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Abstract The individual level of subjective well-being (SWB) has been shown to predict a number of future observable outcomes. Behaviour may however also be affected by the slope of SWB with respect to certain variables. We here use latent-class analysis to model both intercept and slope heterogeneity in the SWB-income relationship, and construct a continuous measure of the marginal utility of income. We show this marginal utility does predict future behaviour: those who value income more (who have a higher income elasticity of well-being) are less likely to retire. This correlation is found conditional on both the level of income and the level of well-being.

Keywords: Subjective Well-being, Retirement, Marginal Utility of Income, Latent Class Models.

JEL classification: I31, C35.

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1 Introduction

While the retirement decision has been at the heart of much research across OECD countries, this work has mostly concentrated on the "objective" characteristics of the individual and the job that lead to retirement (such as age, health, income and partner's labour-force status). Relatively less is known about the relationship between subjective well-being and retirement. Most of the literature in this area has focused on how retirement affects life satisfaction (Wottiez and Theeuwes [1998]; Kim and Moen [2001]; Lindeboom et al. [2002]; Charles [2004]; Borsch-Supan and Jurges [2007]; Seitsamo [2007]; Bonsang and Klein [2012]). Shultz et al. [1998] consider the relative importance of "push" (e.g. poor health) and "pull" (e.g. leisure) factors on retirement satisfaction, Elder and Rudolph [1999] investigate the role of financial planning and expectations, Panis [2004] relates annuities and wealth to both retirement satisfaction and measures of depression, and Bender [2004] emphasises the non-economic determinants of well-being in retirement.

Perhaps of greater policy interest is the reverse relationship: does well-being when working predict the age at which the individual retires? With pension systems needing to be re-designed to become sustainable, and the preferred option in many countries consisting in encouraging individuals to stay on at work, understanding who retires and when is of great practical policy interest. Yet, although subjective well-being has been shown to predict a variety of future behaviours in panel data, it has almost never been used to predict retirement (an exception is Debrand and Sirven [2009], who confirm a negative impact of job satisfaction on retirement). This is what we do here.

We use data from the American Health and Retirement Study (HRS) to estimate the relationship between well-being when at work and subsequent retirement. We indeed find that those who are happier when working are less likely to retire over the next two years. But our main contribution is to allow heterogeneity in individual well-being functions, and specifically in terms of how much individuals value income. One of the key characteristics of retirement is the associated loss of income. However, it is entirely possible that some individuals value income more than do others. If this is the case, then those whose well-being is the most strongly-related to income should be (ceteris paribus) less likely to retire.[1] The broad approach here is to allow heterogeneity into individual well-being functions, in terms of the estimated coefficients in the well-being regression: this is slope heterogeneity. We then use the variation across individuals in these estimated coefficients to predict their future behaviour.

For this to work, we obviously need some variability across individuals in the estimated coefficient on income in a well-being regression. We could obtain this in an *ex ante* manner, by estimating separate equations by age, education, gender and so on (or by introducing interactions).[2] We here take an *ex post* approach, and let the data themselves decide: we appeal to a finite mixture model (FMM) to model heterogeneity in the correlation between income and well-being, whereby individuals are sorted (probabilistically) into different classes. The model strongly rejects the hypothesis of an equal effect of income on well-being across groups. We use the estimated income coefficients in each group, and the individual's probability of belonging to each group, to construct a continuous individual-specific measure of the marginal utility of income. We then see whether each individual's estimated marginal utility of income affects their future retirement behaviour.

We believe that this work adds to the existing literature on well-being and retirement in a number of ways. First, we introduce heterogeneity into the income to well-being relationship. This allows us to explore the determinants of class mem-

[1]This is somewhat similar to the argument made in Jakubson [1988], where the presence of the marginal utility of wealth introduces an individual fixed effect into labour supply. We here try to explicitly measure this marginal utility, and allow it to change within individual over time.

[2]This is what Finkelstein et al. [2013] do, by interacting health and permanent income in a subjective well-being regression. They find that the marginal utility of income falls as health worsens.

bership. Our results suggest that "money buys happiness" much more for one group than for another, and also provide us with information about "for whom it buys the most happiness". Second, our retirement model suggests a significant negative effect of this estimated marginal utility of income: those who value income the least are more likely to retire. We can then encourage labour-force participation via income measures for those who are most "income-sensitive", but much less so for the other groups. Finding that the slope of the estimated well-being function predicts future behaviour is also a new finding in the empirical literature on the validation of subjective well-being measures.

The remainder of the paper is organised as follows. In the next section, we provide a brief overview of the existing literature on the marginal utility of income. Section 3 then describes the data and the initial results, and Section 4 explains the econometric methodology. In Section 5 we present our results and answer the question of the impact of the marginal utility of income on the probability of retirement. Last, Section 6 concludes.

2 The Retirement Decision and the Marginal Utility of Income

2.1 The marginal utility of income in structural models of retirement

Retirement behaviour has been at the core of a considerable body of theoretical analysis (see Lumsdaine and Mitchell [1999]). The retirement decision is usually modeled in a dynamic framework based on the maximization of the worker's lifetime utility, and which allows for heterogeneity between workers, as in Gustman and Steinmeier [1986]. Stock and Wise [1990] introduced the option-value model, where individuals compare at any age the expected present value of retiring at any future age with the expected present value of retiring immediately, up to the mandatory age of retirement. The maximum of this difference is called the option value, and workers will delay their retirement as long as the option value is positive. In Stock and Wise's model, the indirect utility from future income can be written as follows: $V_t(r) = \sum_{s=t}^{r-1} \beta^{s-t} U_w(Y_s) + \sum_{s=r}^{T} \beta^{s-t} U_R(B_s(r))$, where $U_w(Y_s)$ is the indirect utility of future wage income Y_s and $U_R(B_s(r))$ is that of future retirement benefits $B_s(r)$. Individuals live until age T. The utilities of future wage and retirement income are parameterized as:

$U_w(Y_s) = Y_s^\gamma + \omega_s$ and $U_R(B_s(r)) = (kB_s(r))^\gamma + \xi_s$, where ω_s and ξ_s are individual-specific random effects. There is heterogeneity in the effect of income on utility here, as the marginal utility of income when working is different from that when retired (if $k \neq 1$). This heterogeneity in the marginal utility of income appears within individuals between periods, but not between individuals. Between-individual heterogeneity here comes from the individual-specific random effects, ω_s and ξ_s, which do not affect the marginal utility of income. Gustman and Steinmeier [2005] develop this model by allowing individuals to have differing time preferences. Individuals with high time preferences (i.e. with a high discount factor) perceive the actuarial level of Social Security benefits to be unfair (even though they are designed to be actuarially fair). As such, they have a greater incentive to retire as soon as benefits become available. This helps explain why so many individuals collect benefits at the earliest opportunity, at the cost of reduced social security wealth (at an age when the option value is still positive).

We here add to this rich retirement literature by allowing the marginal utility of income $U_w'(Y_s)$ to differ across individuals, so that $U_{w,i}'(Y_s)$ for individual i may differ from $U_{w,j}'(Y_s)$ for individual j. In line with the option value model above, those who value their labour income more (who have a higher marginal utility of income when at work) will have a higher option value and will so retire later.

