Retirement and the Marginal Utility of Income

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Abstract

Subjective well-being (SWB) has been shown to be a strong predictor of future outcomes, whether on the labour market (e.g job quits, unemployment duration) or in other domains of life (e.g marital break ups). In order to overcome the issue of heterogeneity in SWB functions, empirical work has introduced individual-specific effects into well-being regressions. However, this latter only addresses "level heterogeneity". If SWB functions are interpersonally comparable, then their slopes with respect to the variables of interest will also affect behaviour. We here appeal to latent-class analysis to model both intercept and slope heterogeneity in SWB, and then evaluate the impact these slopes on transitions to retirement. We identify several groups of individuals whose SWB is not affected in the same way by income. We use this slope heterogeneity to construct a continuous measure of the marginal utility of income. When we estimate retirement probability as a function of this income elasticity of well-being, we find that the more individuals value a unit of income, the less likely they will retire. This correlation is found conditional on both the level of income and the level of well-being.

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1 Introduction

While the retirement decision has been at the heart of much work across OECD countries, it has essentially concentrated on the "objective" characteristics inducing older individuals to retire, with far less being known about the relationship between subjective well-being and retirement. Most of the literature dealing with well-being and retirement has focused 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 [2004]; Borsch-Supan and Jurges [2007]; Seitsamo [2007]; Bonsang and Klein [2011]). With pension systems needing to be re-designed to become sustainable, and the preferred option in many countries consisting in increasing the legal retirement age, the effects of retiring on subjective well-being are of great interest for policymakers. In a very similar vein, other work has examined retirement satisfaction. Shultz, Morton, and Weckerle [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. However, although well-being has been shown to predict future behaviour, it has rarely been considered in the context of retirement (an exception is Debrand and Sirven [2009], who confirm a negative impact of job satisfaction on retirement).

In this paper we estimate the impact of well-being on retirement using the Health and Retirement Study (HRS), and explicitly allow for slope heterogeneity across (latent) groups of individuals. We appeal to a finite mixture model (FMM) with panel data to model heterogeneity in the marginal utility of income, and then see whether this marginal utility of income affects retirement. The data identify two latent classes of individuals in terms of the relationship between well-being and income. The model strongly rejects the hypothesis of an equal effect of income on well-being across these two groups. We use the estimated slopes and individual group membership probabilities to construct a continuous measure of the marginal utility of income. We then estimate retirement probability as a function of this elasticity of well-being to income.

We add 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 membership. 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". Last, our retirement model suggests a significant negative effect of this estimated marginal utility of income: those who value their 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 (SWB) 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 retirement probability. Last, Section 6 concludes.

2 The Marginal Utility of Income

The impact of the marginal utility of income on retirement is at the heart of the current paper. As such, our first step is to estimate this marginal utility of income. We will here use subjective well-being scores as proxy measures of utility. By doing so, we are not measuring *ex ante* decision utility but rather *ex post* experienced utility (Kahneman, Wakker, and Sarin [1997]). One suspicion amongst economists is that what individuals say may not always reveal their preferences (and thus their behaviour). A valid response to this suspicion is to note 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 to discontinue activities associated with lower well-being levels (see Kahneman, Fredrickson, Schreiber, and Redelmeier [1993]; Frijters [2000]; Shiv and Huber [2000]). An example of such work is job satisfaction predicting future job quits, even when controlling for wages, hours of work and other standard individual and job variables (see, amongst others, Freeman [1978]; Clark, Georgellis, and Sanfey [1998]; Clark [2001]; Kristensen and Westergaard-Nielsen [2006]). 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. Further, Iaffaldano and Muchinsky [1985] and Ostroff [1992] report that higher job satisfaction within a firm is positively correlated with its performance. Equally, Rogers, Clow, and Kash [1994] find that job satisfaction is also correlated with increased customer satisfaction within service industries. This predictive power is also found in other domains. Life satisfaction predicts marital break-up (Guven, Senik, and Stichnoth [2012]), as well as future morbidity and mortality. This literature shows that individual subjective well-being scores are at least partly interpersonally comparable, otherwise they would not be able to predict future individual behaviour and outcomes.

