Retirement and the Marginal Utility of Income

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Abstract

The relationship between income and utility is at the core of microeconomic theory, but most empirical estimations use relatively simple specifications of the utility function without taking into account unobserved individual heterogeneity. One solution to overcome this heterogeneity issue consist in using subjective measures of well-being such as life satisfaction, inversed depression scores, or domain-specific indices such as job or income satisfaction. In order to control for the potential bias introduced by the fact that every individual has his own vision of life, which may be rather pessimistic or optimistic, many studies introduce individual-specific effects in their ordinal regressions of well being. But intercept heterogeneity is not sufficient as the utility function may differ across individuals. Therefore in that study we implement latent class analysis to model both intercept and slope heterogeneity, and to identify several groups of individuals with distinct marginal utilities of income. Using these results, we construct a continuous measure of the marginal utility of income and estimate the probability of retiring as a function of this elasticity of well-being to income. As expected, the more individuals value their income, the less likely they will retire.

Keywords: 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 core of many studies across OECD countries, and much has been made of the "objective" characteristics inducing older individuals to retire sooner or later, much less is known about the relationship between subjective well-being and retirement transitions. Most literature dealing with well-being and retirement focuses on the effect of retirement on life satisfaction (Wottiez and Theeuwes [1998]; Kim and Moen [June 2001]; Lindeboom, Portrait, and van den Berg [2002]; Charles [2002]; Borsch-Supan and Jurges [2007]; Seitsamo [2007]; Bonsang and Klein [2011]). Indeed, as pension systems need to be re-designed in order to become sustainable, and the preferred option in many countries consists in increasing the legal age of retirement, the effects of retiring on subjective well-being are of most interest for policymakers. In almost the same vein, other studies directly examine retirement satisfaction. Shultz, Morton, and Weckerle [1998] examine 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 on retirement satisfaction, Panis [2004] relates annuities and wealth to both retirement satisfaction and measures of depression, and Bender [2004] insists on the non-economic determinants of well-being in retirement. However, although well-being has been validated as a strong predictor of future behaviour, it has rarely been investigated as a potential predictor of retirement transitions. There is at least one study though (Debrand and Sirven [2009]) that confirms a negative impact of job satisfaction on retirement transitions.

In this paper we estimate the impact of well-being on retirement using the Health and Retirement Study (HRS) and explicitly allowing for slope heterogeneity across latent and complex sub-groups of individuals. In other words, we use a finite mixture model (FMM) in a panel data setting to model heterogeneity in the marginal utility of income, and then exploit that source of heterogeneity to infer the effect of marginal utility of income on retirement transitions. The data identify two classes of individuals that could not be identified by discriminating *ex ante* by the usual characteristics (e.g., age, race, gender, or education) that potentially capture much of the heterogeneity in the well-being response to income. They also strongly reject the hypothesis that the effect of well-being on income is the same across classes. By yielding the probabilities of belonging to these two latent classes, this model allows us to construct a continuous measure of the marginal utility of income and estimate the probability of retiring as a function of this kind of elasticity of well-being to income.

The current study adds to the existing literature on well-being and retirement in multiple dimensions. First, it represents an attempt at modelling heterogeneity in the marginal utility of income and leads to abandoning the assumption of homogeneity in the well-being response to additional income. Further the use of finite mixture models allows prior and posterior characterization of the component groups. Put differently, this econometric strategy makes it possible to explore the determinants of class membership. In other words our results suggest that "money buys happiness" for one group much more than for the other, but they also provide us with information about "for whom it buys the most happiness". Last, our probability model of retirement points to a significant negative effect of the marginal utility of income, which is policy-relevant in that it reveals that those who value their income the least are more likely to retire. In terms of encouraging continuing labour force participation, it seems straightforward that those who are least "income-lover"-whom we can easily identify using prior and posterior probabilities based on the observables of our model- should be targeted by labour-supply policy more specifically. These findings also contribute to validating SWB (Subjective Well-Being) measures as predictors of objective behaviour, in line with the "validation literature" that is detailed below.

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

2 The Marginal Utility of Income

As the core of the current study lies in the impact of marginal utility of income on retirement transitions, a first step will consist in deriving an estimate of this marginal utility of income. Thus it seems reasonable to question the notion of utility and the way we will retrieve it in our data. By using subjective data such as well-being scores, we do not measure *ex ante* utility but rather *ex post* experienced utility (Kahneman, Wakker, and Sarin [1997]). One potential drawback of using this kind of subjective micro data is the common suspicion amongst economists that what workers say does not reveal their preferences (and thus their behaviour). One way of tackling this issue is to appeal to a strand of the well-being literature that has validated the use of subjective well-being to predict future behaviour. Some studies have used panel data to show that individuals clearly choose to discontinue activities associated with low levels of well-being (see Kahneman, Fredrickson, Schreiber, and Redelmeier [1993]; Frijters [2000]; Shiv and Huber [2000]). A number of labour market studies have shown that job satisfaction is a strong predictor of job quits, even when controlling for wages, hours of work and other standard individual and job variables (see, for example, Freeman [1978]; Clark, Georgellis, and Sanfey [1998]; Clark [2001]; Kristensen and Westergaard-Nielsen [2006]). Further, Iaffaldano and Muchinsky [1985] and Ostroff [1992] report that higher job satisfaction within a firm is positively correlated with its performance. Furthermore Rogers, Clow, and Kash [1994] find that job satisfaction is also correlated with increased customer satisfaction within service industries. A recent example using data on the self-employed is found in Georgellis, Sessions, and Tsitsianis [2007]. Clark [2003] shows that mental stress scores on entering unemployment predict unemployment duration: those who suffered the sharpest drop in well-being upon entering unemployment were the quickest to leave it. In another domain, measures of life satisfaction have also been shown to predict future marital break-up (Brown, Gardner, Oswald, and Qian [2005]). In line with this validation literature we consider that subjective scores do reflect respondents' substantive feelings of well-being, and are at least partly interpersonally comparable. Therefore what we call "utility" in the following refers to a subjective measure of well-being.

Then, once we assume as it is commonly accepted in the Economics of well-being that SWB can be used as a proxy for underlying utility, it is possible to examine the relationship between utility and income, and estimate the marginal utility of income, but there is still the issue of the interpretation of reported satisfaction. As stated in Senik [2005],

> interpreting subjective satisfaction data implies (i) relating discrete verbal satisfaction judgements to a latent, unobserved, continuous utility variable, and (ii) associating utility levels to observable characteristics. At each stage of this process, strong assumptions must be accepted: (a) the link between observable variables (income for instance) and latent utility is the same for

all individuals, *i.e.* the parameters of the individual satisfaction function are identical for all agents (Tinbergen [1991]), (b) the association between a verbal satisfaction label and a latent utility level is the same for everybody. If either of these two assumptions is not verified, any interpretation of reported satisfaction will be misleading because of an "anchoring effect" (Winkelmann and Winkelmann [1998]).

A traditional approach of getting rid of this problem of unobserved heterogeneity has consisted in controlling for individual-specific fixed effects (see Clark and Oswald [2002]; Ferrer-i Carbonell and Frijters [2004]; Senik [2004]).