2.2 Measuring the marginal utility of income

As we wish to evaluate the role of the marginal utility of income in predicting retirement, our first task is the estimation of the former. For this we require a proxy measure of utility, which will here be the subjective well-being score available in the HRS. One suspicion amongst economists is that what individuals say, including about their well-being, may not always reveal their true feelings and preferences (and thus their behaviour): see Adler [2013]; Clark [2015]. A useful response to this suspicion comes from the literature in which cross-section distributions of well-being predict individual future behaviour in panel data. The underlying idea here is that individuals can be shown to discontinue activities that are associated with lower well-being (see Kahneman et al. [1993]; Frijters [2000]; Shiv and Huber [2000]). One such example is job satisfaction predicting future job quits, even when controlling for wages, hours of work and other standard individual and job characteristics (see, amongst others, Freeman [1978]; Clark et al. [1998]; Clark [2001]; Kristensen and Westergaard-Nielsen [2006]); this can also be applied to the duration of self-employment Georgellis et al. [2007]. Clark [2003] shows that the change in mental stress on entering unemployment predicts unemployment duration: those who suffered the sharpest drop in well-being were the quickest to leave. In the realm of work, job satisfaction is correlated with other observable outcomes: with firm performance in Iaffaldano and Muchinsky [1985] and Ostroff [1992], and with customer satisfaction in service industries in Rogers et al. [1994]. This predictive power is also found in other domains of life. Life satisfaction predicts marital break-up (Guven et al. [2012]), as well as future morbidity and mortality (Steptoe et al. [2012]) and child-bearing (Cetre et al. [2015]). This literature has therefore arguably shown that individual subjective well-being scores are at least partly interpersonally comparable in the cross-section, otherwise they would not be able to predict the future cross-section distribution of individual behaviour and outcomes.

We here consider the relationship between SWB and income in order to estimate the marginal utility of income, and will do so via a finite mixture model. The underlying idea in these models is that the unknown population distribution with respect to the regression coefficients may be empirically approximated by a mixture of distributions with a finite number of classes. The path-breaking work on the expectations-maximization (EM) algorithm (by Dempster et al. [1977] and Aitkin and Rubin [1985]) made latent-class models accessible to applied researchers. In recent years, the finite mixture model has been used in a number of applications, e.g. in Eckstein and Wolpin [1999]; Morey et al. [2006], and the work of Deb who has contributed a great deal in rendering these models attractive (see Deb and Trivedi [1997]; Ayyagari et al. [2009]; Deb et al. [2009]). Clark et al. [2005] model intercept and slope heterogeneity using latent class techniques to allow the parameters of the unobserved individual utility function to differ across individuals. In this paper we follow the same approach. Our data here identify two classes of individuals, and strongly reject the hypothesis that the marginal effect of income on well-being is identical across classes. It is worth underlining that the introduction of individual fixed effects (intercept heterogeneity) would not capture this effect of different estimated coefficients between groups (slope heterogeneity).

Last, in the existing SWB literature marginal utility is traditionally estimated (taking unobserved heterogeneity into account or not) conditional on a wide range of other right-hand side variables (these commonly include gender, marital- and labour-force status, health, education, *etc.*). The danger here is that some of these right-hand side variables may themselves be functions of income: one obvious candidate is health (see Dolan et al. [2011]). As such, their use as explanatory variables means that we potentially condition out a large part of the correlation between income and SWB. As we would like to establish the overall effect of income on utility, including any of these indirect effects, we first regress SWB on income and a few other exogenous variables, such as age, gender, and race. As a robustness check, we also consider a specification with additional variables in the SWB equation.

3 Data

We use data from the US Health and Retirement Study (HRS), which is a nationally-representative longitudinal survey of individuals aged over 50 and their spouses. The first 1992 wave covered 12,652 individuals from 7,702 households and was face-to-face; subsequent interviews were conducted by telephone. The HRS initially sampled persons in birth cohorts 1931 through 1941 in 1992, with follow-up interviews every two years. In 1998, individuals from the 1924 to 1930 and 1942 to 1947 cohorts were added to the original sample; and in 2004 it was the turn of individuals from the 1948 to 1953 cohorts. Our analysis here uses Version I of the data prepared by RAND, which is a cleaned and processed version of the HRS data. We have 10 waves of data available from 1992 to 2010, of which we use Waves 2 to 8, i.e. from 1994 to 2006.

The measure of subjective well-being in the RAND-HRS data appears in all waves, but with a different response scale in Wave 1 which cannot easily be converted to that in later waves. We thus drop Wave 1. We do not use the last two waves as occupation there is coded differently, and in a way that makes comparisons with the previous waves tricky.[3] The well-being measure is an abridged version of the Center

[3] In the data up to 2006, the 1980 SOCs (Standard Occupational Codes) were collapsed into 17 categories following a hierarchical structure taking into account knowledge, skill level and experience. From year 2008 onwards (waves 9 and 10), on the other hand, the 2000 SOCs were collapsed into 25 categories, which are grouped according to "job families". The general concept behind this new classification consists in combining people who work together producing the same kinds of goods and services regardless of their skill level, for example doctors, nurses, and health technicians. In addition, the 2000 SOCs have more professional, technical, and service occupations and fewer production and administrative-support occupations, which makes it more difficult to convert one classification into the other. Although a "'crosswalk" was created for this very purpose, it only covers the management/professional

for Epidemiologic Studies-Depression (CESD) Scale (Radloff [1977]). The CESD depression scale originally comprised twenty items. The HRS only retains eight of these: depressive feelings, everything seen as an effort, restless sleep, could not get going, loneliness, sadness, enjoyment, happiness. All of the questions behind the CESD score are binary Yes/No indicators of the respondent's feelings "much of the time during the past week prior" to the interview. The between-item validity of the CESD scale (Cronbach's alpha = 0.72) is sufficiently high for the well-being measure to be considered as robust. The resulting depression score is the number of questions to which the individual answers "Yes" for the first six items and "No" for the last two. We then reverse this depression score to produce a subjective well-being scale, where 0 indicates the worst level of psychological wellbeing and 8 the best.[4]

Our regression sample from the HRS is defined as follows. For the purpose of our analysis, we require that the individual be in work at wave t and also be observed at wave $t+1$. We concentrate on individuals who are at "prime retirement age" in the US, 55-70, at both waves t and $t+1$. We also drop those who are retired in the first period in which we observe them (as we then have no pre-retirement observation when they were employed). We keep the observations only on individuals who are in employment; any subsequent observations once they are retired are dropped. The approach is then to relate the individual's current characteristics when employed to their probability of being retired two years later. Last, some individuals are observed to retire but subsequently re-enter the labour market. We drop all observations on these individuals, and as such consider retirement as an absorbing state. Our final estimation consists of 22,075 observations on individuals in employment, representing 7,975 individuals, amongst whom 41% will retire over the seven waves of data.

categories.

[4]CESD scores are missing for about 7% of the observations we could have used in our regressions. We have checked to see whether the sample is balanced according to the presence/absence of CESD. We find differences only with respect to gender and education, both of which we control for in our empirical analysis.

We have information about the usual socio-demographic and economic variables (gender, marital status, number of children, age, education, race, health, total household wealth, total household income) and job-related variables (number of hours worked, occupation). The HRS includes both objective and subjective (self-assessed) health. As in Finkelstein et al. [2013], we consider the objective measure, the number of health conditions (although our results are remarkably similar with self-assessed health). Individuals are asked whether they have the eight following health conditions: high blood pressure or hypertension; diabetes or high blood sugar; cancer or a malignant tumor of any kind except skin cancer; chronic lung disease except asthma, such as chronic bronchitis or emphysema; heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; stroke or transient ischemic attack (TIA); emotional, nervous, or psychiatric problems; and arthritis or rheumatism. No problems are reported by 30% of the sample, and only one in eight report three or more health conditions. The average number of health conditions is just over one.