We then use self-reported SWB as a proxy for utility, and appeal to the relation between the former and income to provide an estimate of the marginal utility of income. There does still remain the issue of the interpretation of reported satisfaction scores. 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]).

The traditional approach to dealing with unobserved heterogeneity is the use of individual-specific fixed effects (see Clark and Oswald [2002]; Ferrer-i Carbonell and Frijters [2004]; Senik [2004]).

The development of finite mixture models in the statistical literature in the 1960s and 1970s, is an alternative way of capturing unobserved heterogeneity. The underlying idea in 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. in Eckstein and Wolpin [1999]; Thacher and Morey [2003], and the work of Deb who has contributed a great 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 Van 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. 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. The use of individual fixed effects (intercept heterogeneity) therefore seems insufficient, and we need to also consider 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 (common ones are gender, marital and labour-force status, health, education, *etc.*). This therefore misses out the indirect effects of the variable of interest here (income) on utility. Income is commonly-believed to have a positive effect on health, for example. And health and SWB are positively correlated (see Dolan, Fujiwara, and Metcalfe [2011]). We want to establish the overall impact of income on utility, including any indirect effects of income via other right-hand side variables. When we estimate the marginal utility of income using FMM, we first regress SWB on income only with no other explanatory variables. As a specification check (but aware that this may bias the estimated coefficient on income), we include a number of different sets of additional control variables in the SWB equation.

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 aged over 50 and their spouses. In the first interview in 1992, HRS participants included 12,652 individuals from 7,702 households. The HRS initially sampled persons in birth cohorts 1931 through 1941 in 1992, with follow-up interviews every two years. In 1998, people 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 cohort. Our analysis here uses data from Version I of the data prepared by RAND, which is a cleaned and processed version of the HRS data. As of today, these data are made of 10 waves from 1992 to 2010, of which we use waves 2 to 8, i.e. from year 1994 to 2006. As explained below, our measure of subjective well-being has been incorporated from wave 2 on, leading us to discarding wave 1. We chose not to use the last two waves for the job occupation variables were recoded in a way that allows no direct equivalence. 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 (waves 9 and 10), on the other hand, the 2000 SOCs have been 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 build an equivalence between the two classifications. Although a "'crosswalk" was created in this very purpose, it only concerns the management/professional category.

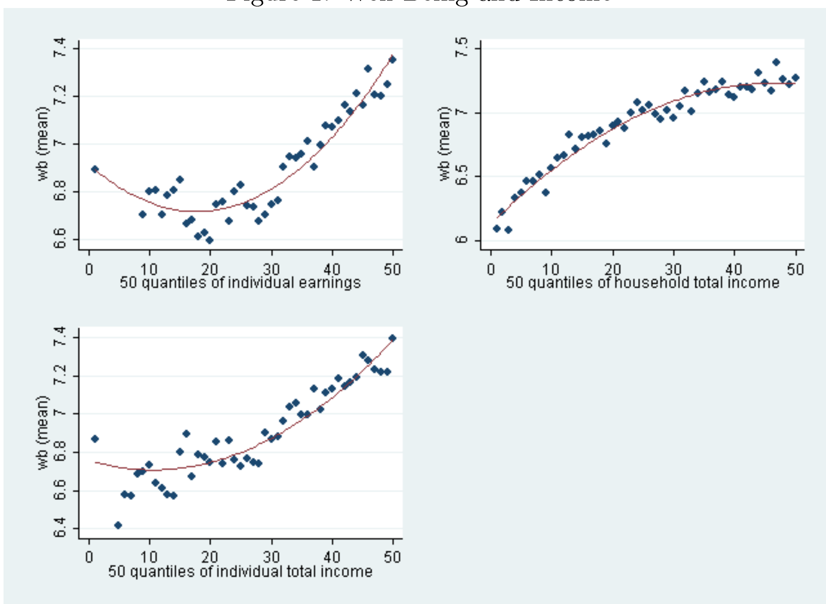
The RAND-HRS data have included an abridged version of the Center for Epidemiologic Studies-Depression (CESD) Scale (Radloff [1977]) since wave 2. The CESD depression scale originally comprised twenty items. The HRS only retains eight of them: depressive feelings, everything seen as an effort, restless sleep, could not get going, loneliness, sadness, enjoyment, happiness. All the questions asked to derive the CESD score are 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 replies positively for the first six items, and negatively 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 (on 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. In addition 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 emphasising. One is on risk aversion, on a scale from 1 to 4, where 1 indicates the least risk-averse preferences. 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. If the individual answered these questions at a number of different waves, we take the mean answer. The sample size falls with the inclusion of the risk-aversion variable. Most of our sample is risk-averse, with 60% giving the most risk-averse answers and only 12% the most risk-loving 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 and expenditure, 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 SWB distribution is shown in Table 5. 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 confirms the prevalence of high scores of SWB as over 70 per cent of the individuals recorded an 8 score at least once while less than 2 per cent have given 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 gave a score of zero gave it at every wave. This either reflects measurement error, or that most people who reported low scores had indeed had a bad year, and had better years in other waves.

