economic and social determinants of psychological well-being and perceived social support in england. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *168*(3), 513–537.

Shields, M. A., Price, S. W., & Wooden, M. (2009). Life satisfaction and the economic and social characteristics of neighbourhoods. *Journal of Population Economics*, *22*(2), 421–443.

Stone, A. A., Schneider, S., & Broderick, J. E. (2017). Psychological stress declines rapidly from age 50 in the united states: Yet another well-being paradox. *Journal of psychosomatic research*, *103*, 22–28.

Stone, A. A., Schwartz, J. E., Broderick, J. E., & Deaton, A. (2010). A snapshot of the age distribution of psychological well-being in the united states. *Proceedings of the National Academy of Sciences*, *107*(22), 9985–9990.

Stutzer, A., & Lalive, R. (2004). The role of social work norms in job searching and subjective well-being. *Journal of the European Economic Association*, *2*(4), 696–719.

Ulloa, B. F. L., Møller, V., & Sousa-Poza, A. (2013). How does subjective well-being evolve with age? a literature review. *Journal of Population Ageing*, *6*(3), 227–246.

Van de Kraats, C., Galama, T., & Lindeboom, M. (forthcoming). Mental health disparities by socioeconomic status over the life cycle. *TI Working Paper*.

Warr, P., Jackson, P., & Banks, M. (1988). Unemployment and mental health: Some british studies. *Journal of social issues*, *44*(4), 47–68.

Weissman, M. M., Bland, R. C., Canino, G. J., Faravelli, C., Greenwald, S., Hwu, H.-G., ... others (1996). Cross-national epidemiology of major depression and bipolar disorder. *Jama*, *276*(4), 293–299.

Winkelmann, L., & Winkelmann, R. (1998). Why are the unemployed so unhappy? evidence from panel data. *Economica*, *65*(257), 1–15.

Young, C., & Lim, C. (2014). Time as a network good: Evidence from unemployment and the standard workweek. *Sociological Science*, *1*, 10–27.

A Appendix

A.1 EURO-D scale survey items

1. **Depression:** "In the last month, have you been sad or depressed?"
   0 No
   1 Yes
2. **Pessimism:** "What are your hopes for the future?"
   0 Any hopes mentioned
   1 No hopes mentioned
3. **Suicidality:** "In the last month, have you felt that you would rather be dead?"
   0 No such feelings
   1 Any mention of suicidal feelings or wishing to be dead
4. **Guilt:** "Do you tend to blame yourself or feel guilty about anything?"
   0 No such feelings
   1 Obvious excessive guilt or self-blame, mentions guilt or self-blame, but it is unclear if these constitute obvious, or excessive guilt or self-blame
5. **Sleep:** "Have you had trouble sleeping recently?"
   0 No trouble sleeping
   1 Trouble with sleep or recent change in pattern
6. **Interest:** "In the last month, what is your interest in things?"
   0 No mention of loss of interest, non-specific or uncodeable response
   1 Less interest than usual mentioned
7. **Irritability:** "Have you been irritable recently?"
   0 No
   1 Yes
8. **Appetite:**"What has your appetite been like?"
   0 No diminution in desire for food, non-specific or uncodeable response
   1 Diminution in desire for food
9. **Fatigue:** "In the last month, have you had too little energy to do the things you wanted to do?"
   0 No
   1 Yes
10. **Concentration:**"How is your concentration?" (Difficulty in concentrating on entertainment or reading)
    1 Difficulty in concentrating on entertainment
    2 No such difficulty mentioned
11. **Enjoyment:** "What have you enjoyed doing recently?"
    0 Mentions any enjoyment from activity
    1 Fails to mention any enjoyable activity
12. **Tearfulness:** "In the last month, have you cried at all?"
    0 No
    1 Yes

A.2 Tables

Table 1: *Cross-tabulation of labor market definitions (ages 50-68)*

	Self-reported						
Income-based	(Self-)employed	Unemployed	Retired	Disabled	Homemaker	Undefined	Total
Retired	52	107	15,925	413	23	325	16,845
Employed	20,249	145	284	98	9	87	20,872
Unemployed	429	1,885	1,902	1,775	118	316	6,425
Other	3,447	395	1,319	143	8	276	5,588
Total	24,177	2,532	19,430	2,429	158	1,004	49,730

Table 2: *Summary statistics for unemployed men aged 50-68*

	Men
Outcome	
EURO-D	2.58
	[2.43]
Characteristics	
Age	58.6
	[4.51]
> early ret. age	0.36
> normal ret. age	0.10
Hh income (EUR)	23791.5
	[36957.1]
ADL	0.26
	[0.80]
IADL	0.18
	[0.70]
Education (ISCED-97)	
No	0.066
Primary	0.21
Lower secondary	0.20
Upper secondary	0.33
Post-secondary	0.022
First stage tertiary	0.17
Second stage tertiary	0.0050
Marital Status	
Married	0.68
Partnered	0.072
Separated	0.015
Divorced	0.095
Widowed	0.015
Never married	0.12
Number of observations	6425

Source: SHARE waves 1, 2, 4, 5 and 6

Table 3: *Cross-tabulation for number of observations by countries and waves*

	Wave					
Country	1	2	4	5	6	Total
Austria	458	308	1,361	1,049	722	3,898
Belgium	1,138	954	1,589	1,645	1,626	6,952
Denmark	521	817	714	1,246	1,090	4,388
France	892	826	1,588	1,168	1,002	5,476
Germany	979	798	378	1,691	1,197	5,043
Greece	854	955	0	0	1,191	3,000
Italy	751	825	900	1,183	1,330	4,989
Netherlands	955	832	802	1,157	0	3,746
Spain	553	608	902	1,662	1,221	4,946
Sweden	903	768	434	1,105	795	4,005
Switzerland	288	432	1,109	812	646	3,287
Total	8,292	8,123	9,777	12,718	10,820	49,730

Table 4: *Retirement ages - Men*

	2004		2005		2006		2007		2011		2012		2013		2015	
	E	N	E	N	E	N	E	N	E	N	E	N	E	N	E	N
Austria	61.5	65	62	65	62	65	62	65	62	65	m	m	62	65	62	65
Belgium	60	65	60	65	60	65	60	65	60	65	m	m	60.5	65	61.5	65
Denmark	65	67	65	67	65	67	65	67	65	67	m	m	65	67	65	67
France	56	60	56	60	56	60	56	60	56	60	m	m	56	60.67	57	61.33
Germany	63	65	63	65	63	65	63	65	63	65	63	65.08	63	65.17	63	65.33
Greece	58	65	58	65	58	65	58	65	58	65	m	m	62	67	62	67
Italy	57	65	57	65	57	65	57	65	60	65	m	m	60	66.25	62	66.25
Netherlands	.	65	.	65	.	65	.	65	.	65	m	m	.	65.08	.	65.25
Spain	60	65	60	65	60	65	60	65	61	65	m	m	61	65	61	65
Sweden	.	65	.	65	61	65	61	65	61	65	m	m	61	65	61	65
Switzerland	63	65	63	65	63	65	63	65	63	65	m	m	63	65	63	65

Sources: MISSOC (2017) and OECD (2005, 2007, 2009, 2011, 2013, 2015). *Notes*: E stands for the early retirement age and N stands for the normal retirement age. If there exists no option for early retirement this is indicated with a full stop. Depending on the timing of the SHARE survey waves we do not need data on retirement eligibility ages for all countries for all years. When we did not gather data on retirement eligibility ages for a particular country and year this is indicated with m. In the SHARE data we observe age in months. Therefore, we convert the early and normal and retirement ages from ages into months for our analyses. Additional comments on retirement ages by country in section **??**.