The HRS also includes two less-common subjective variables. The first is risk aversion, on a scale from 1 to 4, where 1 indicates the least risk-averse preferences.[5] The second concerns the financial-planning horizon. Individuals are asked "In deciding how much of your (family) income to spend or save, people are likely to think about different financial planning periods. In planning your (family's) savings and expenditure, which of the time periods listed in the booklet is most important to you [and your husband/wife/partner]?". The variable is coded 1 if the answer is "next

[5] This variable is based on a series of "income-gamble" questions: it is coded 1 if the respondent would take a job with even chances of doubling or halving income; 2 for a job with even chances of doubling income or cutting it by a third; 3 for a job with even chances of doubling income or cutting it by 20%; and 4 if he would take or stay in a job that guaranteed current income given any of the above alternatives. As these questions were not asked in the 1994 and 1996 waves of the HRS, nor in the interviews by proxy, we replace missing values with data from the closest past wave for every individual. The sample size falls when we include risk-aversion. Most of our sample is risk-averse, with 64% giving the most risk-averse answer and only 12% the least risk-averse answer.

few months”, 2 for “next year”, 3 for “next few years”, 4 for “next 5-10 years”, and 5 for “longer than 10 years”. Most individuals say that they think in terms of the next few years or next 5 to 10 years, which are the intermediate answers.[6] We will control for risk-aversion and financial planning in some specifications of our analysis of the determinants of retirement, as they have been shown to be important in existing work.

Table 1 in the Appendix describes our estimation sample. We consider all individuals who were working at the time of the interview. The average CESD score is just under 7 (on the 0 to 8 scale), and 15% of observations in employment are followed by retirement within the next two years. Average household equivalent income (in 2011 dollars) is 72 500$ (we equivalise by the square root of household size, so that this corresponds to total household income of 145 000$ for a family of four). Household net worth (which is not equivalent) can be either positive or negative (in the case of debts). To use this variable in log form, we divide by 100 000, take away the minimum sample value of net worth from each observation (which transformation makes all values weakly positive), add one, and then take the log. Average net worth (before this transformation) in the sample is a little over 450 000$. Household net worth is defined as all assets (including housing) minus all debts, but does not include the value of Individual Retirement Accounts. This latter appears as a separate variable in Table 1.[7]

The distribution of well-being in our estimation sample appears in Table 2. This is largely right-skewed, with over 75 per cent of the pooled sample reporting scores of 7 or 8, and less than 1 per cent a zero score. The “between” distribution shows that just under 70 per cent of the sample recorded an 8 score at least once, while

[6]Financial planning is missing in the same way as risk aversion, as described in the previous note. We take the same “imputation” approach to missing values as described there.

[7]The average value of IRAs in this sample is just under 50 000$. Half of the sample have no IRA savings. As we are dealing with an older sample here, and IRAs were only introduced in 1974, we would expect this “no-IRA” percentage to fall over time.

fewer than 2 per cent have ever produced a zero score. “Within” individuals (in the last column), three-quarters of those who ever reported a score of 8 had a score of 8 at each wave. On the contrary, less than half of the individuals with a score of zero had a score of zero at every wave. This might either reflect measurement error, or that most people who reported such low scores had indeed had a bad year, and had better years in other waves.

Before starting the econometric analysis, we present the bivariate relationships between our three key variables: subjective well-being, income and retirement. Figure 1 shows the non-parametric estimation of mean CESD by quantiles of total household equivalent income.[8] In this cross-section, income is positively correlated with subjective well-being (as is very commonly the case), with the relationship being notably concave.

Figure 1 plots an “average” utility function as if individuals were homogeneous in their valuation of income. However, individuals sharing the same observable characteristics may be more or less happy depending on what we might call their “personality” type. Self-determination theory (see Ryan and Deci [2000]) suggests that behaviour can be intrinsically or extrinsically motivated. An internally-motivated individual derives much more utility from social interactions and community involvement than from accumulating wealth, while the extrinsically-motivated derive their utility from income. Individuals may also be heterogeneous in the way in which they translate their latent unobserved utility into a discrete verbal satisfaction answer. The FMM analysis will allow the relationship between income and well-being to differ between individuals in terms of both the intercept and the slope.

We now turn to the relationship between income at time t and retirement between

[8] Total household income includes earnings from work, household capital income, income from employer pensions or annuities, unemployment insurance or worker’s compensation, social security retirement or disability benefits, other government transfers (veteran’s benefits, food stamps, *etc.*), and other household income such as alimony or lump sums from insurance, pensions or inheritances.

waves t and $t+1$. The effect of income here is ambiguous, as retirement is a labour-supply decision. If leisure is a normal good, people should consume more leisure as income increases (the income effect). On the other hand, if that income stems from a higher wage rate, the worker will substitute work for leisure, by substituting away from leisure due to its higher opportunity cost (the substitution effect). Figure 2 shows that there is a clear negative relationship between household income and retirement (consistent with the substitution effect dominating the income effect). This may not persist in multivariate analysis. Those at the top of income distribution are likely to be in better health and to work in "nicer" occupations, due to their higher education, and the fact that they retire less may not only reflect income and substitution effects.

Last, as shown in Figure 3, SWB and retirement seem to be negatively correlated, especially at the two tails of the SWB distribution. The happier retire less, at least in a bivariate sense.

The following section describes the methodology that we use to put all of these pieces together in a multivariate sense. Little work has considered the impact of SWB, even in levels, on the retirement transition. We will estimate CESD as a function of income in order to have an estimate of the marginal utility of income: this latter is then used to predict retirement, together with the levels of income and CESD.

4 Econometric Methods

4.1 First Step: Estimating the Marginal Utility of Income

This paper is one of only few to use latent class models to analyse individual unobserved heterogeneity in the marginal utility of income, and we believe the first to use the analysis results to predict future behaviour.

The FMM distinguishes between a finite, usually small, number of latent classes of individuals (this number is called C in the presentation below). Each class corresponds to a separate regression in which both the intercept and the estimated coefficients differ. We are particularly interested here in the estimated coefficient on income in the different classes of CESD regressions.

The basic econometric model used to model SWB is:

$$E(WB_t|INC_t, X_t) = \alpha INC_t + \beta X_t \tag{1}$$

where our key explanatory variable is INC, the logarithm of total equivalent household income, and X_t is a vector of individual characteristics (sociodemographic, labour-market and wealth variables, and region dummies). Equation 1 is first estimated by OLS, and here $\alpha/100$ is the absolute change in WB resulting from a 1% increase in income. However, if WB is drawn from distinct subpopulations, the OLS estimate of α may hide considerable heterogeneity. We therefore estimate a finite mixture model, where sub-populations are assumed to be drawn from normal distributions.

In the FMM the random WB variable is considered as a draw from a population which is an additive mixture of C distinct classes in proportions π_j such that:

$$g(WB_i \mid X_i; \theta_1, ..., \theta_C; \pi_{i1}, ..., \pi_{iC}) = \sum_{j=1}^{C} \pi_{ij} \prod_{t=1}^{T_i} f_j(WB_{it} \mid X_{it}, \theta_j), \tag{2}$$

$$0 \leq \pi_{ij} \leq 1, \qquad \textstyle\sum_{j=1}^{C} \pi_{ij} = 1, \qquad \forall i = 1, ..., N;$$

where θ_j is the associated set of parameters, $T_i = 1, ..., 7$ is the number of times the individual i is observed, and the density of component j for observation i is given by:

$$f_j(WB_{it} \mid X_{it}, \theta_j) = \frac{1}{\sigma_j \sqrt{2\pi}} exp\left(-\frac{1}{2\sigma_j^2}(WB_{it} - \alpha_j INC_{it} - \beta_j X_{it})^2\right) \tag{3}$$

The finite mixture model is estimated using maximum likelihood and cluster-corrected (for within-individual correlation) robust standard errors. Starting from the initial estimates of component proportions π_j, we then re-estimate the model assuming a prior component probability of the form:

$$\pi_{ij}(Z_i \mid \delta) = Z_i'\delta, \qquad 0 \leq \pi_{ij} \leq 1, \qquad \sum_{j=1}^{C} \pi_{ij} = 1, \forall i = 1, ..., N. \tag{4}$$

The prior component probability π_j now depends on observables Z and so varies across observations: individuals with different observable characteristics then likely have different probabilities of belonging to the various classes. The same individual with different values of the Z at different points in time will have time-varying probabilities of being in the various classes.