3.2 Initial Results

Figure 1: Well-Being and Income

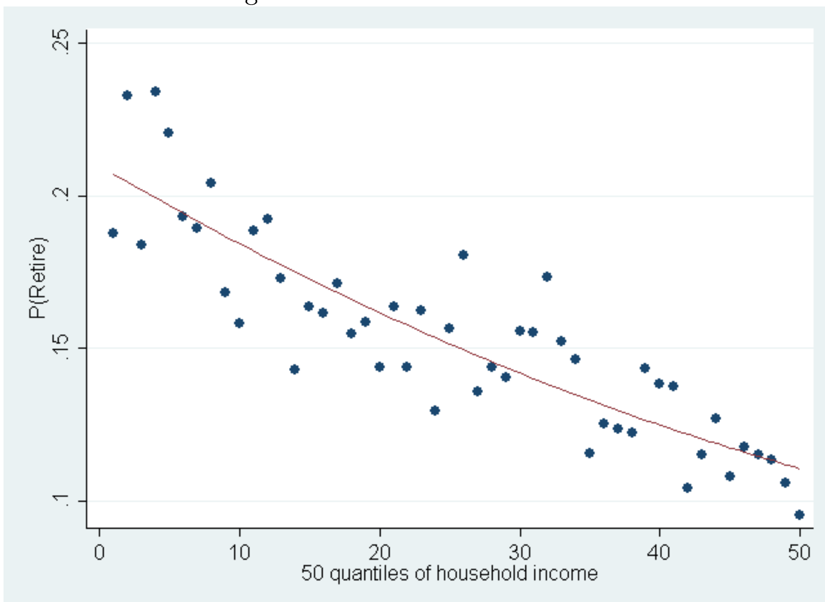


Before starting the econometric analysis, we present the descriptive statistics of our key variables, *i.e* subjective well-being and income for the first estimation step, and a retirement dummy for the following probability model. Figure 1 shows the non-parametric estimation of mean well-being by income quantiles, where income is successively measured as individual earnings from work, individual total income, and total household income. In the estimations we will use the latter, which is the most widely-used measure for the estimation of the marginal utility of income. 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. We here graph an "average" utility function as if people 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 gains. Individuals may also 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 room for heterogeneity in their response. Our FMM analysis allows the relationship between income and well-being to differ between individuals in terms of both the intercept and the slope. We will use the panel dimension of the HRS, and separate the time-series and cross-sectional information it provides, *i.e.* "between" movements (between distinct subjects) and "within" movements (panel 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 much less variation within individuals at different points in time. This method does 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 $t+1$ also deserves attention. As retirement is a labour-supply decision, the impact of income may not be straightforward. If leisure is a normal good, people should consume more leisure as income increases (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 (substitution effect). The net impact of these two effects is ambiguous. Figure 2 shows 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, 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. Little work has considered the impact of SWB, even in levels, on the retirement transition. Fawaz [2009] finds no significant effect of SWB (measured by another inverted-depression score,

Figure 2: Retirement and Income



the EURO-D scale) on retirement probability when job satisfaction and satisfaction with various job domains (pay, hours, work itself, *etc.*) are controlled for. However, these latter variables do significantly affect retirement probability with the expected sign. We thus expect happier individuals to retire less, as our key SWB variable is a global measure of satisfaction encompassing domain-specific measures of satisfaction such as job satisfaction.