Table 5: *Men - OLS*

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Ret_{ac}	-0.843***	0.343	-0.335	-0.819***	-0.813***	-0.397
	(0.115)	(0.273)	(0.361)	(0.116)	(0.122)	(0.379)
Age		-0.0779***	-0.666***			-0.730***
		(0.0163)	(0.206)			(0.215)
Age^2			0.00535***			0.00593***
			(0.00186)			(0.00194)
Primary				-0.290**	-0.156	-0.123
				(0.135)	(0.142)	(0.142)
Lower secondary				-0.744***	-0.544***	-0.537***
				(0.138)	(0.145)	(0.144)
Upper secondary				-0.839***	-0.600***	-0.589***
				(0.134)	(0.141)	(0.141)
Post-secondary				-0.957***	-0.797***	-0.792***
				(0.240)	(0.257)	(0.256)
First stage tertiary				-1.049***	-0.774***	-0.747***
				(0.143)	(0.151)	(0.151)
First stage tertiary				-1.278***	-0.810*	-0.789*
				(0.438)	(0.451)	(0.450)
Partnered				0.00902	-0.0322	-0.0516
				(0.118)	(0.128)	(0.128)
Separated				0.508**	0.452*	0.403*
				(0.248)	(0.243)	(0.242)
Divorced				0.755***	0.638***	0.606***
				(0.105)	(0.106)	(0.106)
Widowed				1.132***	1.135***	1.137***
				(0.245)	(0.241)	(0.240)
Never married				0.567***	0.367***	0.314***
				(0.0945)	(0.0991)	(0.0994)
ADL					0.521***	0.525***
					(0.0496)	(0.0495)
IADL					0.350***	0.345***
					(0.0574)	(0.0573)
HH income ('0 000 EUR)					-0.0173*	-0.0163*
					(0.00911)	(0.00909)
Constant	2.567***	6.623***	22.92***	3.147***	2.881***	25.01***
	(0.136)	(0.858)	(5.747)	(0.189)	(0.204)	(5.997)
Observations	6425	6425	6425	6365	5516	5516
R^2	0.023	0.027	0.028	0.053	0.112	0.117
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 6: *Men - first-differences*

Specification	(1)	(2)	(3)	(4)	(5)	(6)
D.RetFrac˙Men˙average3	-1.101***	-0.333	-0.368	-1.119***	-1.192***	-0.923
	(0.313)	(0.507)	(0.640)	(0.315)	(0.349)	(0.707)
Age		-0.0704*	-0.108			-0.490
		(0.0376)	(0.451)			(0.494)
Age^2			0.000333			0.00383
			(0.00402)			(0.00439)
Partnered				-0.446	-0.499	-0.481
				(0.561)	(0.764)	(0.763)
Separated				1.675*	1.558	1.526
				(0.896)	(0.977)	(0.957)
Divorced				0.906*	1.261**	1.298**
				(0.508)	(0.526)	(0.523)
Widowed				0.916*	0.720	0.729
				(0.488)	(0.601)	(0.598)
Never married				-1.198*	-1.145	-1.182
				(0.654)	(0.839)	(0.855)
ADL					0.246**	0.247**
					(0.122)	(0.122)
IADL					0.0761	0.0837
					(0.154)	(0.155)
HH income ('0 000 EUR)					0.00519	0.00386
					(0.00730)	(0.00752)
Observations	2062	2062	2062	2038	1710	1710
R^2	0.005	0.006	0.006	0.011	0.018	0.020

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 7: *Threshold ages - Men*

	Austria	Belgium	Denmark	France	Germany	Greece	Italy	Netherlands	Spain	Sweden	Switzerland
Wave 1											
Age_{33}	58	59	62	60	61	61	57	61	61	64	62
Age_{67}	61	63	64	62	64	65	61	65	65	66	66
Age_{90}	63	66	69	64	66	68	68	67	67	67	67
Wave 2											
Age_{33}	58	58	62	59	61	61	57	61	62	64	62
Age_{67}	61	61	64	62	64	66	59	64	65	66	65
Age_{90}	64	66	66	63	66	70	66	66	70	67	66
Wave 4											
Age_{33}	60	60	62	59	62	.	60	62	62	64	63
Age_{67}	63	64	65	61	65	.	63	64	65	66	65
Age_{90}	66	67	66	63	67	.	68	66	67	67	66
Wave 5											
Age_{33}	60	60	63	60	63	.	60	63	62	64	64
Age_{67}	63	64	65	62	65	.	64	65	65	66	65
Age_{90}	66	66	67	65	66	.	.	66	.	67	66
Wave 6											
Age_{33}	60	61	63	60	63	60	61	.	62	64	64
Age_{67}	63	64	65	62	65	67	65	.	65	66	65
Age_{90}	67	66	67	64	67	.	69	.	68	67	66