As put forward in Deb et al. [2009], finite mixture models have many advantages, but also some drawbacks. A finite mixture model may only fit the data better than a basic OLS due to outliers, which are picked up in the FMM via additional mixture components. As such, even if the use of FMM is motivated by *ex ante* reasoning, the different latent classes should be justified *ex post*.

The FMM model yields the prior and posterior probabilities of being in each of the latent classes, conditional on all observed covariates (and also on the observed WB outcome for the posterior probability). Using Bayes' theorem, the posterior probability of being in component k is:

$$Pr(i \in k \mid \theta, WB_i) = \frac{\pi_{ik} \prod_{t=1}^{T_i} f_k(WB_{it} \mid X_{it}, \theta_k)}{\sum_{j=1}^{C} \pi_{ij} \prod_{t=1}^{T_i} f_j(WB_{it} \mid X_{it}, \theta_j)}, \qquad \forall k = 1, 2, ..., C. \tag{5}$$

The posterior probability varies across observations, as does the prior probability when re-estimated conditional on Z. The difference between these two is that posterior probabilities are also conditional on the outcome WB_i. The latter can of course be used to explore the determinants of class membership, but in what follows we stick to the prior probabilities for reasons that we will set out in Section 5.

4.2 Second Step: Using the FMM Results to Predict Retirement

Latent-class analysis provides different estimates of the marginal utility of income for each group, the α_k, $\forall k = 1, 2, ..., C$, along with the prior probabilities $\pi_k(Z_i \mid \delta)$ and posterior probabilities $Pr(i \in k \mid \theta, WB_i)$ of belonging to class k. We exploit this individual heterogeneity to create a continuous measure of the marginal utility of income, defined as:

$$e = \sum_{k=1}^{C} \alpha_k \pi_k(Z_i \mid \delta) \tag{6}$$

We will then investigate the effect of e on the probability of retirement by wave $t+1$ for individuals who are in work at wave t. Our probit retirement-probability model is:

$$Pr(Retire_{i,t+1} = 1 \mid V_{i,t}) = \Phi(V'_{i,t}\gamma_t) \tag{7}$$

where Pr denotes the probability, ϕ is the cumulative distribution function of the standard normal distribution, and V is a vector of covariates. The parameters γ are estimated by maximum likelihood. $Retire_{i,t+1}$ is a dummy coded 1 if individual i stops working between waves t and $t+1$ and declares themselves to be "fully retired" at wave $t+1$, which is the case for 15 per cent of our pooled sample.

5 Results

5.1 Well-Being Results From Finite Mixture Models

We here estimate the marginal utility of income, which we argue is reflected by the coefficient on log equivalent household income in a subjective well-being regression, using both a simple OLS regression and a number of specifications of a finite mixture model. The results are presented in Table 3. As argued in Section 2, we only introduce very few variables as controls in the main equation, namely gender, age, and race, which are unambiguously exogenous. This way, we are sure to pick up both the direct and indirect effects of income on SWB. The robustness section will test specifications which include other explanatory variables. The model selection criteria (AIC/BIC) at the foot of the table clearly favour a 2-component mixture model as compared to the 1-component OLS model. The 3-component model fails to converge after a reasonable number of iterations, suggesting that the third component is trying to fit only a small number of outliers.

The OLS results suggest a significant correlation between log income and SWB with an estimated coefficient of 0.31: SWB rises by 0.31 points as income doubles. The FMM identifies two latent classes. The probability of class membership is estimated by a multinomial logit regression (here actually a simple logit, as we only have two classes). The results of this estimation will be discussed in Table 4 below. In this model, each observation has a non-zero probability of belonging to each class. Within-individual, this probability will change over time with the values of the individual right-hand side variables in Table 4. All standard errors are clustered at the individual level.

The estimated average probability over all observations of belonging to Class 1 is 32%. In this first "smaller" group, income has a significant effect on SWB with a coefficient of 0.329; by way of contrast, in the "larger" second group the effect of income on SWB is only small (0.039). There is thus evidence of striking differences in the SWB-income relationship, which was masked in OLS estimation. The two identified groups are dissimilar, with the high marginal utility of income group (Class 1) being less happy on average (with a mean SWB score of 5.25) than those in Class 2 (mean SWB of 7.75).[9] Figure 4 shows that the distribution of predicted SWB in

[9]These mean SWB figures come directly from the estimated coefficients in Table 3, and reflect the predicted CESD of a hypothetical individual who is 100% in the class in question, and with an income equal to the sample average.

the second group is massed at the right end of the distribution: individuals here have high SWB scores of between 7 and 8.[10] The predicted SWB distribution in Class 1 is far less concentrated (as the coefficient on log income is over seven times larger) and mostly lies between 4 and 6.

Any number of specifications of the mixture model can be estimated according to the explanatory variables Z_i included in the multinomial logit determining class membership. Table 4 illustrates five possibilities for the logit equation predicting membership of Class 1, going from an extremely stripped-down version in column (1), where it is only log equivalent household income which determines class membership, to column (5), which is the most complete specification.[11] Column (5) is our preferred specification, as it corresponds to the smallest AIC and BIC.[12] It is this specification which is behind the FMM well-being estimates shown in Table 3. This specification includes socio-demographic and job variables, as well as the log of net worth and the log of the value of the individual's IRA.

The results show that women, singles, non-whites, the less-educated, and those with worse health are more likely to be in the less-happy high marginal utility of income group. Neither age nor the number of children predict class membership. Income reduces the probability of being in class 1, even when we control for wealth.

[10] This predicted SWB distribution can be inferred from the numbers in Table 3. In Class 2, the estimated constant is 7.208, with a coefficient on equivalent log income of 0.039. A household with income of zero has a value of log income of zero also (as we add one to ensure positive values), and thus predicted well-being of 7.208. That the distribution is extremely tight comes from both the log transformation and the small estimated coefficient on income. A household with equivalent income of 100 000$ can be seen to have a predicted level of well-being of 7.65; doubling equivalent income to 200 000$ only increases this fitted value to 7.68.

[11] Note that the model with socio-demographic variables in column (2) fits the data better than that with the labour-market variables in column (3), so that the latter variables predict class membership less efficiently.

[12] The Akaike information criterion (AIC) is a measure of the relative goodness of fit of a statistical model. It is based on the concept of information entropy, and offers a relative measure of the information lost when a given model is used to describe reality. Given a set of candidate models for the data, the preferred model is that with the lowest AIC value. The AIC rewards goodness of fit but discourages overfitting, as it includes a penalty that rises with the number of estimated parameters. The AIC penalises the number of parameters less than does the Bayesian information criterion (BIC), but here the two goodness-of-fit measures yield the same results.

Those in lower-status occupations (Service, Clerical and Administrative, Mechanics, Construction, compared to Manager and Technician Sup) are more likely to be in this first class. Last, in column (5), both net worth and IRA are negative, but only the latter is significant.

The well-being and income results in Table 3 are robust to alternative specifications of the Z_i in Table 4. We continue to find two groups with different valuations of income. For the majority of our sample, with higher SWB scores, income has only a small effect on SWB. In the other smaller group, which is less happy, SWB is much more sensitive to income. Broadly, the small less-happy group, with higher marginal utility of income, is made up of individuals with characteristics that are less well-rewarded on the labour market, while the majority of our sample is happier with better characteristics in this respect, with well-being that is much less affected by income. Our results are not the same as those from the ECHP data in Clark et al. [2005], who find 4 classes of individuals, amongst which "one group is both highly satisfied and has large marginal effects of income on well-being, while another is the least satisfied and has the lowest marginal effects of income on well-being" (page C127). This may reflect that our sample is restricted to those who are in work and age 50 or more, while theirs is not restricted in this way.