These relationships between SWB and income first, income and retirement secondly, and SWB and retirement, should be analysed multivariately. The following section uses the results from the estimation of the first relationship in order estimate intercept and slope heterogeneity in the impact of SWB on retirement probability.

4 Econometric Methods

4.1 First Step: Estimating the 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 to analyse individual unobserved heterogeneity in panel data regarding the marginal utility of income.

The advantage of panel data in the identification of latent class models was underlined by Greene [2001].

We model individual heterogeneity in a flexible way, making no distributional assumptions for the unobserved individual effects. The FMM distinguishes between a finite, usually small, number of latent classes of individuals (this number is C in the presentation below), which can differ in both the level of well-being and the relationship to the regression covariates. Here we specifically concentrate on income. Conventional panel data models (with fixed or random effects) only consider intercept heterogeneity.

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 household income, and X_t is a vector of individual characteristics (sociodemographic, labour market, economic, regional and time variables). 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 is the average of the effects across subpopulations and may hide considerable heterogeneity. We therefore estimate a finite mixture model, where subpopulations 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, $T_i = 1, ..., 8$ 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 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 different classes.

As put forward in Deb, Gallo, Ayyagari, Fletcher, and Sindelar [2009], finite mixture models have many advantages, but also some drawbacks. A finite mixture model may fit the data better than a basic OLS model due to outliers, which are captured in the FMM via additional mixture components. Even if the use of FMM is motivated by *ex ante* reasoning, the different latent classes need to 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.

4.1.2 Between Vs. Within

We use the panel nature of the data to distinguish the between-individual and within-individual effects of our right-hand side variables. With respect to income, we can see whether the marginal utility of income differs between individuals, but remains fairly constant within-person over time. Deb and Trivedi [2011] provide a simplified computation method to estimate a mixture of normal distributions 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 for the estimation of a latent-class model with fixed effects. This kind of estimation can then proceed in the same way as the standard FMM in cross-section data. We use the same method to estimate "between" effects too, replacing (wb_{it}, x_{it}) by the "between transformation" $(\bar{wb}_i, \bar{x}_i)$, where $\bar{x}_i = \sum_{t=1}^{T_i} x_{it}/T_i$, and then estimating a standard finite mixture model on these transformed variables.

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 look for an impact of e on retirement probability 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 Results From Finite Mixture Models

5.1.1 Results from Pooled Estimations

We estimate the marginal utility of income using a simple OLS regression and a number of specifications of a finite mixture model. The model selection criteria (AIC/BIC) clearly support 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 a small number of outliers. Table 1 shows

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

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

the results from a constant-probability mixture model and a varying-probability mixture model, which are to be compared to those from a traditional OLS regression of SWB on log income. As argued in Section 2, we do not include any controls in the main equation, in order to pick up both the direct and indirect effects of income on SWB. The robustness section will test other specifications including other explanatory variables. The OLS results suggest a significant correlation between income and SWB with an estimated coefficient of 0.23, so that SWB would increase by 0.23 points were income to double (*i.e.* to increase by 100 per cent). When no covariates are used to model the component probabilities, the FMM identifies two latent classes with proportions of 0.32 and 0.68. In the first smaller group, income has a significant effect on SWB with a higher coefficient than in the OLS regression (0.39). By way of contrast, in the larger second group the effect of income on SWB is only small (0.05). There is thus evidence of striking differences in the SWB-income relationship, which was masked in OLS estimation. Our two identified groups are dissimilar, with that with the higher marginal utility of income being less happy on average (with a mean SWB score of 5.21) than the other (mean SWB of 7.75). Figure 4 shows that the density of predicted mean SWB in 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 of close to 8. This distribution for the first low-SWB group is less concentrated and lies between 4.8 and 5.8.