Table 8: *Men - OLS*

Specification	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\text{Age}_{33} \leq \text{Age}_{it} < \text{Age}_{67})$	-0.421***	-0.0131	-0.133	-0.415***	-0.386***	-0.134
	(0.0739)	(0.102)	(0.113)	(0.0740)	(0.0778)	(0.118)
$\mathbb{1}(\text{Age}_{67} \leq \text{Age}_{it} < \text{Age}_{90})$	-0.361***	0.308*	-0.0709	-0.391***	-0.389***	-0.182
	(0.130)	(0.174)	(0.233)	(0.129)	(0.135)	(0.243)
age˙90Men˙2	-0.292	0.503	-0.0477	-0.200	-0.0980	0.0268
	(0.276)	(0.308)	(0.382)	(0.274)	(0.290)	(0.399)
Age		-0.0681***	-0.653***			-0.740***
		(0.0118)	(0.240)			(0.251)
Age^2			0.00519**			0.00597***
			(0.00213)			(0.00222)
Primary				-0.303**	-0.200	-0.164
				(0.141)	(0.148)	(0.148)
Lower secondary				-0.743***	-0.562***	-0.569***
				(0.143)	(0.150)	(0.150)
Upper secondary				-0.848***	-0.628***	-0.623***
				(0.140)	(0.147)	(0.146)
Post-secondary				-0.998***	-0.864***	-0.865***
				(0.248)	(0.266)	(0.265)
First stage tertiary				-1.080***	-0.820***	-0.791***
				(0.149)	(0.157)	(0.157)
First stage tertiary				-1.394***	-0.951*	-0.917*
				(0.472)	(0.488)	(0.487)
Partnered				0.00389	-0.0219	-0.0542
				(0.122)	(0.131)	(0.131)
Separated				0.548**	0.497**	0.444*
				(0.256)	(0.250)	(0.250)
Divorced				0.784***	0.674***	0.626***
				(0.109)	(0.110)	(0.110)
Widowed				1.177***	1.168***	1.157***
				(0.256)	(0.251)	(0.250)
Never married				0.574***	0.385***	0.309***
				(0.0971)	(0.102)	(0.102)
ADL					0.527***	0.532***
					(0.0514)	(0.0513)
IADL					0.349***	0.346***
					(0.0594)	(0.0592)
HH income ('0 000 EUR)					-0.0169*	-0.0158*
					(0.00945)	(0.00943)
Constant	2.441***	6.133***	22.62***	3.039***	2.779***	25.40***
	(0.139)	(0.655)	(6.803)	(0.194)	(0.208)	(7.100)
Observations	6054	6054	6054	5996	5195	5195
R^2	0.022	0.027	0.028	0.052	0.112	0.119
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 9: *Men - first-differences*

Specification	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\text{Age}_{33} \leq \text{Age}_{it} < \text{Age}_{67})$	-0.420***	-0.302**	-0.334**	-0.442***	-0.478***	-0.409**
	(0.120)	(0.141)	(0.151)	(0.119)	(0.133)	(0.165)
$\mathbb{1}(\text{Age}_{67} \leq \text{Age}_{it} < \text{Age}_{90})$	-0.578**	-0.342	-0.430	-0.614**	-0.793***	-0.686*
	(0.272)	(0.306)	(0.337)	(0.274)	(0.297)	(0.364)
$\mathbb{1}(\text{Age}_{it} \geq \text{Age}_{90})$	-1.131	-0.778	-0.958	-1.166	-0.168	-0.0653
	(0.905)	(0.931)	(0.972)	(0.907)	(0.680)	(0.774)
Age		-0.0539*	-0.323			-0.392
		(0.0294)	(0.449)			(0.503)
Age^2			0.00236			0.00299
			(0.00392)			(0.00439)
Partnered				-0.363	-0.327	-0.309
				(0.630)	(0.845)	(0.844)
Separated				2.290***	2.519***	2.482***
				(0.856)	(0.754)	(0.715)
Divorced				1.074**	1.553***	1.579***
				(0.526)	(0.532)	(0.529)
Widowed				0.855	0.684	0.719
				(0.548)	(0.707)	(0.710)
Never married				-1.043	-0.862	-0.912
				(0.698)	(0.883)	(0.889)
ADL					0.265**	0.269**
					(0.132)	(0.132)
IADL					0.0942	0.101
					(0.167)	(0.168)
HH income ('0 000 EUR)					0.00785	0.00554
					(0.00713)	(0.00736)
Observations	1887	1887	1887	1863	1563	1563
R^2	0.006	0.008	0.008	0.015	0.025	0.027

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

A.3 Figures

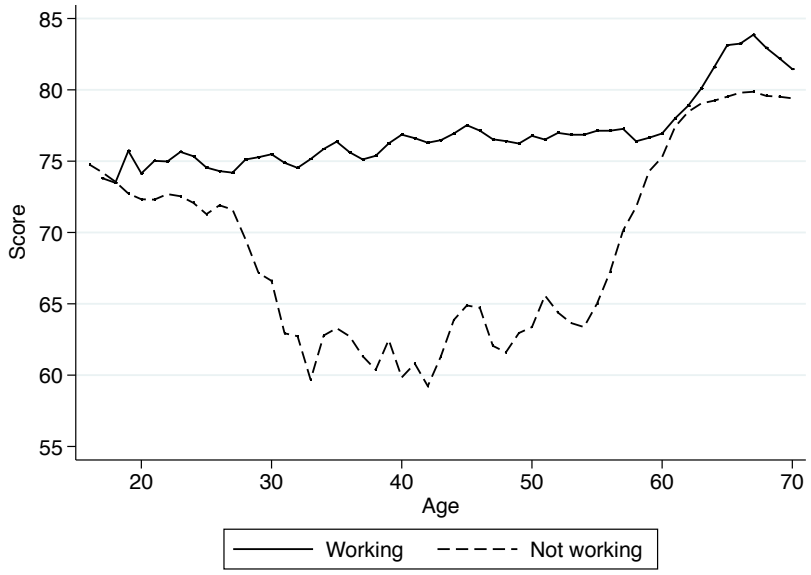


Figure 1: *Life cycle plot of MHI-5 score for Dutch men.*

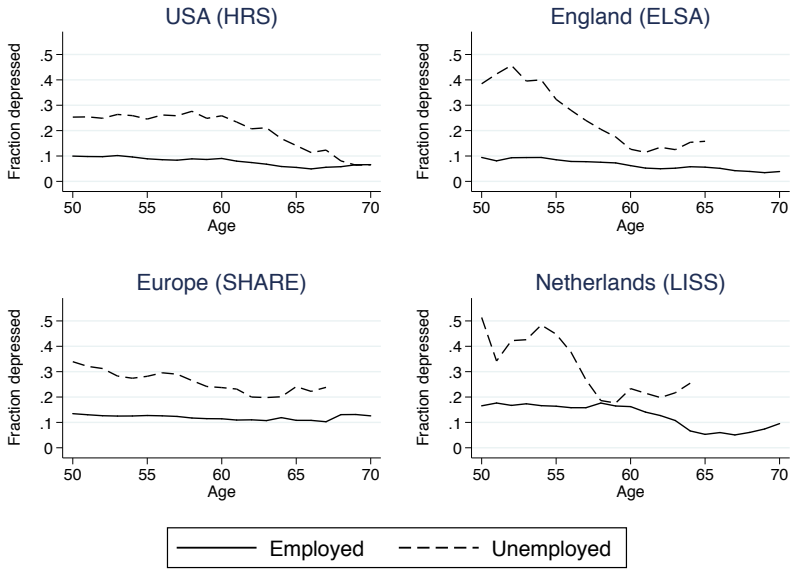


Figure 2: *Fraction of individuals with a mental health score that is clinically indicative of mental ill-health. The plots use data from the Health and Retirement Study, the English Longitudinal Study of Aging, the Survey of Health, Aging, and Retirement in Europe and the Longitudinal Internet Studies for the Social sciences for the USA, England, Europe and The Netherlands, respectively.*