5.2 Does the Marginal Utility of Income Affect Retirement?

We now use the two estimated marginal utilities of income and the prior probabilities to calculate an individual-specific continuous measure of the marginal utility of income (see Equation 6 in Section 4.2). Figure 5 plots out the density of the prior probability. With only two groups, this marginal utility is a linear function of π_1 (from Table 3, our marginal utility variable $e = 0.329\pi_1 + 0.039(1 - \pi_1)$, so $e = 0.29\pi_1 + 0.039$), and therefore has a very similar distribution to that shown in Figure 5. The mean value of e is 0.134 with a standard deviation of 0.043. We can see from Figure 6 that e is a decreasing function of income: the well-being impact of income is lower for the richer. Retirement implies stopping work and often lower income, and we thus suspect that this marginal utility of income may play a role in the retirement decision. In particular, we expect lower marginal utility of income to increase retirement, *ceteris paribus*, conditional on the levels of both well-being and income.

The results from the probit estimation of retirement appear in Table 5 for the main coefficients, and Table 6 in the Appendix for those on the other controls. The five columns here have a triangular structure. Column (1) includes only the marginal utility of income, income itself, and well-being in order to predict retirement over the next two years. The coefficient on the marginal utility of income turns out to be positive, because of its high correlation with the socio-demographic variables, which are absent from this specification. Since individuals who are women, less educated, non-white, single, and with a worse health status, are more likely to retire, but also more likely to have a higher marginal utility of income, the coefficient of our key variable is here positively biased. Columns (2) through (5) then add progressively sociodemographic characteristics, job-related variables, net worth and the amount of the IRA, and risk aversion and financial planning. Once any additional controls are introduced, the estimated coefficient on the marginal utility of income is negative and significant. As income is controlled for here, the estimated e coefficient means that at a given level of income, the individual evaluation of this income helps predict retirement. Income itself attracts either a negative or a zero estimated coefficient. The main effect of SWB on retirement is consistently negative: those who are happier when working retire less. The marginal effect of the marginal utility variable is large: a one standard deviation rise of 0.043 can be seen to reduce the probability of retirement by 6.6 percentage points in the fifth specification, (where the average probability of retirement is 15%).

Regarding the other controls (see Table 6), we find reasonable results. For example, women, the less-educated, and those in worse health retire more (as in Maurer et al. [2011]). The age dummies attract broadly hump-shaped coefficients, with a peak at age 64 (meaning this is the peak age at which individuals will retire over the coming two years: individuals are eligible for Medicare at age 65), and a smaller peak at age 61 (individuals are eligible for early Social Security retirement benefits at age 62). Part-time workers retire more, perhaps because they have already started their retirement transition by reducing their work hours. The estimated coefficients on net worth and the value of the IRA are both insignificant. Those with a pension in the current job are more likely to retire, while those with current or ex-employer health insurance retire less. Last, with respect to the behavioural variables, the risk-averse are more likely to retire, while those with longer planning horizons retire less.

5.3 Robustness Checks

As explained in Section 2, we estimate the marginal utility of income by regressing SWB on income, with very few exogenous covariates in order to capture both the direct and indirect effects of income. We have also tested other specifications of this equation which include additional control variables. The left-hand panel of Table 7 reproduces the results from Table 3 for comparison purposes. The right-hand panel of Table 7 includes a few additional control variables in the well-being equation, such as educational attainment and region. The data again can be seen to sort into two groups with different valuations of income, in the same way as beforehand. We can use this new specification to calculate the marginal utility of income, and then evaluate the role of the latter in retirement. The results appear in Table 8. These confirm our previous results.

We can also re-estimate the specification corresponding to column (5) of Table 4 for various sub-samples (e.g. individuals in a couple, with low/high education, and men and women). For brevity, we only describe the salient features here. There are no sharp sex differences in general. The effect of marginal utility on retirement is larger for those with less than high-school education, and insignificant for those with college education and above. Last, the retirement of women in couples is more sensitive to the marginal utility of income than that of men in couples .

Equally, the nature of the job variables included in Table 5 can be fleshed out. In particular, we can add a variable indicating whether individual is an employee or self-employed, and introduce hours of work continuously (instead of just having a dummy for part-time work). Neither of these inclusions affects our conclusion regarding the marginal utility of income. The estimated coefficient on self-employed itself is negative and significant, and the estimated coefficient on income itself becomes insignificant (suggesting that income was proxying for hours of work in the retirement decision). We can also reconsider our definition of "retirement" itself. In particular, we can tighten it to those who both retire and at the same time claim social-security benefits. This does not change our qualitative results.

While Section 3 discussed missing values on the dependent variable, missing entire observations (i.e. attrition) could be equally important. We investigated by estimating a probit equation for being missing in Wave $t+1$ conditional on being observed in Wave t. The right-hand side variables in this equation are all those used to predict retirement in Tables 5 and 6. While some of these did turn out to be significant (race, marital status and number of children, for example) neither the level of well-being nor our estimated marginal utility predicted attrition.

The value of the marginal utility of income in Table 5 is calculated as the result of the estimation of the FMM model. We should therefore bootstrap the probit retirement estimation (the marginal utility of income is not data, it is an estimate). We have done so, and find bootstrapped confidence intervals that almost always differ from those in columns 2 through 5 of Table 5 by ten per cent or less.

The last, but arguably most important, point is that we do not know the correct specification of the utility function in terms of income. Countless empirical articles in Economics use log specifications, and this is true of work on subjective well-being as well. One interpretation of our negative estimated coefficient on the marginal utility of income is that the correct specification of the relationship between well-being and income is flatter than log. We therefore tried a transformation that is indeed flatter than log (the log of the log of income), but continued to find negative significant estimates for our marginal utility variable in a retirement regression. Of course we cannot prove that with the correct functional form between well-being and income marginal utility would no longer be a significant predictor of retirement. However, we do not think that this means that our work here is of no use; rather the interpretation of the estimated coefficient is different. It would then not be marginal utility that mattered in determining behaviour as such, but rather that this term acts as an individual-level correction factor. Latent-class estimation would then be one way of modelling behaviour based on utility maximisation without having to know exactly what the utility function looks like.

6 Conclusion

We here modeled heterogeneity in the relationship of income to subjective well-being via latent-class analysis on a nationally-representative sample of US workers close to retirement. We identify two classes of individuals with distinct marginal utilities of income. Our main results indicate considerable heterogeneity across the two latent classes. A smaller group is relatively unhappy, with high marginal utility of income, and is made up of individuals with characteristics which are less well-rewarded on the labour market, while the majority group is happier, with better-rewarded characteristics, with well-being that is less affected by income.

We then use these latent-class results to investigate the impact of the marginal utility of income on retirement. We thus add to the existing retirement literature by considering a "slope" as well as a "level" impact of well-being upon the probability of retiring. We find a negative significant effect of the marginal utility of income on retirement, even controlling for the main effects of income and well-being. Those who value income more retire less, controlling for how much income they have and how happy they are. As retirement often implies lower income, a higher marginal utility of income produces a greater well-being gap between working and retirement, and thus later retirement.

These findings are pertinent in the current context of pensions. That the majority of workers close to retirement care relatively less about the income drop from retirement, while a smaller group is much more sensitive to this loss, might help policy makers in designing labour-supply policy (by targeting the latter group). In general, most empirical work estimates conditional means: but we have no guarantee that what works "on average" will work for the group that is most affected by a particular policy. We also contribute to the validation of SWB scores, by showing that both the level and slope of self-reported SWB predict future behaviour.

A more general implication is that slope heterogeneity is probably worthy of further investigation: individuals differ in ways that are not captured by simple fixed effects. Here this heterogeneity helped to predict labour supply. Future applied work could usefully appeal to slope heterogeneity to model a wide variety of other behaviours. Finite mixture models are likely to become a useful complement to the standard toolbox that economists use to predict individual behaviour.