Since finite mixture models appeared in the statistical literature in the 1960s and 1970s, they have proved to be a useful way of modeling and capturing unobserved heterogeneity. The key idea behind these models is that the unknown population distribution may be empirically approximated by a mixture of distributions with a finite number of components. The path-breaking work on the expectations-maximization (EM) algorithm (by Dempster, Laird and Rubin [1977] and Aitkin and Rubin [1985]) made the computation of the latent class models accessible to applied researchers. In recent years, the finite mixture model has found many applications, e.g. with Eckstein and Wolpin [1999]; Thacher and Morey [2003], and the work of Deb who has contributed a lot to render these models attractive (see Deb and Trivedi [1997]; Ayyagari, Deb, Fletcher, Gallo, and Sindelar [2009]; Deb, Gallo, Ayyagari, Fletcher, and Sindelar [2009]). Clark, Etilé, Postel-Vinay, Senik, and der Straeten [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 consisting in letting the data speak. The data identify two classes of individuals, and reject strongly the hypothesis that the marginal effect of income on well-being is identical across classes. Hence introducing intercept heterogeneity is insufficient and there is a need to model slope heterogeneity too.

Last, the existing SWB literature has in common that marginal utility is traditionnaly estimated-whether unobserved heterogeneity is taken into account or not- controlling for every variable that is tested to have some significant effect on that utility (e.g, gender, health status, educational attainment, *etc.*). One caveat of that strategy is that it does not factor in the indirect effects of the variable of interest (income) on utility. For instance income has positive effects on health, which will then impact on SWB, thus increasing the relative contribution of income to SWB (see Dolan, Fujiwara, and Metcalfe [2011]). What we are interested in is the global impact of income on utility, including all indirect effects of income through all other potential explanatory variables. Therefore, when estimating the marginal utility of income using FMM, we first regress SWB on income with no other explanatory variables. Then, because we are aware of the potential bias this method could lead to, we test other specifications including several sets of control variables.

3 Data and Initial Results

3.1 Data

We use data from the Health and Retirement Study (HRS), which is a nationally representative longitudinal survey of individuals over 50 years and their spouses. At baseline in 1992, HRS participants included 12,652 individuals from 7,702 households. Data were originally collected through face-to-face interviews, but later interviews were completed by telephone or mail. The HRS initially sampled persons in birth cohorts 1931 through 1941 in 1992, with follow-up interviews every two years. In 1998, persons from the 1924 to 1930 cohort and the 1942 to 1947 cohort were added to the original sample. In 2004, persons from the 1948 to 1953 cohort were added to the survey. Our study uses data from Version I of the data prepared by RAND, which is a cleaned and processed version of the HRS data. The RAND HRS data were created by the RAND Center for the Study of Aging with the goal of easing the work of researchers.

The RAND-HRS data have included an abridged version of the Center for Epidemiologic Studies-Depression (CESD) Scale (Radloff [1977]) since the second wave. The CESD depression scale originally comprised twenty items. The HRS only retains eight of them: depressive feelings, everything seen as an effort, restless sleep, could not get going, loneliness, sadness, enjoyment, happiness. All the questions asked to derive the CESD score were yes/no indicators of the respondent's feelings much of the time over the 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 supplies a positive answer for the first six items, and negative answers for the last two. We then reverse this depression score to produce a SWB scale where 0 indicates the worst level of psychological wellbeing and 8 the best.

Tables 3 and 4 in the appendix present information about our estimation sample. We consider all individuals who were working at the time of the interview. This produces 36,283 observations (and 11,719 individuals) for whom we have non-missing information, over the last seven waves of the HRS. We note that the sample statistics appear reasonable and fall within expectations. Additionnally to the usual socio-demographic and economic variables (gender, marital status, number of children, age, education, race, health status, total household wealth, total household income) and job-related variables (number of hours worked, occupation), two subjective variables are worth some precision. One is risk aversion, on a scale from 1 to 4, where 1 indicates the least risk averse preferences. This variable was created based on a set of "income gamble" questions. The risk aversion variable is coded 1 if the respondent would take a job with even chances of doubling income or cutting it in half, 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 interview by proxies, we replace missing values with data from the closest past wave for every individual. If the individual answered these questions at several waves, we take the mean of his answers. Nonetheless the sample size is smaller due to the inclusion of that measure of risk aversion. Most of our sample is highly risk-averse since 60% of individuals give the most risk averse answer while only 12% give the most risk lover answer. We take the same "imputation" approach for the financial planning horizon variable. 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 ans spendings, which of the time periods listed in the booklet is most important to you [and your husband/wife/partner]?". Our measure of planning behaviour is coded 1 if their answer is "next few months", 2 corresponds to "next year", 3 to "next few years", 4 to "next 5-10 years", and 5 to "longer than 10 years". Most individuals declare thinking in terms of the next few years or next 5 to 10 years, which are intermediate answers.

The distribution of our measure of SWB is shown in the appendix (see Table 5). It 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 confirms the prevalence of high scores of SWB as over 70 per cent of the individuals experienced an 8 score at least once while less than 2 per cent have known a zero score. “Within” individuals (see last column), 73 per cent of those who ever reported a score of 8 remained at that level. On the contrary only 44 per cent of the individuals who once experienced a null score have experienced it at all their observations. These figures either illustrate the presence of measurement errors, or suggest that most people who reported low scores did so because of a bad year, and thus reported higher scores in other years.

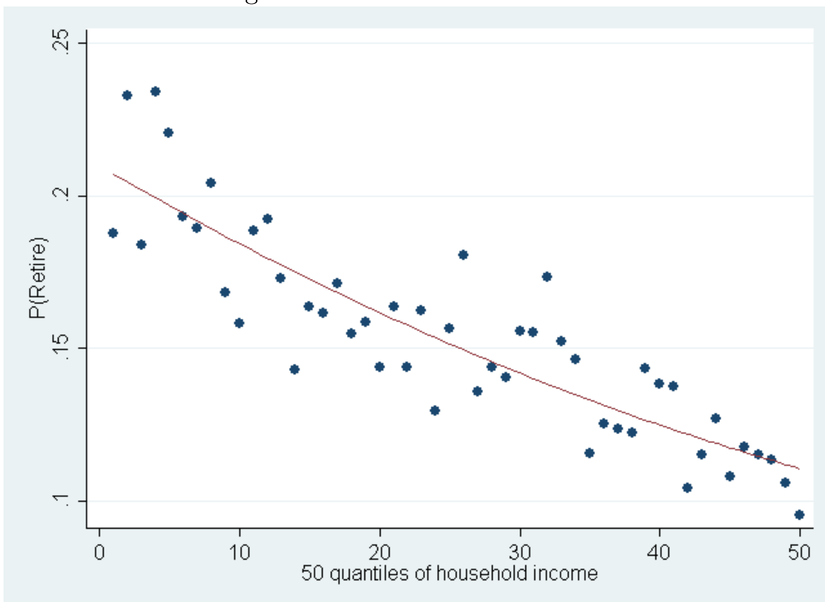
3.2 Initial Results

Figure 1: Well-Being and Income

Before going deeper into the econometric analyses, we provide some descriptive statistics about the key variables of our analyses, *i.e* subjective well-being and income for the first step of our estimations, and a retirement dummy for the probability model that will follow. Figure 1 displays non-parametric estimations of the mean of well-being by income quantiles, where income is measured as individual earnings from work, individual total income, or total household income. In the following we will use the latter, which is the most widely used income measure when estimating marginal utility of income. Total household income includes earnings from work, household capital income, income from employer pension or annuity, 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, pension or inheritance. Here we graph one "average" utility function as if people were homogeneous in their valuation of income. But individuals sharing the same observable characteristics may be more or less happy depending on their "personality". Self-determination theory (e.g., [Ryan and Deci, 2000]) suggests that behaviour can be intrinsically or extrinsically motivated. An internally motivated individual derives much more utility from social interaction and community involvement than from accumulating wealth, while extrinsically motivated individuals derive their utility from income gains. Besides, individuals might be heterogeneous in the way they translate their latent unobserved utility into a discrete verbal satisfaction answer. Depending on interactions with the surveyor, mood effects, or question formulation, there is a lot of room for heterogeneity in their response. The parametric analysis (the FMM) will allow the utility curve to differ between individuals in its intercept and its slope. We will use the panel dimension of the HRS, and disentangle between the time-series and cross-sectional information it provides, *i.e.* "between" variations (between distinct subjects) and "within" variations (time-series information for one subject). We expect to find a great deal of heterogeneity between individuals as their heterogeneous valuations of income might depend on their personality, but hardly any variation within individuals at different points in time. This method will not allow the two potential sources of heterogeneity (in the utility function and in the reports of utility) to be disentangled though.