Including a set of covariates Z_i here 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 remains around 8 times larger in the second group. We estimate a number of specifications of the varying probability mixture model, according to the different set of explanatory variables Z_i included. Our preferred specification, which is the varying probability model shown in Table 1, includes socioeconomic variables, labour-force variables, and the two behavioural variables detailed above (risk aversion and financial planning horizon) to predict the probability of being in each component group. Table 6 shows what happens when we estimate the prior probability equations with different subsets of these covariates. The final column corresponds to our preferred specification, with the smallest AIC and BIC.[1] The AIC/BIC can be seen to fall when we include new covariates, indicating that the additional information brought by these covariates improves model accuracy but does not add too much to its complexity. Note that the model with socio-demographic variables fits the data better than that with the labour market variables, indicating that the latter variables predict class membership less efficiently. Our preferred specification is that with all of the variables that are considered here, and it is that which appears in the last column of Table 1.

The results show that individuals who are female, single, non-white, less educated, and with lower self-assessed health are more likely to be in the less-happy group. Age does not predict class membership when all covariates are included (although in other specifications the younger are more likely to appear in the first less-happy high marginal utilty group). The same holds for income, which negatively affects the probability of being in group 1, but becomes insignificant when we control for wealth. Those in lower-status occupations (Service, Farming, forestry and fishing, Mechanics, Construction, compared to Manager and Technician Sup) are more likely to be in the first group; individuals in this group are also less wealthy. Last, the risk averse, as well as those whose financial horizon is longer, are more likely to be found in the happier group. As such, those with

[1] 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 penalizes the number of parameters less than does the Bayesian information criterion (BIC), but here the two measures of goodness-of-fit yield the same results.

a longer-term perspective have well-being that is less sensitive to income. The impact of risk aversion may be thought to be surprising, as we might expect the more risk averse to suffer more from an income loss and thus to be in found in group 1.

These qualitative conclusions from the use of FMM are robust to alternative specifications. We continue to find that 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 some poorer characteristics, while the majority of our sample is happier with better characteristics in this respect, and are less affected by income. Our results are not the same as those from ECHP data in Clark, Etilé, Postel-Vinay, Senik, and Van Der Straeten [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". This may reflect that our sample is restricted to those who are in work, theirs is not restricted in this way.

5.1.2 Between Vs. Within

At this stage, we do not know if the positive income-SWB relationship comes from between-individual or within-individual effects. We disentangle these by carrying out the same regressions using the "between" and "within" transformations of the variables as noted above.

Within individuals, OLS yields a significant but small coefficient of 0.02 on income, which is barely one-tenth of the pooled estimate. The FMM here fails to converge , suggesting that we do not have enough within-variability for the data to sort the observations within individual into distinct classes. As such, the impact of a marginal increase in income for a given individual leads to only a small increase in SWB, and we cannot say that this increase is heterogeneous over time (*i.e.* within individual). We therefore expect the largest part of the impact of income on SWB to come from between-individual variation, and equally heterogeneity in the marginal utility of income to be individual-specific. Table 7 does indeed reveal the same pattern as found in the pooled estimates, but stronger. When we look at differences between individuals (rather than individual-year observations), there is again a larege significant impact of household income on SWB

(0.29) in OLS, which FMM decomposes into two distinct marginal utilities of income, in the same way as above. Heterogeneity in the marginal utility of income seems to reflect individual-specific time-invariant characteristics.

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 income elasticity of well-being (see Equation 6 in Section 4.2). We use the prior rather than posterior probabilities as the latter also rely on the observed well-being outcome to sort individuals into the latent classes, and therefore yield only a small range of values for the group probabilities. The observed well-being score is such a good predictor of group membership that the posterior probability is (almost) either 0 or 1. Figure 5 plots out these densities of the prior and posterior probabilities.

In line with Boyce and Wood [2011] and Schurer and Yong [2010], we consider that the marginal utility of income varies with personality traits. Therefore, every individual -rather than observation- in our sample is now attributed a measure of the marginal utility of income. This comes from the between regressions, so that one individual is assigned only one value of the marginal utility of income across all 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 can see that e is a decreasing function of income in Figure 7: 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. We expect a lower marginal utility of income to increase retirement, ceteris paribus.