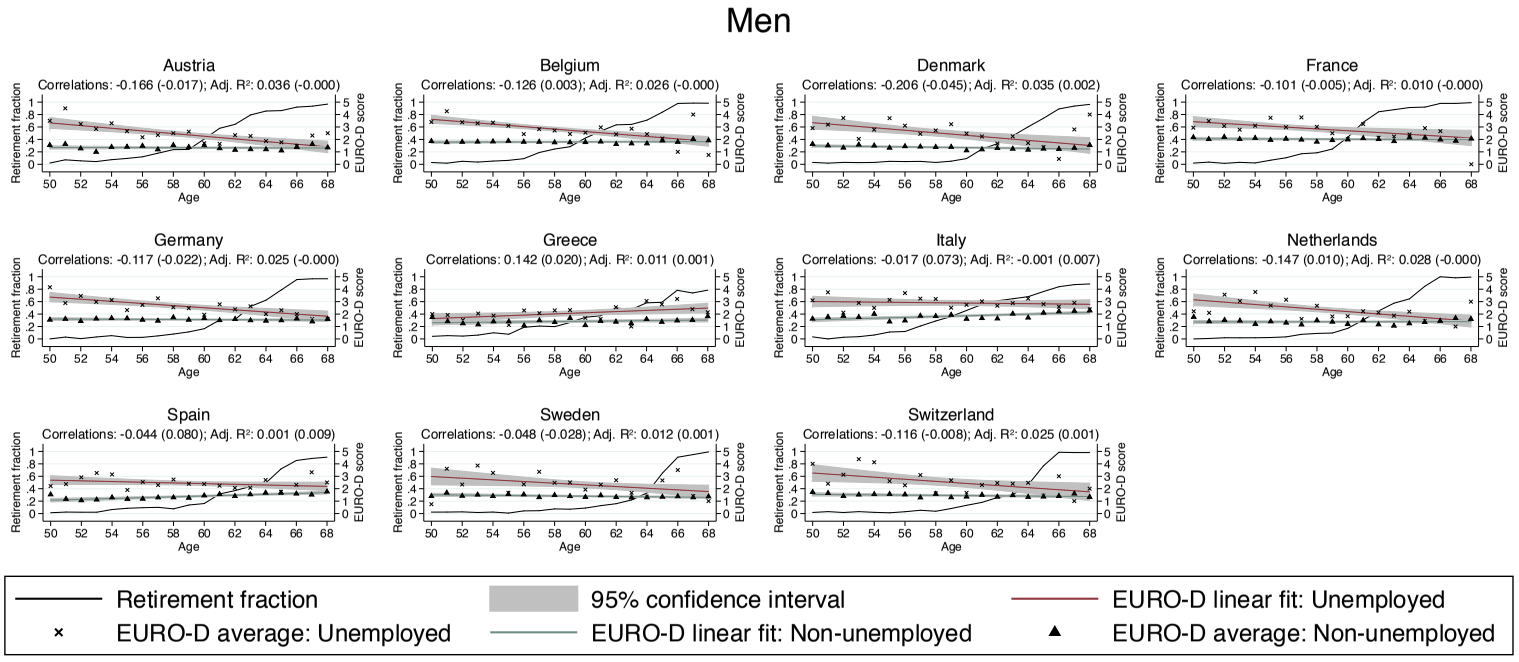


Figure 3: *Retirement fraction by country and age and EURO-D scores for unemployed and non-unemployed individuals by country and age.*

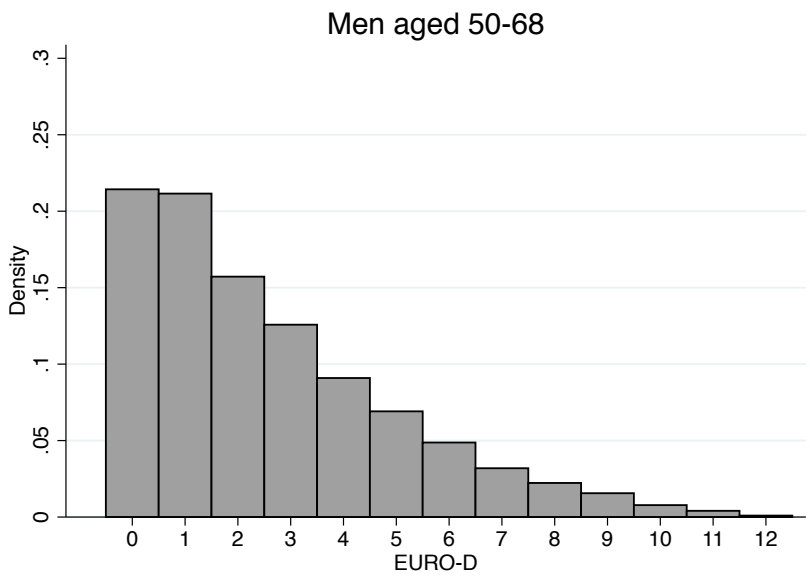


Figure 4: *Histogram of EURO-D scores for unemployed men aged 50-68.*

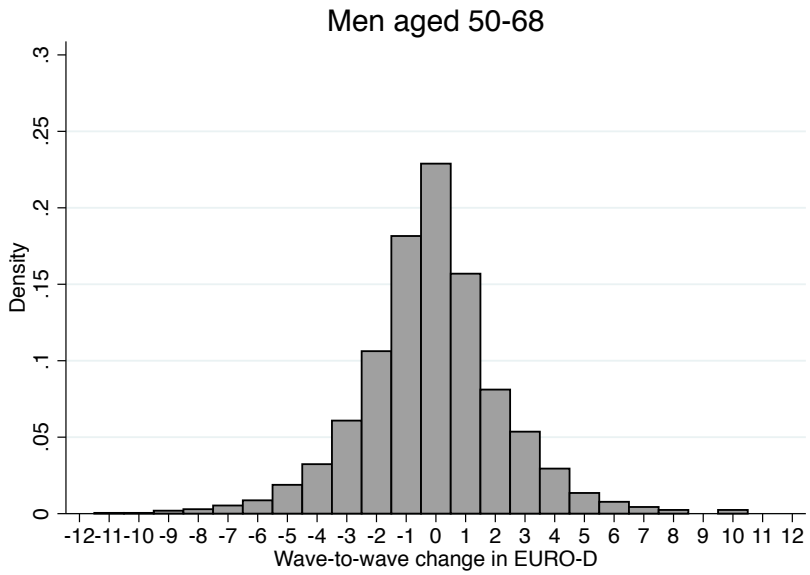


Figure 5: *Histograms of wave-to-wave changes in EURO-D scores for unemployed men aged 50-68.*