The relationship between income at time t and the non-parametric estimation of the probability of retiring between waves t and $t+1$ deserves some attention too. As retirement is a labour supply decision, the impact of income cannot be straightforward. Indeed assuming that leisure is a normal good, people should consume more leisure as income increases (income effect). On the other hand, if that income rise stems from a wage rate rise, the worker will substitute work hours for leisure hours, that is, will work more hours to take advantage of the higher wage rate, or in other words substitute away from leisure because of its higher opportunity cost (substitution effect). The net impact of these two effects is ambiguous and depends on the circumstances. Figure 2 shows a clear negative relationship between household income and retirement. Hence simple bivariate correlations suggest that in our data the substitution effect is greater than the income

Figure 2: Retirement and Income



effect, which may not persist in the multivariate analysis. Indeed those at the top of income distribution are likely to be in better health and to work in "nicer" occupations, due to their higher educational attainment, so that the fact that they retire less may not be a consequence of these income and substitution effects.

Last, SWB and retirement seem negatively correlated, especially at the two tails of the SWB distribution. The happier retire less, at least in a bivariate framework. Few studies examine the impact on SWB, even in level, on retirement transitions. Fawaz [2009] finds no significant effect of SWB (measured by another inversed depression score, namely the EURO-D scale) on the probability of retiring when job satisfaction and satisfaction with various job domains (pay, hours, work itself, *etc.*) are controlled for. However, these latter variables do impact significantly the retirement probability with the expected sign. Thus we expect happier individuals to retire less because our measure of SWB is a global measure of satisfaction that encompasses domain-specific measures of satisfaction such as job satisfaction.

These relationships between SWB and income first, income and retirement secondly, and SWB and retirement, need to be investigated in a multivariate framework. More precisely, in the following we use the results of the estimation of the first relationship in order to get the intercept and slope impacts of SWB on retirement.

4 Econometric Methods

4.1 First Step: Estimate Marginal Utility of Income

4.1.1 A Latent Class Panel Data Model

This paper is to our knowledge the first to use the latent class framework for analysing individual unobserved heterogeneity in a panel data model for marginal utility of income. The desirability to have panel data to identify the latent class model is pinpointed by Greene [2001], according to whom the richness of the panel in terms of between variation improves the ability to estimate the model.

The latent class approach models individual heterogeneity in a flexible way that assumes no distribution for the unobserved individual effects. Furthermore, it allows the distinction between a finite, usually small, number of latent classes (this number is C in the below modelization) of individuals, which can vary as to the expected level of well-being as well as to the responses to the covariates considered. Therefore, it is possible to assess to which extent the effects of the socio-economic factors considered in this study vary across different groups whose valuations of income are heterogeneous. This possibility is ruled out in conventional panel data models (fixed or random effects) that consider only heterogeneity in the intercept as explained before.

The basic econometric model for SWB is:

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

where the variable of interest is INC, the logarithm of household's total income, and X_t is a vector of individual characteristics (sociodemographic, job-related, economic, regional and time variables). Equation 1 is first estimated by OLS. $\alpha/100$ is the absolute change in WB for a 1% increase in income. However, if WB is drawn from distinct subpopulations, the OLS estimate of α is the average of the effects across subpopulations and may hide important differences between these subpopulations. Therefore we estimate a finite mixture model, where subpopulations are assumed to be drawn from normal distributions.

In the FMM the random variable WB is postulated 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, $T_i = 1, ..., 8$ 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 reestimate 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. Hence individuals with different observable characteristics might have different probabilities of belonging to either component.

As put forward in Deb, Gallo, Ayyagari, Fletcher, and Sindelar [2009], finite mixture models entail many assets but some drawbacks too. A finite mixture model may fit the data better than a basic OLS model because of outliers. If such observations are present in the data, the FMM might capture them through additional mixture components. Therefore even if the use of FMM is motivated by *ex ante* reasoning, a careful study of the latent classes is necessary in order to justify it *ex post*.

One of the reasons why we use FMM to model heterogeneity is to calculate the prior and posterior probabilities of being in each of the latent classes, conditional on all observed covariates (and outcome for the posterior probability). Using Bayes' theorem, the posterior probability of being in component k is:

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

Thus the posterior probability varies across observations, as the prior probability when reestimated conditional on Z. What differs between these two probabilities is that posterior probabilities are also conditional on outcome wb_i. The latter could be used to explore the determinants of class membership, but in the following we stick to prior probabilities for reasons we detail in section 5.

4.1.2 Between Vs. Within

We use the panel feature of the data to investigate which part of the effects of the covariates goes through between-individual heterogeneity, and which one is due to within-individual variability. In other words, we question the source of the heterogeneity in the marginal utility of income, and look for evidence that this marginal utility of income differ between individuals, but remains constant for one individual across observations. Deb and Trivedi [2011] provide a simplified method of computation to estimate a mixture of normals with fixed effects. Replacing (wb_{it}, x_{it}) by $(\tilde{wb}_{it}, \tilde{x}_{it})$, where $\tilde{}$ denotes the "within transformation", *i.e.* $\tilde{x}_i = x_{it} - \bar{x}$, and then maximizing the mixture likelihood, is numerically equivalent to applying the full EM algorithm to estimate a latent class model with fixed effects. So this kind of estimation can proceed in the same way as for the standard FMM in cross-section data. We replicate this method in order to estimate "between" effects too, by replacing (wb_{it}, x_{it}) by its "between transformation" $(\bar{wb}_i, \bar{x}_i)$, where $\bar{x}_i = \sum_{t=1}^{T_i} x_{it}/T_i$, and then estimate a standard finite mixture model on these transformed variables.

4.2 Second Step: Use FMM Results to Predict Retirement

Latent class analysis provides distinct estimations of the marginal utility of income for distinct groups, 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 the individual heterogeneity in income valuations 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 test the impact of e on the probability to retire by wave $t+1$ for individuals still working at wave t, using a probit model. Thus our retirement probability model takes the form:

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

where Pr denotes 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 mentions a "fully retired" status at wave $t+1$, which is the case for 15 per cent of our pooled sample.