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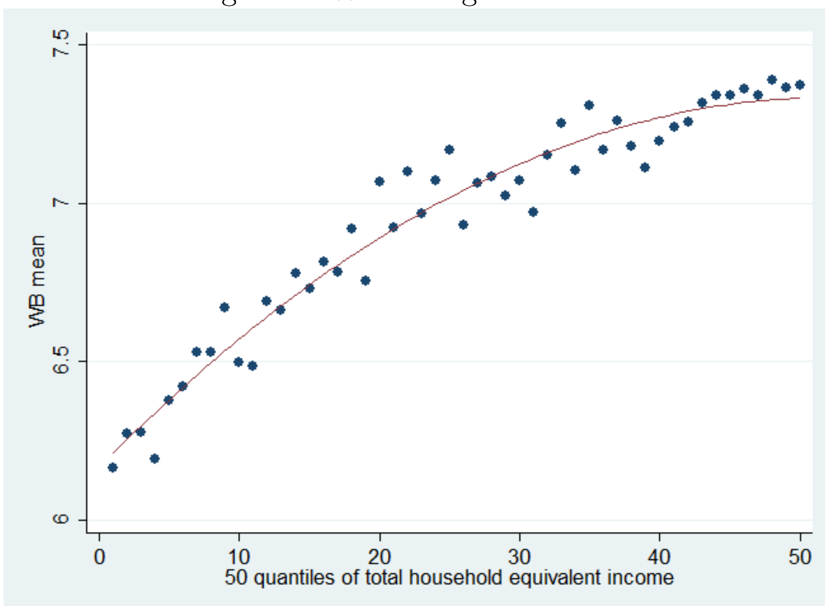
7 Appendix

Figure 1: Well-Being and Income



The OLS line corresponds to a regression of WB on *income* (50 quantiles) and $income^2$:

$$\hat{WB} = 6.167 + 0.045 income - 0.0004 income^2; \; R^2 = 0.043.$$

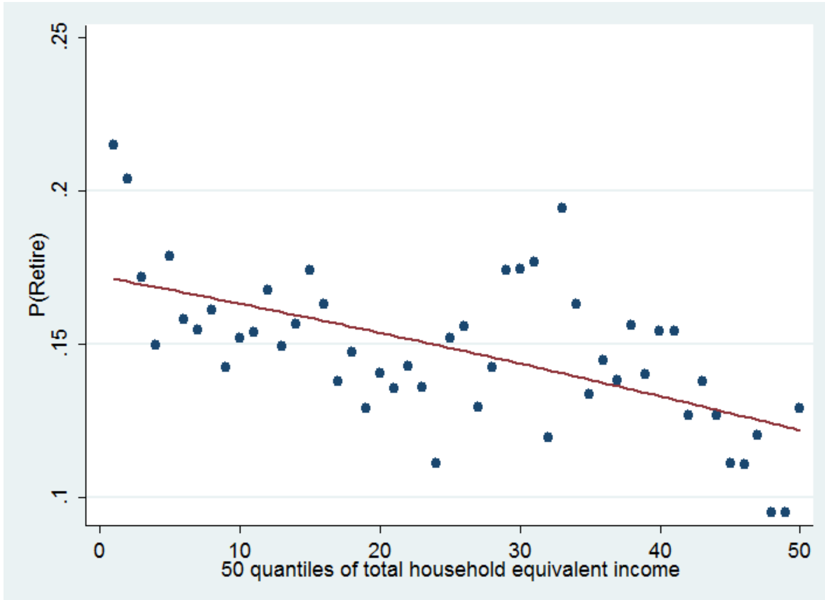
Table 1: Summary statistics

Variable	**Mean**	**(Std. Dev.)**	**N**
Well-being (0-8 scale)	6.94	(1.64)	22,074
Retire	0.15	(0.35)	22,074
Socio-demographic variables			
Female	0.51	(0.5)	22,074
Married or partnership	0.75	(0.43)	22,074
Number of children	3.19	(2.02)	22,074
Age	59.92	(3.59)	22,074
Education: less than High school	0.2	(0.4)	22,074
Education: High-school grad	0.54	(0.5)	22,074
Education: College and above	0.26	(0.44)	22,074
White	0.84	(0.37)	22,074
Number of health conditions	1.23	(1.09)	22,074
Job Characteristics			
Works 0-29 hours per week	0.2	(0.4)	22,074
Manager or tech sup	0.33	(0.47)	22,074
Sales	0.11	(0.31)	22,074
Clerical and administrative	0.17	(0.37)	22,074
Service	0.16	(0.36)	22,074
Farming, forestry and fishing	0.03	(0.16)	22,074
Mechanics, construction	0.09	(0.29)	22,074
Operator	0.12	(0.33)	22,074
Armed forces	0	(0.02)	22,074
Wealth			
Ln(net worth)	4.32	(0.11)	22,074
Ln(IRA)	0.25	(0.44)	22,074
Ln(hh income)	10.76	(0.91)	22,074
Behavioural variables			
Risk aversion	3.31	(1.05)	14,794
Financial planning horizon	3.14	(1.16)	15,497

Table 2: Distribution of the Well-Being Score (CESD)

	Overall		**Between**		**Within**
SWB	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
0	137	0.6	121	1.5	47.6
1	267	1.2	241	3	50.1
2	379	1.7	346	4.3	46.7
3	512	2.3	458	5.7	44.1
4	737	3.3	665	8.3	43.2
5	1,186	5.4	1,015	12.7	43.9
6	2,103	9.5	1,710	21.4	45.3
7	4,881	22.1	3,409	42.7	52.4
8	11,873	53.8	5,503	69	75.2
Total	22,074	100	13,468	168.9	59.2

Figure 2: Retirement and Income



The OLS line corresponds to a (linear probability model) regression of *Retire* on *income* (50 quantiles) and $income^2$: $\hat{Retire} = 0.172 - 0.00086 income - 2.86 * 10^{-6} income^2$; $R^2 = 0.0017$.

Figure 3: Retirement and Well-Being

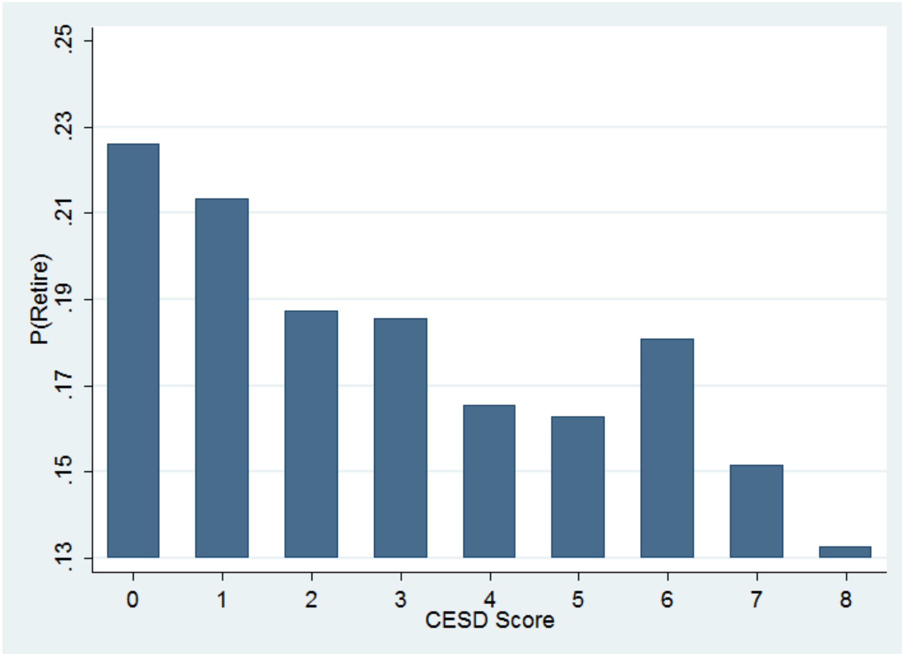


Table 3: OLS vs FMM

	OLS	**FMM**	
		Class 1	**Class 2**
Ln(hh income)	0.311***	0.329***	0.039***
	(0.017)	(0.035)	(0.005)
Female	-0.228***	-0.310***	-0.007
	(0.030)	(0.067)	(0.009)
Age/10	0.154***	0.372***	0.010
	(0.033)	(0.080)	(0.012)
White	0.183***	-0.143*	0.079***
	(0.044)	(0.083)	(0.016)
Constant	2.630***	-0.239	7.208***
	(0.277)	(0.607)	(0.091)
Mean of predicted SWB		5.25	7.75
Prob of class membership		$\pi_1 = 0.32$	$\pi_2 = 0.68$
AIC	83437	61957	
BIC	83477	62333	
Observations	22,074		

Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Predicted WB by FMM Classes

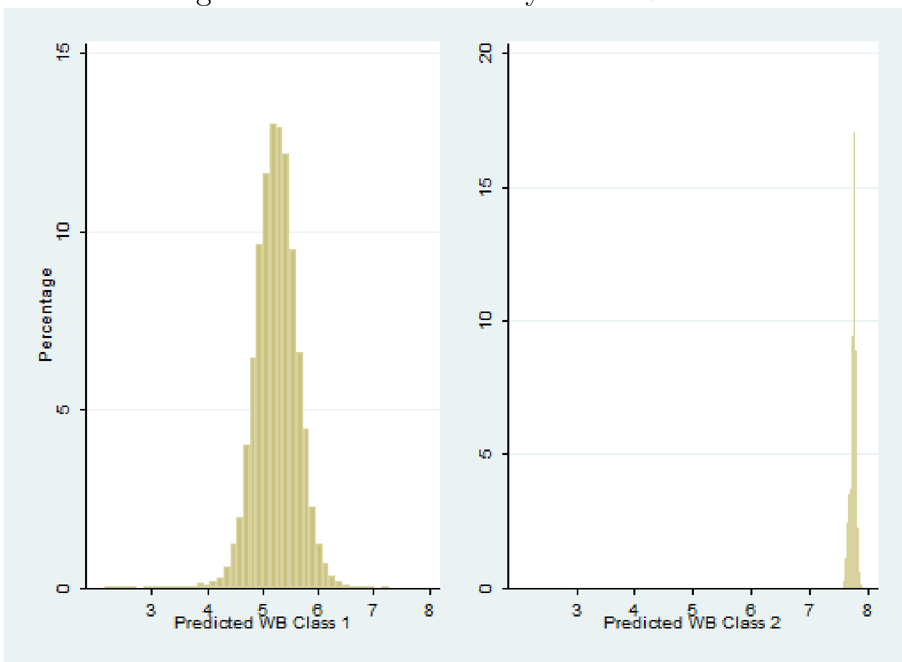


Figure 5: Density of the prior probability of belonging to Class 1

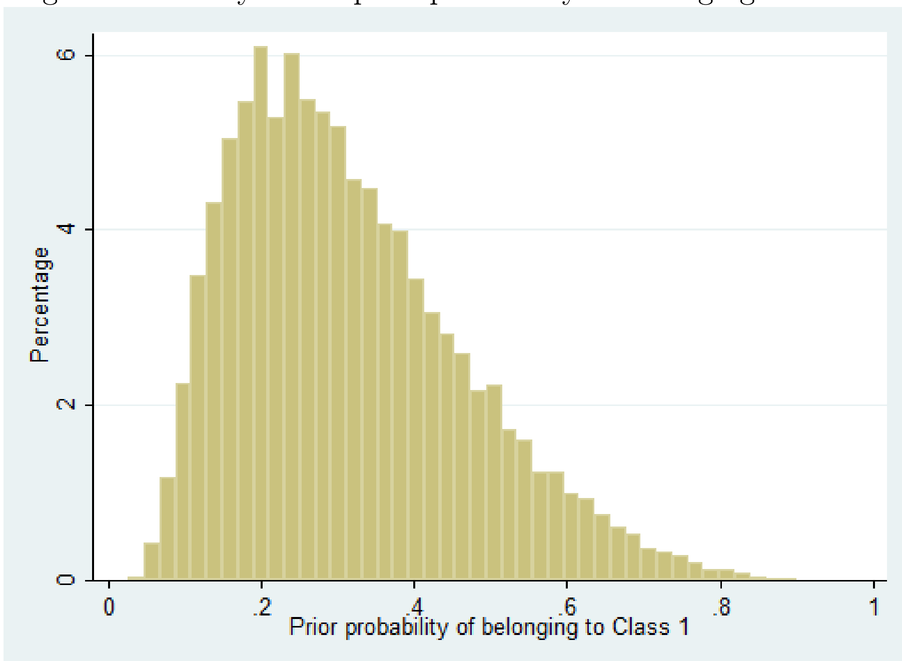


Table 4: Determinants of Prior Probabilities (Class 1)

	(1)	(2)	(3)	(4)	(5)
Ln(hh income)	-0.081***	-0.026***	-0.061***	-0.021***	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Female		0.038***		0.049***	0.049***
		(0.011)		(0.013)	(0.012)
Married or partnership		-0.132***		-0.132***	-0.123***
		(0.014)		(0.014)	(0.014)
Age/10		-0.366		-0.390	-0.318
		(0.339)		(0.340)	(0.340)
Age^2/100		0.022		0.024	0.019
		(0.028)		(0.028)	(0.028)
Number of children		0.003		0.003	0.002
		(0.003)		(0.003)	(0.003)
White		-0.047***		-0.038**	-0.032**
		(0.015)		(0.016)	(0.015)
Educ: High-school graduate		ref.		ref.	ref.
Education: less than High school		0.111***		0.093***	0.089***
		(0.015)		(0.016)	(0.016)
Education: College and above		-0.065***		-0.038***	-0.030**
		(0.013)		(0.015)	(0.015)
Number of health conditions		0.077***		0.077***	0.076***
		(0.005)		(0.005)	(0.005)
Works 0-29 hours per week			-0.017	-0.012	-0.007
			(0.011)	(0.012)	(0.012)
Manager and tech sup			ref.	ref.	ref.
Sales			0.028	0.027	0.026
			(0.019)	(0.020)	(0.020)
Clerical and administrative			0.080***	0.039**	0.039**
			(0.017)	(0.018)	(0.018)
Service			0.143***	0.077***	0.074***
			(0.018)	(0.020)	(0.020)
Farming, forestry and fishing			0.026	0.053	0.050
			(0.034)	(0.035)	(0.035)
Mechanics, construction			0.066***	0.065***	0.060***
			(0.021)	(0.023)	(0.023)
Operator			0.133***	0.101***	0.097***
			(0.019)	(0.021)	(0.021)
Armed forces			-0.118	-0.068	-0.063
			(0.127)	(0.170)	(0.184)
Ln(net worth)					-0.008
					(0.048)
Ln(IRA)					-0.077***
					(0.013)
AIC	63152	62140	62991	62102	62054
BIC	63328	62388	63231	62414	62382
Observations			22,074		

Marginal effects; robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Controls for wave and region dummies are included.