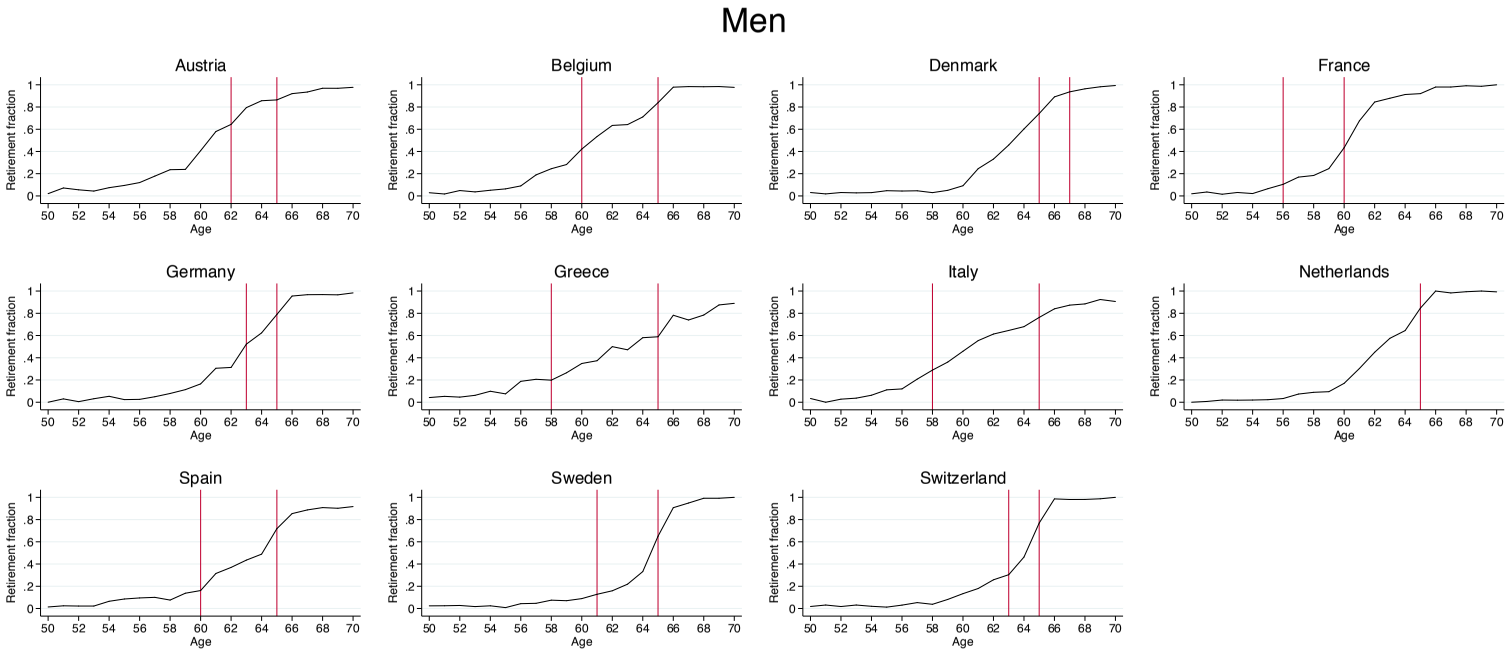


Figure 6: *Retirement fraction by country and age. Red lines indicate approximate early and normal retirement ages.*

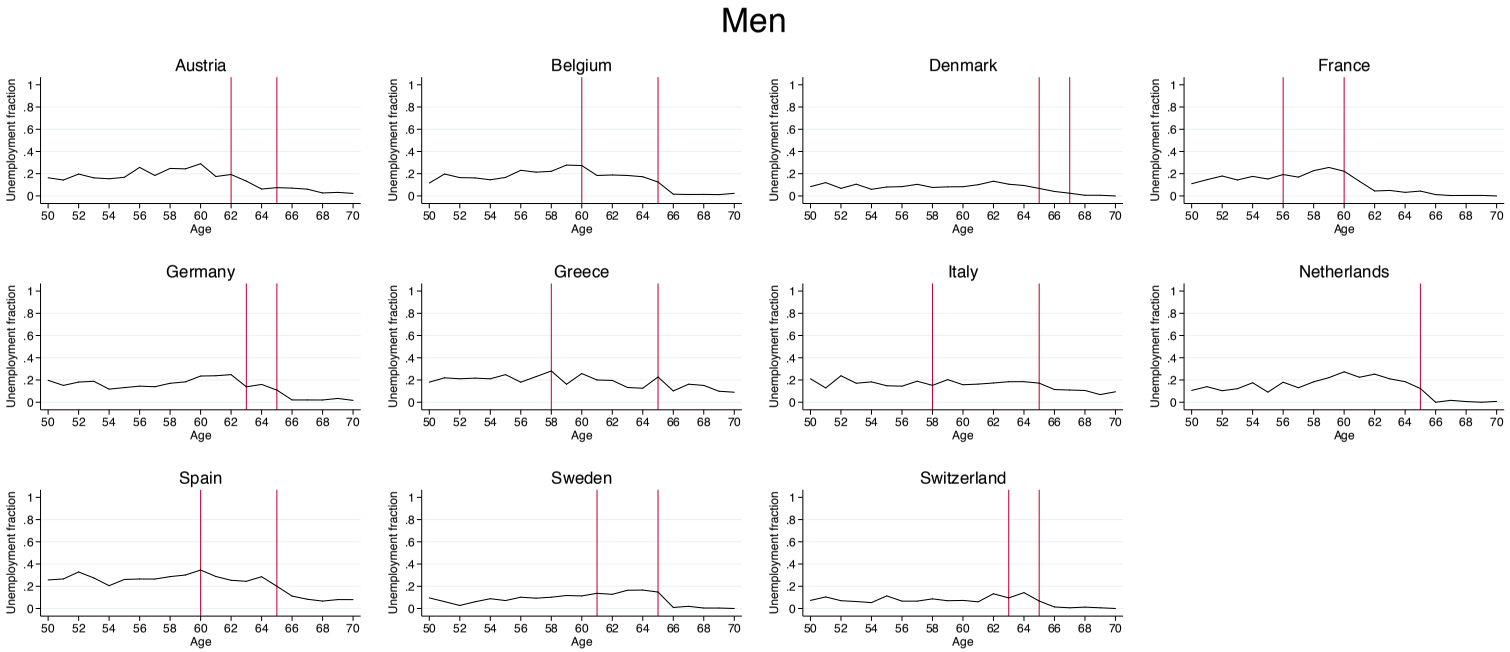


Figure 7: *Unemployment fraction by country and age. Red lines indicate approximate early and normal retirement ages.*