5 Results

5.1 Results From Finite Mixture Models

5.1.1 Results from Pooled Estimations

Table 1: OLS vs FMM

	OLS	**FMM:Constant Pr.**		**FMM:Varying Pr.**	
		Comp.1	**Comp.2**	**Comp.1**	**Comp.2**
ln(hh income)	0.235***	0.390***	0.050***	0.188***	0.027***
	(18.21)	(12.57)	(11.04)	(7.39)	(7.45)
Mean of predicted SWB		5.21	7.75	5.23	7.76
π_1		0.32		0.32	
AIC	138,348	105,296		102,611	
BIC	138,365	105,356		102,976	
Observations	36,283				

t statistics in parentheses; robust standard errors

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

We estimate the marginal utility of income using a simple OLS regression and several specifications of a finite mixture model. Model selection criteria (AIC/BIC) provide clear evidence in favor of a 2-component mixture model as compared to the OLS 1-component model. The 3-component model fails to converge after a reasonable number of iterations, which suggests that the third component may try to fit a small number of outliers. We first provide in Table 1 estimations from a constant-probability mixture model and a varying-probability mixture model, to be compared to the results of a traditional OLS regression of SWB on the logarithm of income. As argued in section 2, we do not include any control in the main equation, in order to capture both direct and indirect effects of income on SWB, but we will test other specifications including a set of explanatory variables in the robustness check section. OLS results suggest a significant impact of income on SWB with a coefficient of 0.23, meaning that SWB would increase by 0.23 points if income was to double (*i.e.* to increase by 100 per cent). When no covariate is used to model the component probabilities, the FMM identifies two latent classes in proportions of 0.32 and 0.68 respectively. For the first and smaller group, income also has a significant impact on SWB with a higher coefficient than in the OLS regression (0.39). In contrast for the second group, which is bigger, the impact of income on SWB is very weak (0.05). The differences between these two groups in the impact of income on their SWB are striking. This evidence is consistent with our assumption that there is heterogeneity in individuals' valuations in income, which was masked in the single-component model. These two groups seem very dissimilar in that the one with high marginal utility of income is less happy on average (with a mean SWB score of 5.21) than the second one (mean SWB of 7.75), which is much less sensitive to income. Figure 4 shows that the density of predicted mean of SWB for the second group is massed at the extreme right end of the distribution, meaning that individuals belonging to the second group have very high SWB scores, close to 8. The distribution of predicted SWB density for the low-SWB component is less concentrated and lies between 4.8 and 5.8.

Including a set of covariates Z_i does not alter the proportions of the two mixing components, nor does it change their interpretation since the ratio of the two coefficients stays the same, *i.e.* the impact of income on SWB is around 8 times higher in the second group. We estimate several specifications of the varying probability mixture model, differing in the set of explanatory variables Z_i that we include in the probability equation. Our preferred specification, *i.e.* the varying probability model displayed in Table 1, uses socioeconomic variables, job-related variables, and the two behavioural variables we detailed above (risk aversion and financial planning horizon) to predict the probability of being in each component group. Table 6 presents the estimations of the prior probability equations for several subsets of covariates. Last column corresponds to our preferred specification, with the smallest AIC and BIC[1]. In the present case the AIC/BIC decreases

[1]The Akaike information criterion is a measure of the relative goodness of fit of a statistical model. It is grounded in 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 the one with the minimum AIC value. Hence AIC does not only reward goodness of fit, but also discourages overfitting as it includes a penalty that is an increasing function of the number of estimated parameters. Akaike's Information Criterion (AIC) penalizes the number of parameters less strongly than

every time we include a new subset of covariates, which indicates that the additional information brought by these covariates improves the accuracy of the model while not increasing too much its complexity. It is noteworthy though that the model with socio-demographic variables fits the data better than the one with job variables, which indicates that job variables predict class membership less efficiently. Our preferred specification is the one which uses the integrality of the set of covariates to sort individuals into latent classes.

These estimates suggest that individuals who are female, single, non-white, less educated, and whose health status is self-rated less than excellent, are more likely to be in the less-happy component. The impact of age does not come up when all covariates are part of the equation but in other specifications it seems that younger individuals are associated with the first group too. The same goes for income, which impacted negatively the probability of being in component 1, and loses all significance when wealth is factored in. Regarding job characteristics, the results exhibit a negative status profile for individuals in component 1, with people in lower-status occupations (Service, Farming, forestry and fishing, Mechanics, Construction, compared to Manager and Technician Sup) being more likely to be in that group and thus less happy and more "income-lover". Individuals in that class are also less wealthy. Last, risk aversion and financial planning horizon also affect the likelihood of being in each component. Indeed, those who are more risk averse, as well as those whose financial horizon is longer, are more prone to sort themselves into the happier group. Put differently, those with a long-term perspective are less affected by income variation as they base their decisions on a longer time horizon. The impact of risk aversion is rather surprising since we would expect more risk averse individuals to suffer more from an income loss and thus to be in component 1.

The qualitative conclusions that we draw from the use of FMM to model heterogeneity in the marginal utility of income are robust to the alternative specifications used. We find that there are two components with heterogeneous valuations of income, which were masked in the OLS model. For most of our sample, who are close to the maximum level of SWB, income has a very weak influence on SWB. The other smaller group, which is less happy, is much more sensitive to income. The latter group is made of female, single, non-white, those with low educational attainment, less healthy and wealthy, whose job is

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does the Bayesian information criterion (BIC), but in our case the two measures of goodness-of-fit yield the same results.

of lower quality. We also find that individuals in the less-happy component are less likely to be risk-averse, and have a shorter financial planning horizon. In a nutshell, the small unhappy lot, whose marginal utility of income is higher, is made of individuals with poor characteristics, while the majority of our sample is happier, with nicer characteristics, and less affected by income. Our results are at odds with Clark, Etilé, Postel-Vinay, Senik, and der Straeten [2005], who identify 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". This major discordance with our findings may be due to our sample made of working individuals, while theirs has no such restriction.

5.1.2 Between Vs. Within

At this stage, we cannot say if the positive impact of income on SWB is due to between or within effects, *i.e.* if additional income distributed to one individual leads to an increase in his SWB (within) or if a rich individual will experience a higher SWB than a poor one (between). Neither can we draw some conclusion as to the origins of the heterogeneity in the marginal utility of income. It could be that there are two distinct classes of individuals who value more or less their income, or this heterogeneity could be at the observation level, so that one individual could transit from one component group to another between waves. In order to disentangle between these two potential sources of variability, we perform the same regressions using "between" and "within" transformations of the variables.

Within individuals, OLS yield a significant but very weak coefficient of 0.02 for the impact of income on SWB, which is barely one tenth of the pooled estimate. As for the FMM, it fails to converge , which may suggest that the within-variability is too small to allow the data to sort into distinct classes. In other words, it seems that the impact of a marginal increase in income for some individual does not lead to a substantial increase in his experienced SWB, nor does it seem to be heterogeneous over time (*i.e.* across observations). Therefore we expect the most part of the impact of income on SWB to be due to between-variation, and the heterogeneity in the marginal utility of income to be individual-specific. Table 7 shows the same pattern as in the pooled estimations, only stronger. When individuals are considered rather than person-year observations, we find again a strong (both in magnitude and significance) impact of household income on SWB (0.29) when using OLS, which can be decomposed into two distinct marginal utilities of income, in the same way as before. Thus the way individuals value their income seems to be related to individual-specific time-invariant characteristics.

5.2 Does the Marginal Utility of Income Impact Retirement?

We then use the two components' valuations of income, along with the prior probabilities we obtained based on the observables of our preferred specification, and compute a continuous measure of income elasticity of well-being (see Equation 6 in section 4.2). We choose to use prior rather than posterior probabilities because the latter also use the well-being outcome to sort individuals into the latent classes, and therefore result in a very small range of values for the component probabilities. Indeed the level of well-being is such a good predictor of being in one component group that the posterior probability is (almost) either 0 or 1. Figure 5 plots the densities of prior and posterior probabilities, and confirms that prior probabilities will allow us to compute a better measure of the income elasticity of well-being.