Figure 6: Marginal Utility of Income, by income quantiles

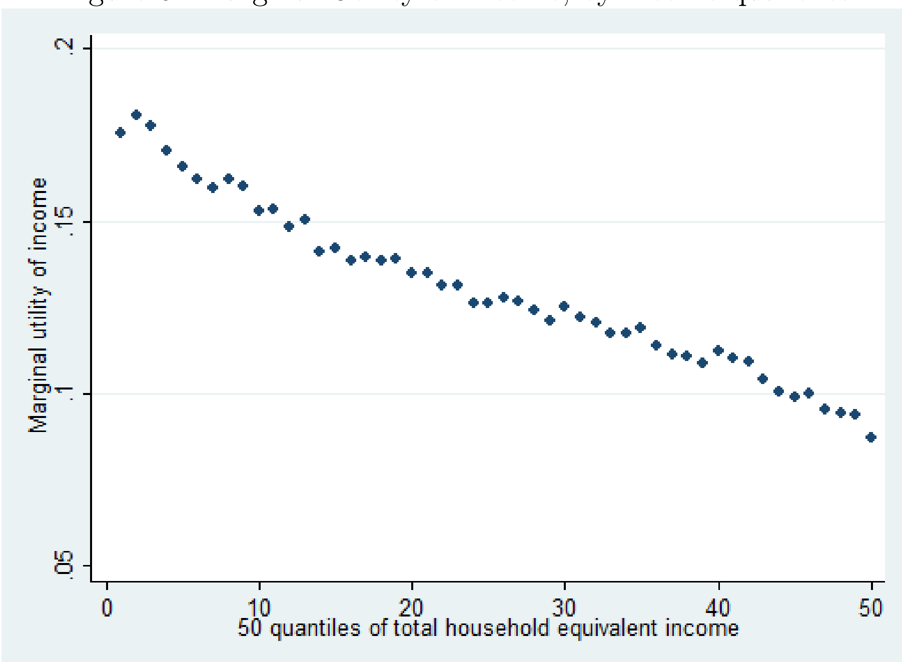


Table 5: Determinants of the Probability of Retiring-Exogenous controls in the WB equation

	(1)	(2)	(3)	(4)	(5)
Marginal utility of income	0.472***	-0.582***	-1.892***	-2.078***	-1.527***
	(0.066)	(0.196)	(0.274)	(0.417)	(0.510)
Ln(hh income)	-0.002	-0.001	-0.008*	-0.008**	-0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Well-being (0-8 scale)	-0.006***	-0.007***	-0.007***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Sociodemo variables	No	Yes	Yes	Yes	Yes
Job variables	No	No	Yes	Yes	Yes
Net worth; amount of IRA	No	No	No	Yes	Yes
Behavioural variables	No	No	No	No	Yes
Observations	22074	21564	19067	19067	12738
AIC	18351	17247	15272	15276	10680
BIC	18495	17510	15618	15637	11038

Marginal effects; robust standard errors in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The sociodemographic variables in this table are as in Table 4, except that we allow for a more flexible age specification using a number of age dummies. The job variables, in addition to those in Table 4, now include pension, private health insurance, and health insurance covering retirees. The estimated coefficients on all of these controls appear in Table 6.

Table 6: Determinants of the Probability of Retiring-Controls

	(1)	(2)	(3)	(4)	(5)
Female		0.020***	0.035***	0.037***	0.039***
		(0.005)	(0.006)	(0.007)	(0.009)
Married or partnership		0.011	-0.041***	-0.048***	-0.024
		(0.010)	(0.014)	(0.018)	(0.021)
Spouse works		-0.036***	-0.035***	-0.035***	-0.029***
		(0.006)	(0.006)	(0.006)	(0.008)
Number of children		-0.003**	-0.002	-0.002	-0.004**
		(0.001)	(0.001)	(0.001)	(0.002)
White		-0.007	-0.011	-0.012	-0.009
		(0.007)	(0.008)	(0.008)	(0.010)
Education: less than High school		0.049***	0.084***	0.089***	0.071***
		(0.010)	(0.012)	(0.016)	(0.018)
Education: College and above		-0.043***	-0.050***	-0.051***	-0.053***
		(0.006)	(0.007)	(0.007)	(0.009)
Number of health conditions		0.035***	0.062***	0.066***	0.053***
		(0.005)	(0.006)	(0.009)	(0.011)
Age 55-60		ref.	ref.	ref.	ref.
Age 61		0.118***	0.101***	0.100***	0.105***
		(0.011)	(0.012)	(0.012)	(0.014)
Age 62		0.078***	0.059***	0.057***	0.060***
		(0.012)	(0.012)	(0.013)	(0.015)
Age 63		0.122***	0.108***	0.106***	0.111***
		(0.013)	(0.014)	(0.015)	(0.017)
Age 64		0.143***	0.122***	0.119***	0.136***
		(0.015)	(0.016)	(0.017)	(0.020)
Age 65		0.100***	0.035**	0.032**	0.043**
		(0.015)	(0.015)	(0.016)	(0.019)
Age 66		0.101***	0.028*	0.025	0.044**
		(0.018)	(0.017)	(0.018)	(0.022)
Age 67-70		0.084***	0.015	0.011	0.040**
		(0.014)	(0.014)	(0.015)	(0.019)
Works 0-29 hours per week			0.043***	0.043***	0.049***
			(0.008)	(0.008)	(0.010)
Has pension from current job			0.047***	0.047***	0.054***
			(0.006)	(0.006)	(0.008)
Covered by current or ex-employer hlth ins.			-0.026***	-0.026***	-0.021**
			(0.007)	(0.007)	(0.009)
Covered by hlth ins. in retirement			0.045***	0.045***	0.044***
			(0.006)	(0.006)	(0.008)
Ln(net worth)				0.003	-0.061
				(0.032)	(0.045)
Ln(IRA)				-0.006	0.007
				(0.010)	(0.012)
Risk aversion					0.007**
					(0.003)
Financial planning horizon					-0.007**
					(0.003)
Constant					
Observations	22,074	21,564	19,067	19,067	12,738
AIC	18392	17321	15337	15341	10710
BIC	18536	17584	15683	15702	11068

These are the controls of the regressions presented in Table 5. Occupation variables are controlled for, although not displayed.
Marginal effects; robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: FMM with additional controls in the WB equation

	(1) Exogenous Controls		(2) Additional Controls	
	Class 1	**Class 2**	**Class 1**	**Class 2**
Ln(hh income)	0.329***	0.039***	0.277***	0.027***
	(0.035)	(0.005)	(0.037)	(0.005)
Constant	-0.239	7.208***	0.126	7.295***
	(0.607)	(0.091)	(0.639)	(0.094)
Mean of predicted SWB	5.25	7.75	5.25	7.76
Prob of class membership	$\pi_1 = 0.32$	$\pi_2 = 0.68$	$\pi_1 = 0.31$	$\pi_2 = 0.69$
AIC	62054		62067	
BIC	62382		62571	
Observations	22,074			

"Exogenous controls" include: gender, race, age at 1st obs, education, and region dummies.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Determinants of the Probability of Retiring-Additional controls in the WB equation

	(1)	(2)	(3)	(4)	(5)
Marginal utility of income	0.631***	-0.541**	-2.283***	-2.470***	-1.893***
	(0.078)	(0.239)	(0.349)	(0.557)	(0.693)
Ln(hh income)	-0.001	-0.001	-0.010**	-0.011**	-0.004
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)
Well-being (0-8 scale)	-0.006***	-0.007***	-0.007***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Sociodemo variables	No	Yes	Yes	Yes	Yes
Job variables	No	No	Yes	Yes	Yes
Behavioural variables	No	No	No	Yes	Yes
Net worth; amount of IRA	No	No	No	No	Yes
Observations	22,074	21,564	19,067	19,067	12,738
AIC	18339	17251	15278	15282	10682
BIC	18483	17514	15624	15643	11040

Marginal effects; robust standard errors in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The sociodemographic variables in this table are as in Table 4, except that we allow for a more flexible age specification using a number of age dummies. The job variables, in addition to those in Table 4, now include pension, private health insurance, and health insurance covering retirees.