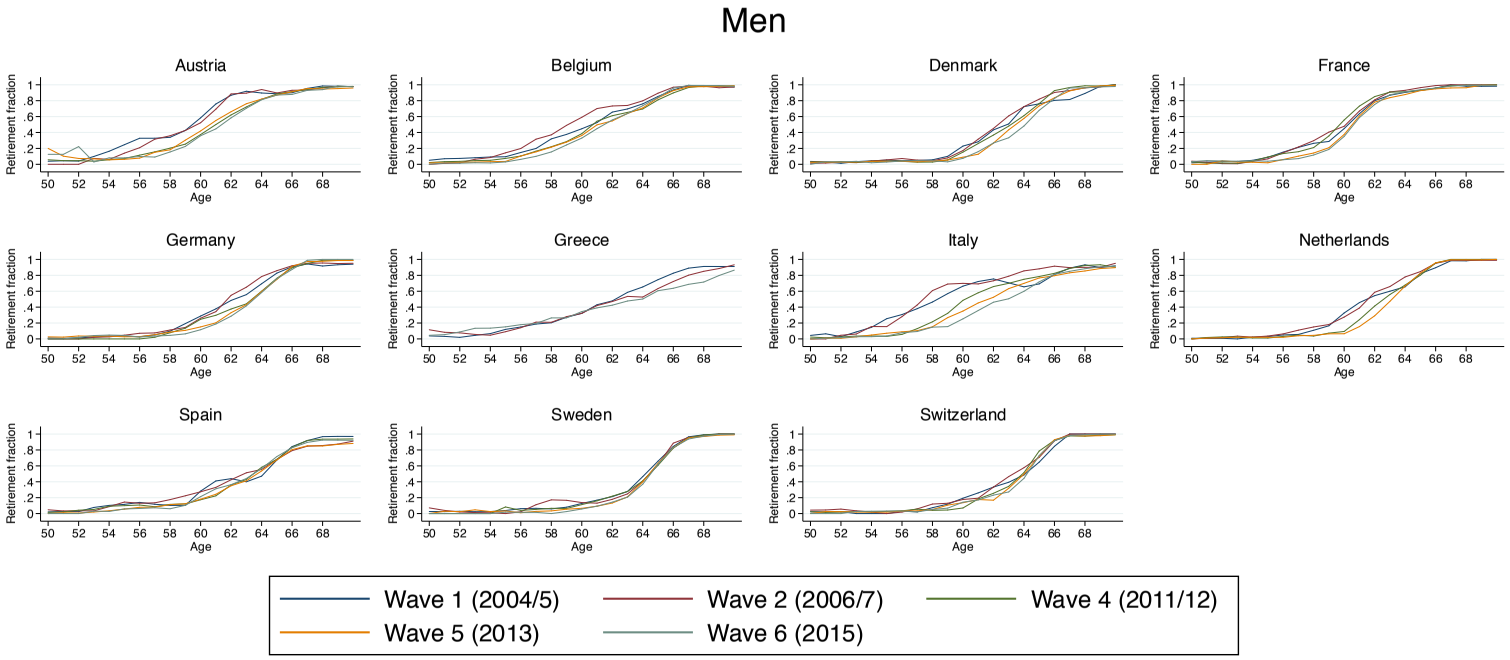


Figure 8: *Retirement fraction Ret_{it} by country and wave over age as used in our main regression specification (see equations 3 and 4).*

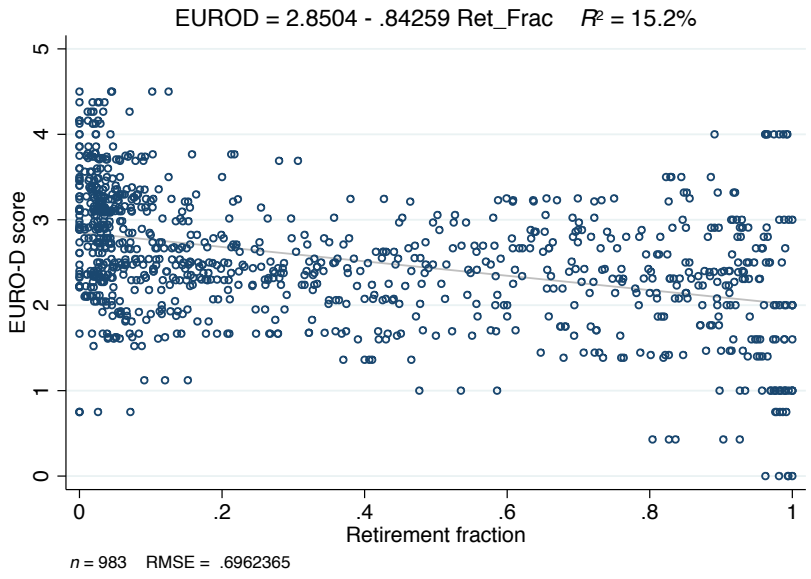


Figure 9: *Scatter plot of EURO-D scores and retirement fraction by age in years from 50-68 years old for each country and wave.*

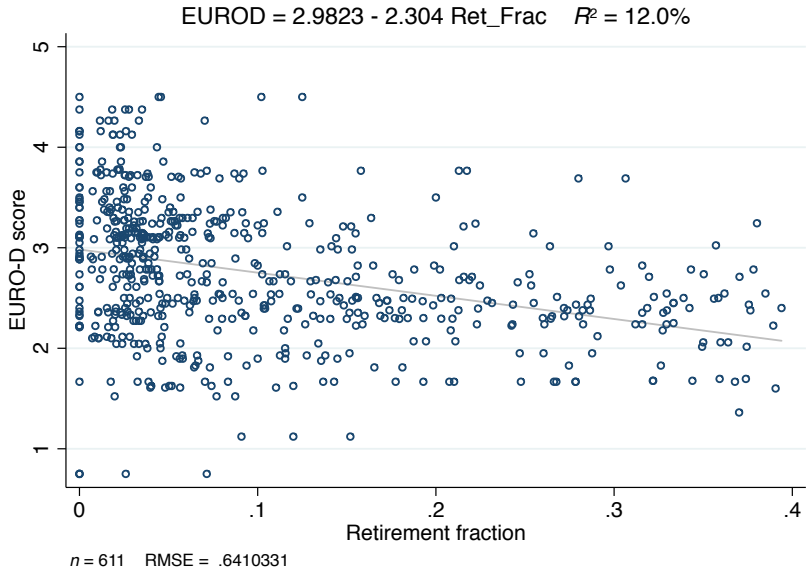


Figure 10: *Scatter plot of EURO-D scores and retirement fraction by age in years from 50-68 years old for each country and wave. The plot only includes points for a retirement fraction below 40%*