From now on, to every observation in our sample is attributed a measure of how sensitive his SWB is with respect to household income. In this section we use the estimates from the pooled regressions, so that one individual may be associated with distinct values of his marguinal utility of income evaluated at different waves. This newly-created variable is almost normally distributed, with a mean of 0.08 and a standard deviation of 0.025 (see Figure 6). We check that e is a decreasing function of income in Figure 7. Thus, the more income people have, the less it affects their well-being. As retirement implies cessation of work and therefore a loss of income most of the time, we are interested in the impact of this valuation of income on the retirement decision. We expect lower valuations of income to be associated with higher retirement probabilities since the loss of income individuals will go through on retirement will be more or less costly to them in terms of SWB depending on their marginal utility of income. All the probit specifications we test indicate a negative impact of our continuous measure of the marginal utility of income on the probability of retiring, except when net worth is included in the set of control variables (see Table 2 for the impact of the variables of interest, and Table 8 in appendix for controls). As we control for income, the impact of e means that for a given level of income, *i.e.* regardless of the fact that some have much more than others, individuals' valuations of income play an important role in the retirement decision. Likewise, for a given level of the marginal utility of income, income has a significant impact on the

Table 2: Determinants of Probability of Retiring

	(1)	(2)	(3)	(4)	(5)	(6)
sensitivity WB-hh income	-0.577***	-0.781***	-0.716***	-1.070***	-1.442***	0.376
	(-6.19)	(-4.01)	(-7.05)	(-4.75)	(-4.85)	(0.83)
ln(hh income)	-0.018***	-0.004**	-0.013***	-0.003*	-0.003*	-0.005***
	(-9.92)	(-2.45)	(-7.25)	(-1.80)	(-1.91)	(-2.72)
well-being on a 0-8 scale	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-5.03)	(-5.79)	(-5.00)	(-5.85)	(-5.85)	(-5.87)
Sociodemo variables	No	Yes	No	Yes	Yes	Yes
Job variables	No	No	Yes	Yes	Yes	Yes
Behavioural variables	No	No	No	No	Yes	Yes
Net worth	No	No	No	No	No	Yes
AIC	24,514	22,522	24,145	22,430	22,422	22,397
BIC	24,664	22,747	24,361	22,722	22,730	22,714
Observations	30,678					

Marginal effects; t statistics in parentheses.

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

See Table 8 for controls

retirement probability. As descriptive statistics suggested, the more income they have, the less they retire. This impact is still significant when sociodemographic and job occupation variables are controlled for, meaning that the negative effect of income cannot be a masked effect of bad health or job characteristics, which tends to validate the assumption of a substitution effect that dominates the income effect. We also control for the level of SWB in order to be sure that the "slope" effect of SWB is not driven by some intercept effect. The sign of the marginal effect of well-being is negative too, which again confirms what descriptive statistics suggested, *i.e.* the happier individuals are, the less they retire. Both income and SWB have significant impacts across all the tested specifications. In contrast, adding the logarithm of net worth in the set of controls totally washes out the impact of the marginal utility of income, which is not surprising if we look at the strikingly high negative correlation between those two variables (61 per cent). As the richer retire significantly more, and wealth is highly correlated with individuals' valuations of income (the wealthier have a lower marginal utility of income), it captures all the negative effect of e on the probability of retiring. In terms of goodness of fit, again the AIC/BIC decreases across specifications every time we add a new subset of control variables, indicating that the model is not overparameterized. Once again, job-related variables add less to the model than sociodemographic variables, meaning that gender, age, health and education are more efficient at predicting retirement than job characteristics.

As for the impact of other independent variables (see Table 8), we find reasonable impacts of every covariate, e.g., women, the low-educated, the older, those whose health status is less than excellent, retire more. Individuals in part-time jobs retire more, probably because they have started a retirement transition by reducing the number of hours they worked.

The qualitative results are not affected when we use one estimation of the marginal utility of income per individual (see between results in Table 9), except that in that case, including net worth among the set of explanatory variables does not wipe out the significance of the impact of the marginal utility of income.

5.3 Robustness Checks

As we explained in section 2, we estimate the marginal utility of income by regressing SWB on income, without adding any other covariates in order to capture both direct and indirect effects of income. In case this method leads to biased estimates of the marginal utility of income, we also test other specifications with control variables. Column (1) of Table 11 presents the same results as in Table 1, where a fmm was estimated with no controls. We then add first a set of exogenous variables, composed of gender, race, age, education, and wave and region dummies, *i.e.* variables that cannot affect income. The data are again sorted into two component groups differing in their valuations of income in the same way as when no covariates were included. When all the variables of the Z_i set are included though, income loses its explanatory power. We use specification (2) to create our continuous measure of the marginal utility of income and estimate the probability of retiring as a function of the latter and other covariates. Table 12 shows that a higher marginal utility of income is still associated with lesser odds of retiring.

Finally, as a sensitivity check we reestimate the fifth specification, which includes all controls except net worth, on various subsamples (e.g. individuals in couple, with a low/high level of educational attainment, for men and women). For brevity we only present estimates of parameters of interest in Table 13. The marginal utility of income keeps a significant negative impact across almost all subsamples. Its magnitude is maximum when income has a significant effect too, *i.e.* for the high-education group within men, and the less educated within women. Contrary to e, income loses its significance power when we impose sample restrictions. The marginal effect of SWB is remarkably stable across specifications. These results show the robustness of the impact of the marginal utility of income on the probability of retiring.

6 Conclusion

This paper first models heterogeneity in individuals' valuations of income using latent class analysis applied to nationally representative data on US workers nearing retirement. Our model allows us to identify two classes of individuals with distinct marginal utilities of income, thus unmasking subpopulations whose well-being is affected in a different manner by a marginal gain or loss of income. Our main results indicate that there is a great deal of heterogeneity across the two latent classes. In a nutshell, one small group is rather unhappy, with high marginal utility of income, and is made of individuals with poor characteristics, while the majority of our sample is happier, with nicer characteristics, and less affected by income. These qualitative findings hold across specifications, which gives us confidence that the results are not spurious. Besides, the use of the panel feature of the data suggests that the source of heterogeneity in the marginal utility of income seems to be at the individual level, meaning that individuals differ in their valuations of income, but these are constant across observations for each individual.

We then use these results from finite mixture models to investigate the impact of marginal utility of income on retirement. Hence we add to the existing retirement literature in that we question the "slope" impact of well-being upon the probability of retiring. We find a negative significant impact of individuals' valuations of income on the retirement probability even though the direct impact of income and of the level of well-being are controlled for in addition to a comprehensive set of explanatory variables. We conclude that those who value the most their income retire less, regardless of how much income they have. In other words, as retirement implies a loss of income for most of older individuals, and given that income does not affect them in a homogeneous way, higher valuations of income are associated with higher subjective losses and therefore induce people to retire less.

Our findings are of particular importance in the current context of crisis of national pension systems. Knowing that a majority of workers close to retirement do not care so much about losing some part of their income with retirement, while a small group is highly sensitive to marginal income losses, might help policy makers in designing their labour-supply policy more efficiently, *i.e.* targeting the latter group. This study also contributes to the validation strand of the SWB literature by showing that individual-specific SWB functions predict future behaviour, and that this effect does not only go through intercept effects.

Another conclusion concerns directions for future work. This paper has shown that slope heterogeneity is worth deeper investigation, in that it predicts retirement outcomes. We established that individuals differ in ways that could not be captured by simple fixed effects, and that their heterogeneity can provide insights to the analysis of labour supply behaviour. Hence we believe that future applied work in microeconomics will increasingly take slope heterogeneity into account when modelling individual behaviour, and exploit finite mixture models as a useful complement to the standard toolbox that economists use to predict labor market behaviour.

7 Appendix

Table 3: Summary statistics

Variable	Mean	(Std. Dev.)
well-being on a 0-8 scale	6.93	(1.65)
female	0.55	(0.5)
married or partnership	0.77	(0.42)
number of children	3.12	(1.98)
age	58.25	(6.64)
educ:low attainment	0.18	(0.39)
educ:high school grad	0.56	(0.5)
educ:college and above	0.26	(0.44)
white	0.82	(0.38)
health:excellent	0.2	(0.4)
works 0-29 hours per week	0.2	(0.4)
net worth(hundreds of thousand)	3.65	(5.01)
hh income(hundreds of thousand)	0.88	(0.71)
risk aversion	3.27	(1.06)
financial planning horizon	3.18	(1.18)
N	36,283	

Table 4: Distribution of Job Occupation

Job occupation	**Freq.**	**%**
Manager or Tech sup	12,063	33.25
Sales	3,746	10.32
Clerical and Administrative	6,360	17.53
Service	5,606	15.45
Farming, Forestry and Fishing	901	2.48
Mechanics, Construction	3,191	8.79
Operator	4,401	12.13
Armed Force	15	0.04
Total	36,283	100

Table 5: Distribution of Well-Being Score

	Overall		**Between**		**Within**
SWB	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
0	246	0.68	214	1.83	44.17
1	433	1.19	385	3.29	44.34
2	615	1.70	560	4.78	41.43
3	868	2.39	764	6.52	39.76
4	1,227	3.38	1,063	9.07	39.77
5	1,929	5.32	1,613	13.76	40.48
6	3,483	9.60	2,785	23.76	41.83
7	8,005	22.06	5,323	45.42	48.83
8	19,477	53.68	8,313	70.94	73.12
Total	36,283	100.00	21,020	179.37	55.75

Table 6: Determinants of Prior Probabilities (Component 1)

	(1)	(2)	(3)	(4)	(5)
ln(hh income)	-0.109***	-0.014***	-0.039***	-0.010***	-0.001
	(-18.58)	(-3.76)	(-5.83)	(-2.85)	(-0.26)
female		0.044***		0.054***	0.057***
		(4.93)		(5.39)	(5.74)
married or partnership		-0.132***		-0.133***	-0.110***
		(-11.58)		(-11.55)	(-9.43)
age/10		-0.122*		-0.125**	-0.097
		(-1.94)		(-1.97)	(-1.53)
$\text{age}^2/100$		0.005		0.006	0.004
		(0.99)		(1.03)	(0.69)
number of children		0.005**		0.005**	0.003
		(2.44)		(2.21)	(1.27)
white		-0.053***		-0.044***	-0.027**
		(-4.42)		(-3.64)	(-2.22)
educ:low attainment		0.106***		0.084***	0.071***
		(8.32)		(6.46)	(5.50)
educ:high school graduate		*(ref.)*		*(ref.)*	*(ref.)*
educ:college and above		-0.073***		-0.047***	-0.039***
		(-7.29)		(-4.13)	(-3.37)
health:excellent		-0.189***		-0.187***	-0.183***
		(-25.45)		(-25.08)	(-24.18)
works 0-29 hours per week			-0.031***	-0.005	0.001
			(-3.41)	(-0.47)	(0.07)
Manager and tech sup			*(ref.)*	*(ref.)*	*(ref.)*
Sales			0.040***	0.030*	0.022
			(2.58)	(1.90)	(1.42)
Clerical and administrative			0.083***	0.030**	0.026*
			(6.33)	(2.21)	(1.91)
Service			0.171***	0.086***	0.069***
			(11.52)	(5.50)	(4.44)
Farming, forestry and fishing			0.100***	0.098***	0.103***
			(3.41)	(3.27)	(3.40)
Mechanics, construction			0.068***	0.054***	0.047***
			(4.10)	(3.04)	(2.69)
Operator			0.150***	0.101***	0.089***
			(9.80)	(6.12)	(5.38)
Armed forces			-0.163	-0.098	-0.093
			(-1.36)	(-0.62)	(-0.54)
ln(net worth)					-0.033***
					(-8.14)
risk aversion					-0.020***
					(-5.29)
financial planning horizon					-0.021***
					(-6.47)
AIC	104,564	102,933	104,304	102,846	102,611
BIC	104,759	103,205	104,568	103,186	102,976
Observations			36,283		

Marginal effects; t statistics in parentheses; robust standard errors; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Retirement and Well-Being

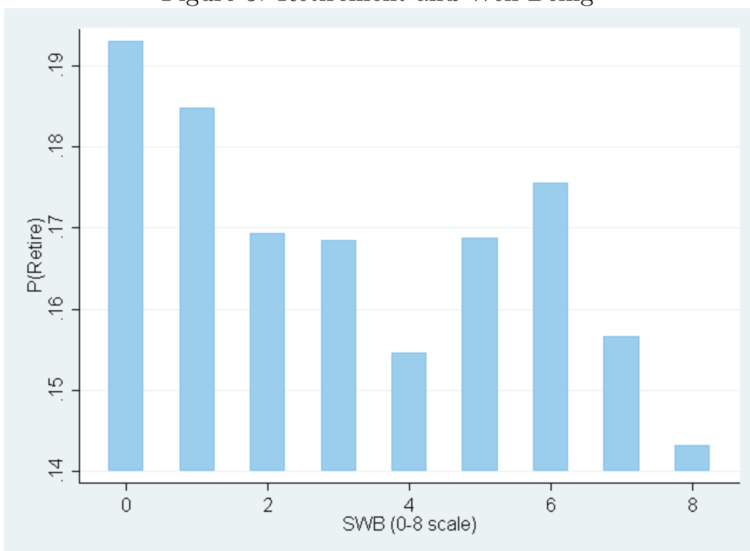

Figure 4: Predicted Means of WB by FMM Component Groups

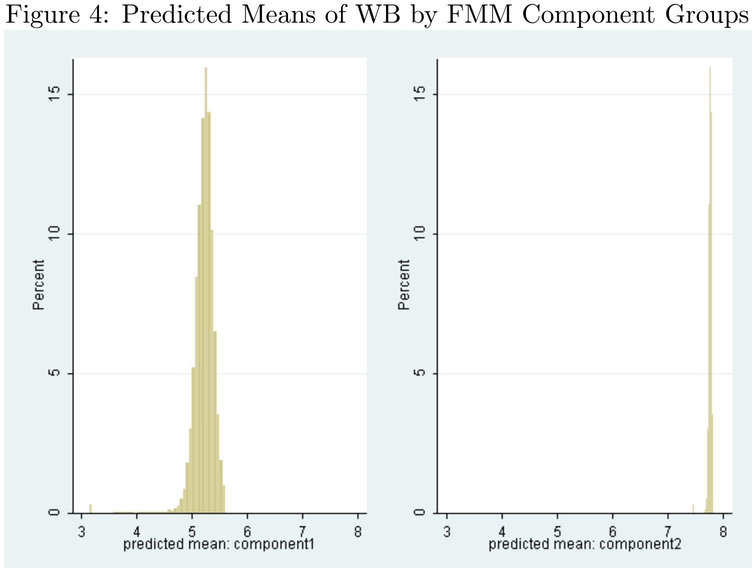

Figure 5: Prior and posterior probabilities (component 1)