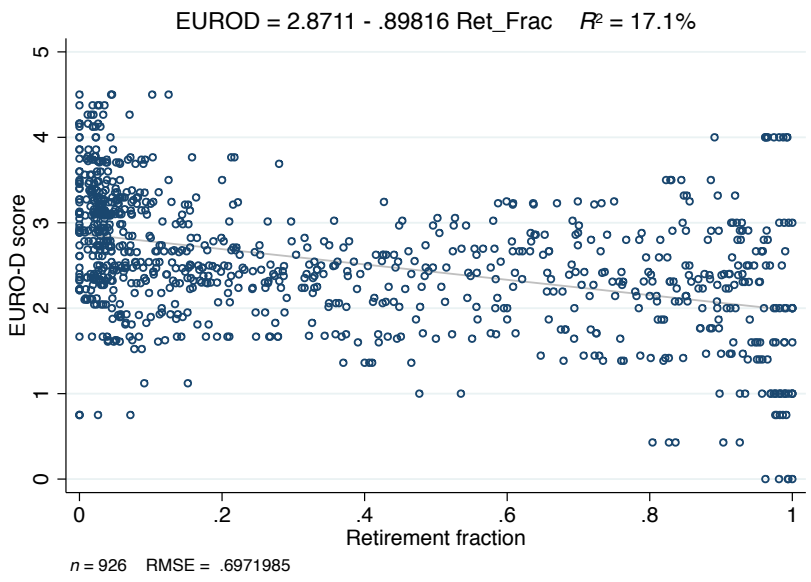


Figure 11: *Scatter plot of EURO-D scores and retirement fraction by age in years from 50-68 years old for each country and wave. Each color represent one country. The plot excludes Greece, Italy and Spain.*

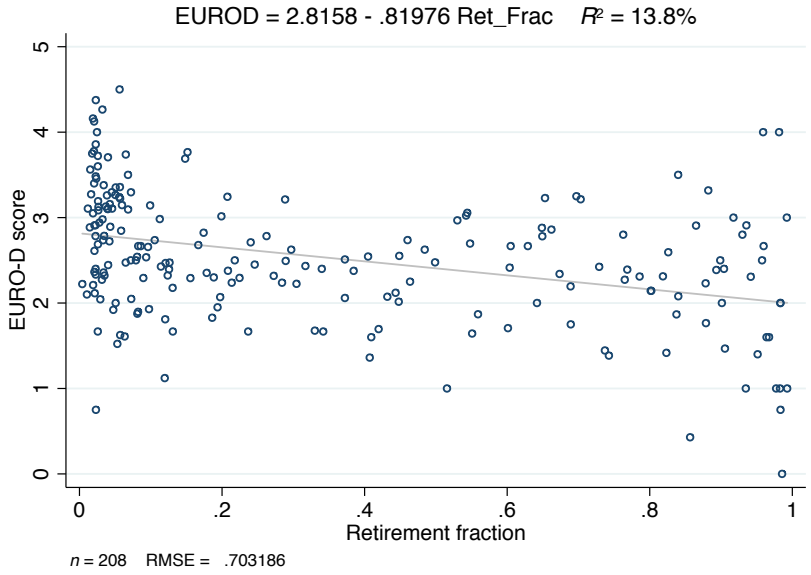


Figure 12: *Scatter plot of EURO-D scores and retirement fraction by age in years from 50-68 years old for each country averaged over the survey waves.*