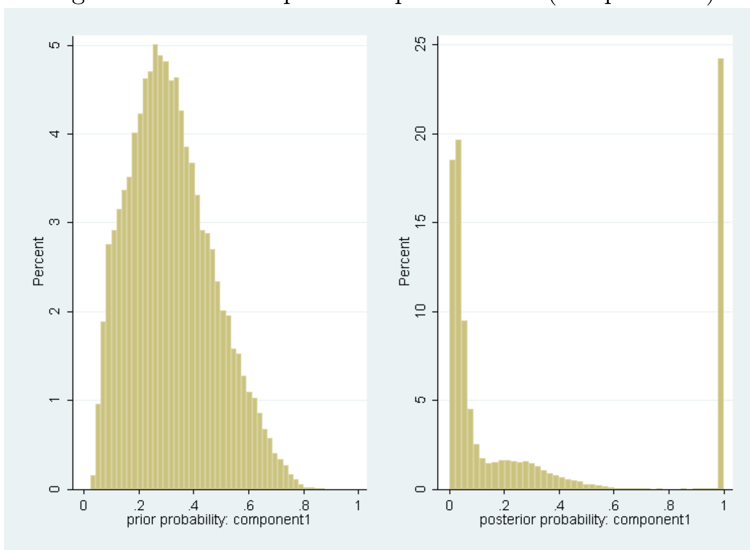

Figure 6: Density of Marginal Utility of Income

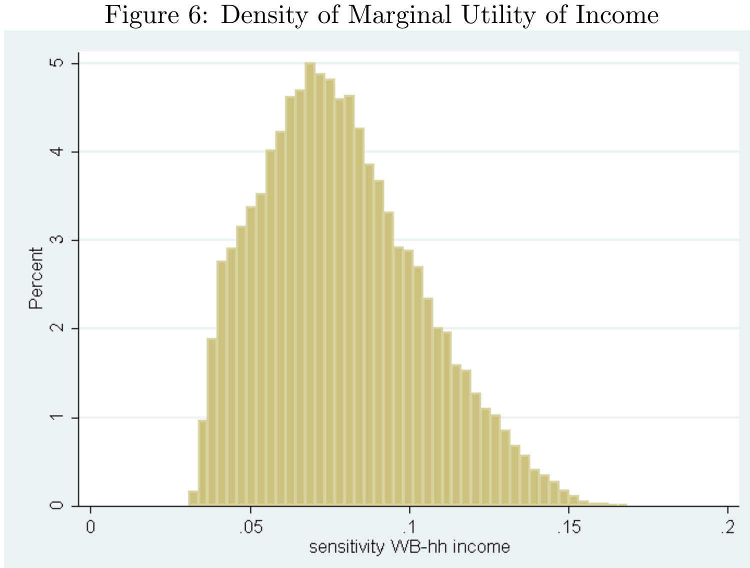

Figure 7: Marginal Utility of Income, by income quantiles

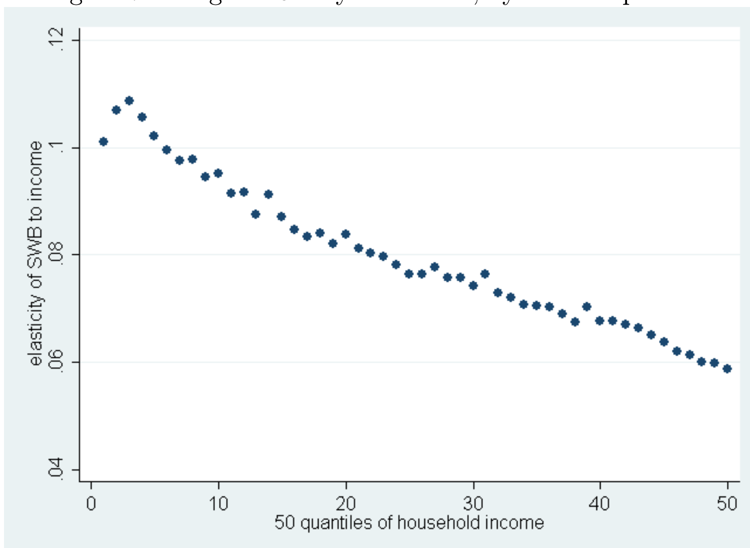

Table 7: OLS vs FMM-Between Results

	OLS	**FMM:Constant Pr.**		**FMM:Varying Pr.**	
		Comp.1	**Comp.2**	**Comp.1**	**Comp.2**
ln(hh income)	0.299***	0.471***	0.049***	0.329***	0.033***
	(13.75)	(13.44)	(6.72)	(9.59)	(4.95)
Mean of predicted SWB		5.63	7.65	5.61	7.65
π_1		0.39		0.38	
AIC	41,889	33,706	.	32,431	.
BIC	41,904	33,758	.	32,748	.
Observations	11,719				

t statistics in parentheses; robust standard errors

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

Table 8: Determinants of Probability of Retiring- Controls

	(1)	(2)	(3)	(4)	(5)	(6)
female		0.016***		0.021***	0.024***	0.008
		(4.06)		(4.72)	(4.93)	(1.44)
married or partnership		-0.001		-0.010	-0.017**	0.011
		(-0.22)		(-1.49)	(-2.19)	(1.28)
age/10		0.700***		0.706***	0.697***	0.718***
		(11.96)		(12.16)	(11.92)	(12.52)
$\text{age}^2/100$		-0.048***		-0.049***	-0.048***	-0.049***
		(-10.03)		(-10.37)	(-10.25)	(-10.57)
number of children		-0.001		-0.001	-0.001	-0.002
		(-1.35)		(-1.15)	(-0.92)	(-1.56)
white		-0.010*		-0.012**	-0.013**	-0.007
		(-1.88)		(-2.10)	(-2.31)	(-1.22)
educ:low attainment		0.025***		0.026***	0.031***	0.009
		(3.93)		(3.99)	(4.27)	(1.19)
educ:high school graduate		*(ref.)*		*(ref.)*	*(ref.)*	*(ref.)*
educ:college and above		-0.022***		-0.019***	-0.020***	-0.014**
		(-4.65)		(-3.74)	(-3.92)	(-2.57)
health:excellent		-0.047***		-0.053***	-0.060***	-0.021*
		(-8.11)		(-8.60)	(-8.33)	(-1.79)
works 0-29 hours per week			0.091***	0.035***	0.035***	0.033***
			(15.87)	(6.69)	(6.68)	(6.43)
Manager and tech sup			*(ref.)*	*(ref.)*	*(ref.)*	*(ref.)*
Sales			-0.001	-0.013**	-0.011*	-0.016***
			(-0.18)	(-2.01)	(-1.75)	(-2.59)
Clerical and administrative			0.018***	0.009	0.010	0.005
			(2.89)	(1.43)	(1.58)	(0.74)
Service			0.025***	0.007	0.011	-0.006
			(3.41)	(0.98)	(1.45)	(-0.81)
Farming, forestry and fishing			0.025*	-0.007	-0.004	-0.028**
			(1.79)	(-0.64)	(-0.32)	(-2.53)
Mechanics, construction			0.059***	0.041***	0.043***	0.032***
			(6.99)	(4.70)	(4.89)	(3.65)
Operator			0.055***	0.032***	0.038***	0.014
			(6.96)	(3.92)	(4.21)	(1.52)
Armed forces			0.144	0.128	0.127	0.147
			(1.26)	(1.03)	(1.02)	(1.13)
risk aversion					0.001	0.007***
					(0.71)	(3.06)
financial planning horizon					-0.006***	-0.001
					(-3.07)	(-0.29)
ln(net worth)						0.015***
						(5.21)
Observations				30,678		

Marginal effects; t statistics in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Determinants of Probability of Retiring-Between Results