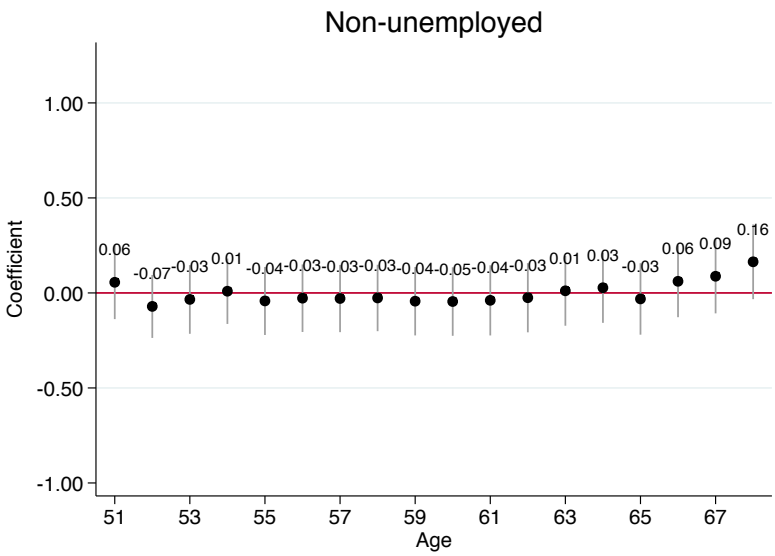


Figure 13

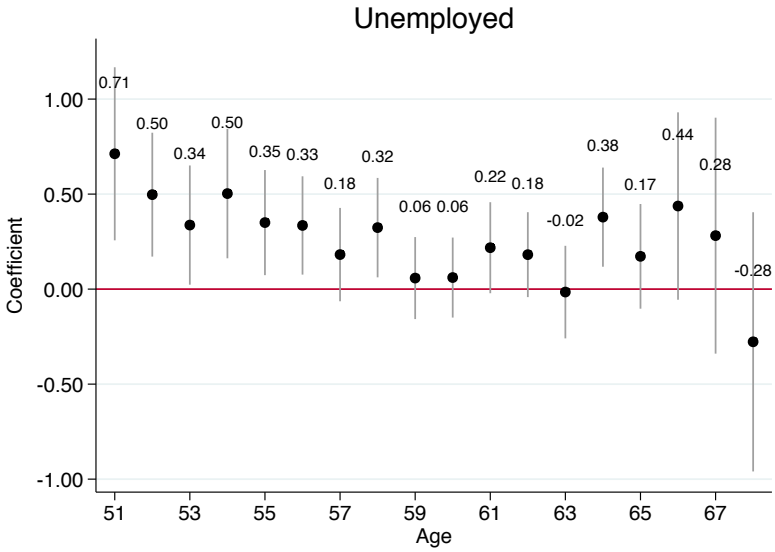


Figure 14

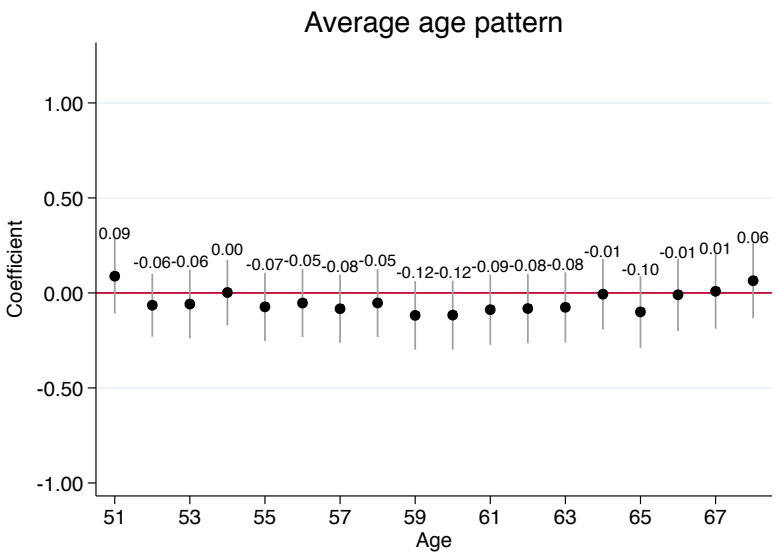


Figure 15

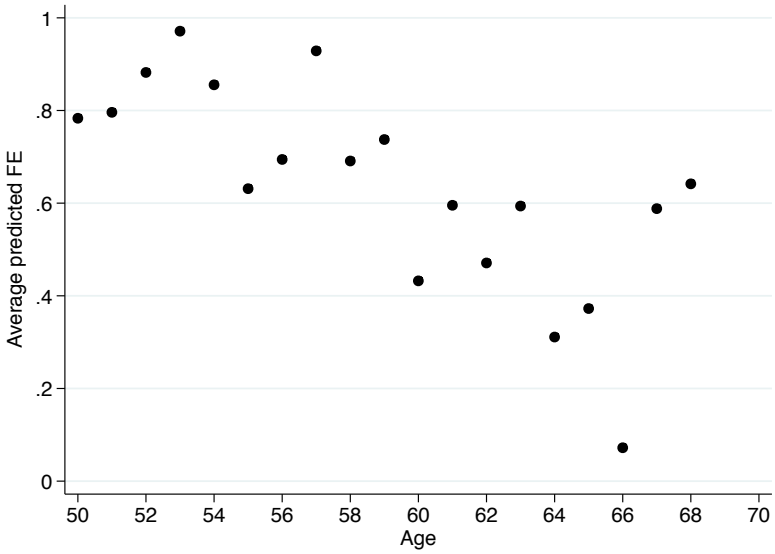


Figure 16

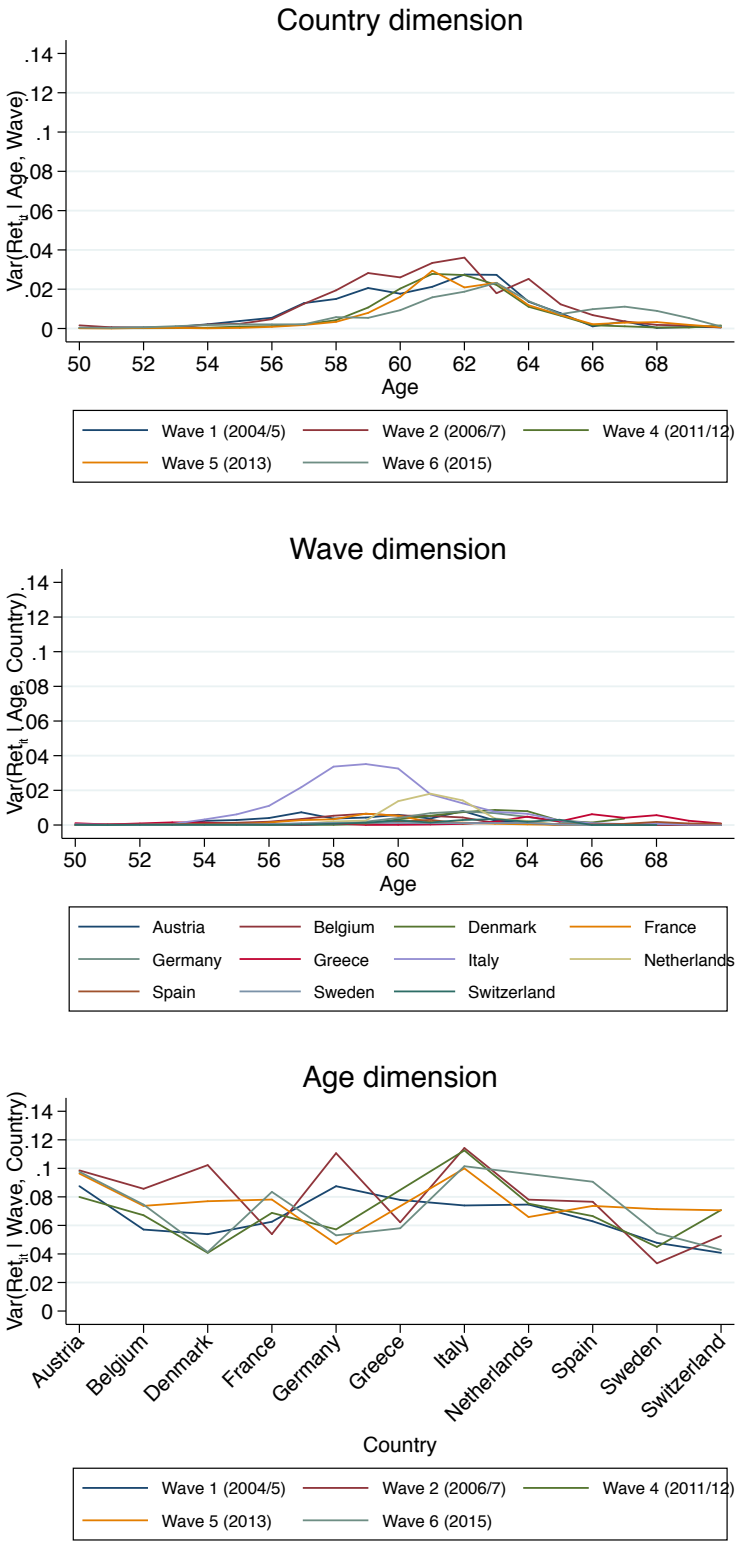


Figure 17: *Conditional variance in the retirement fraction* Ret_{it} *(see equation 4 along the three relevant dimensions.*