	(1)	(2)	(3)	(4)	(5)	(6)
sensitivity WB-hh income	-0.378***	-0.359***	-0.482***	-0.448***	-0.493***	-0.322***
	(-9.48)	(-5.82)	(-11.02)	(-6.74)	(-6.80)	(-3.92)
ln(hh income)	-0.019***	-0.004**	-0.014***	-0.003	-0.002	-0.004**
	(-10.85)	(-2.30)	(-7.98)	(-1.44)	(-1.29)	(-2.51)
well-being on a 0-8 scale	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(-6.01)	(-6.15)	(-6.11)	(-6.25)	(-6.22)	(-6.29)
Sociodemo variables	No	Yes	No	Yes	Yes	Yes
Job variables	No	No	Yes	Yes	Yes	Yes
Behavioural variables	No	No	No	No	Yes	Yes
Net worth	No	No	No	No	No	Yes
AIC	24,461	22,503	24,071	22,406	22,399	22,382
BIC	24,611	22,728	24,288	22,698	22,707	22,699
Observations			30,678			

Marginal effects; t statistics in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Determinants of Probability of Retiring-Controls for Between Results

	(1)	(2)	(3)	(4)	(5)	(6)
female		0.017***		0.022***	0.022***	0.018***
		(4.43)		(5.00)	(4.97)	(3.93)
married or partnership		0.001		-0.005	-0.006	-0.005
		(0.27)		(-0.89)	(-1.14)	(-0.86)
age/10		0.692***		0.698***	0.693***	0.694***
		(11.84)		(12.06)	(11.95)	(12.06)
$\text{age}^2/100$		-0.047***		-0.048***	-0.048***	-0.048***
		(-9.92)		(-10.27)	(-10.21)	(-10.27)
number of children		-0.002		-0.001	-0.001	-0.001
		(-1.63)		(-1.57)	(-1.58)	(-1.29)
white		-0.012**		-0.013**	-0.013**	-0.014**
		(-2.23)		(-2.40)	(-2.39)	(-2.45)
educ:low attainment		0.026***		0.025***	0.026***	0.023***
		(4.31)		(4.17)	(4.23)	(3.81)
educ:high school graduate		*(ref.)*		*(ref.)*	*(ref.)*	*(ref.)*
educ:college and above		-0.024***		-0.019***	-0.019***	-0.019***
		(-5.14)		(-3.96)	(-3.92)	(-3.86)
health:excellent		-0.045***		-0.047***	-0.049***	-0.043***
		(-9.84)		(-10.44)	(-10.48)	(-8.75)
works 0-29 hours per week			0.089***	0.036***	0.036***	0.034***
			(15.66)	(6.86)	(6.90)	(6.58)
Manager and tech sup			*(ref.)*	*(ref.)*	*(ref.)*	*(ref.)*
Sales			0.004	-0.011*	-0.010	-0.011*
			(0.51)	(-1.71)	(-1.58)	(-1.79)
Clerical and administrative			0.025***	0.011*	0.011*	0.010
			(4.00)	(1.74)	(1.75)	(1.61)
Service			0.036***	0.007	0.007	0.006
			(4.81)	(0.98)	(1.05)	(0.83)
Farming, forestry and fishing			0.027*	-0.012	-0.012	-0.017
			(1.87)	(-1.04)	(-1.06)	(-1.58)
Mechanics, construction			0.064***	0.041***	0.042***	0.040***
			(7.49)	(4.79)	(4.84)	(4.69)
Operator			0.068***	0.034***	0.036***	0.031***
			(8.23)	(4.29)	(4.37)	(3.86)
Armed forces			0.112	0.109	0.109	0.119
			(1.05)	(0.93)	(0.93)	(0.97)
risk aversion					0.002	0.004**
					(1.34)	(1.96)
financial planning horizon					-0.005***	-0.004**
					(-2.81)	(-2.43)
ln(net worth)						0.009***
						(4.32)
AIC	24,461	22,503	24,071	22,406	22,399	22,382
BIC	24,611	22,728	24,288	22,698	22,707	22,699
Observations			30,678			

Marginal effects; t statistics in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: FMM with Varying Probabilities-with/without Controls

	(1)		**(2)**		**(3)**	
Controls:	**No**		**Exogenous**		**All**	
	Comp.1	**Comp.2**	**Comp.1**	**Comp.2**	**Comp.1**	**Comp.2**
ln(hh income)	0.188***	0.027***	0.149***	0.016***	0.039	0.005
	(7.39)	(7.45)	(5.70)	(4.45)	(1.31)	(1.37)
AIC	102,611	.	102,288	.	102,034	.
BIC	102,976	.	102,994	.	102,994	.
Observations			36,283			

Exogenous controls include:gender, race, age, education, wave and region dummies.

All controls include: exogenous controls, plus marital status, number of children, health status, job variables, net worth, risk aversion, and financial planning horizon, *i.e.* all Z_i variables.

t statistics in parentheses; robust standard errors;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Determinants of Probability of Retiring- Using specification (2) from Table 11

	(1)	(2)	(3)	(4)	(5)	(6)
sensitivity WB-hh income	-0.462***	-0.944***	-0.600***	-1.351***	-1.886***	0.675
	(-3.73)	(-3.91)	(-4.47)	(-4.81)	(-5.01)	(1.10)
ln(hh income)	-0.016***	-0.005***	-0.012***	-0.004**	-0.005**	-0.005**
	(-8.98)	(-2.65)	(-6.48)	(-2.17)	(-2.44)	(-2.47)
well-being on a 0-8 scale	-0.005***	-0.006***	-0.005***	-0.006***	-0.006***	-0.006***
	(-4.37)	(-5.77)	(-4.38)	(-5.85)	(-5.87)	(-5.85)
Sociodemo variables	No	Yes	No	Yes	Yes	Yes
Job variables	No	No	Yes	Yes	Yes	Yes
Behavioural variables	No	No	No	No	Yes	Yes
Net worth	No	No	No	No	No	Yes
AIC	24,538	22,523	24,172	22,430	22,420	22,396
BIC	24,688	22,748	24,388	22,721	22,728	22,713
Observations	30,678					

Marginal effects; t statistics in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

See Table 8 for controls

Table 13: Sensitivity Checks for P(Retire)

	Men				Women			
Subsamples	Benchmark	Couple	High Edu	Low Edu	Benchmark	Couple	High Edu	Low Edu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sensitivity WB-hh income	-1.223***	-1.127**	-2.310**	-0.352	-1.378***	-1.818***	-1.846**	-2.879***
	(-2.59)	(-2.12)	(-2.35)	(-0.28)	(-3.48)	(-3.68)	(-2.16)	(-2.77)
ln(hh income)	-0.004	-0.005	-0.012**	-0.002	-0.003	-0.003	0.006	-0.015***
	(-1.51)	(-1.42)	(-2.20)	(-0.30)	(-1.32)	(-0.88)	(1.02)	(-3.44)
well-being on a 0-8 scale	-0.006***	-0.007***	0.002	-0.006	-0.006***	-0.005***	-0.003	-0.009***
	(-3.18)	(-3.33)	(0.61)	(-1.37)	(-4.86)	(-3.23)	(-1.00)	(-3.41)
Observations	13,860	11,952	4,104	2,795	16,811	11,638	3,618	3,016
AIC	10,645	9,091	2,767	2,537	11,745	7,704	2,397	2,398
BIC	10,908	9,342	2,975	2,727	12,015	7,954	2,589	2,591

Marginal effects; t statistics in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Controls for socioeco variables, job-related variables, behavioural variables, and wave and regional dummies

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