In all of our probit specifications we do indeed find a negative estimated coefficient on the marginal utility of income (see Table 2 for the key coefficients, and Table 8 in the Appendix for those on the other controls). 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 a significant negative estimated coefficient in this regression, as was suggested by the descriptive statistics. This impact remains significant when we control for sociodemographic and labour-market variables, so that the income effect is not masking health or job characteristics. This is consistent with the substitution effect dominating the income effect. The main effect of SWB is also

Table 2: Determinants of Probability of Retiring-Between Results

	(1)	(2)	(3)	(4)	(5)	(6)
Estimated marginal utility of 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;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

See Table 8 for controls.

negative too, again confirming the suggestion in the descriptive statistics that happier individuals retire less. The estimated coefficients on income and SWB are significant across all specifications. Adding the log of net worth (column (6) compared to column (5)) renders the impact of the marginal utility of income weaker in terms of maagnitude but does not alter its significance. As those with more wealth retire more, and wealth is a strong negative predictor of the marginal utility of income (the wealthier have a lower marginal utility of income), this variable seems to capture some of the negative effect of e on the probability of retiring. In terms of goodness of fit, the AIC/BIC falls as we add new control variables, indicating that the model is not overparameterized. Again, labour-market variables affect prediction less than do sociodemographic variables, so that gender, age, health and education are better predictors of retirement than are labour-market characteristics.

Regarding the other controls (see Table 8), we find reasonable results. For example, women, the less-educated, the older and those in worse health retire more. Part-time workers retire more, perhaps because they have already started their retirement transition by reducing their work hours.

5.3 Robustness Checks

As explained in Section 2, we estimate the marginal utility of income by regressing SWB on income, without any other covariates in order to capture both the direct and indirect effects of income. We have also tested other specifications with control variables. Column (1) of Table 9 presents analogous results to those from the FMM with no controls in Table 1. We start with the more exogenous variables: gender, race, age, education, wave and region. The data again sort into two groups with different valuations of income in the same way as beforehand. When all the variables in the Z_i set are included, income loses its explanatory power (probably because it is well-predicted by these Z_i)). We thus use the second specification (2) to create a new marginal utility of income and see whether this affects retirement: Table 10 confirms our previous results in this respect.

Finally, we re-estimate our fifth specification, includes all controls except net worth, for various subsamples (e.g. individuals in a couple, with low/high education attainment, and men and women). For brevity, we only present the estimates of the key parameters in Table 11. The marginal utility of income remains significant and negative in almost all subsamples. It has a larger effect when income is also significant: for the high-education male group and the less-educated female group. The marginal effect of SWB is remarkably stable across specifications.

6 Conclusion

This paper first modeled heterogeneity in the valuations of income using latent-class analysis on nationally-representative data on US workers close to retirement. We identify two classes of individuals with distinct marginal utilities of income. Our main results indicate that there is a great deal of heterogeneity across the two latent classes. A smaller group is relatively unhappy, with high marginal utility of income, and is made of individuals with some poorer characteristics, while the majority group is happier, with some nicer characteristics, and are less affected by income. The panel nature of our data suggests that heterogeneity in the marginal utility of income is mostly between individuals, rather than within-individual.

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" 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, regardless of how much income they have. As retirement often implies lower income, a higher marginal utility of income yields greater subjective and therefore 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). We also contribute to validating 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 worth 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 many other kinds of individual behaviour. Finite mixture models are likely to become a useful complement to the standard toolbox that economists use to predict a wide variety of behaviour.

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7 Appendix

Table 3: Summary statistics

Variable	**Mean**	**(Std. Dev.)**
Well-being on a 0-8 scale (CES-D)	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 thousands)	3.65	(5.01)
Household income(hundreds of thousands)	0.88	(0.71)
Risk aversion (1-4)	3.27	(1.06)
Financial planning horizon (1-5)	3.18	(1.18)
N	36,283	

Table 4: Distribution of Occupations

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 Forces	15	0.04
Total	36,283	100

Table 5: Distribution of Well-Being Score (CES-D)

	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)
$Age^2/100$		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

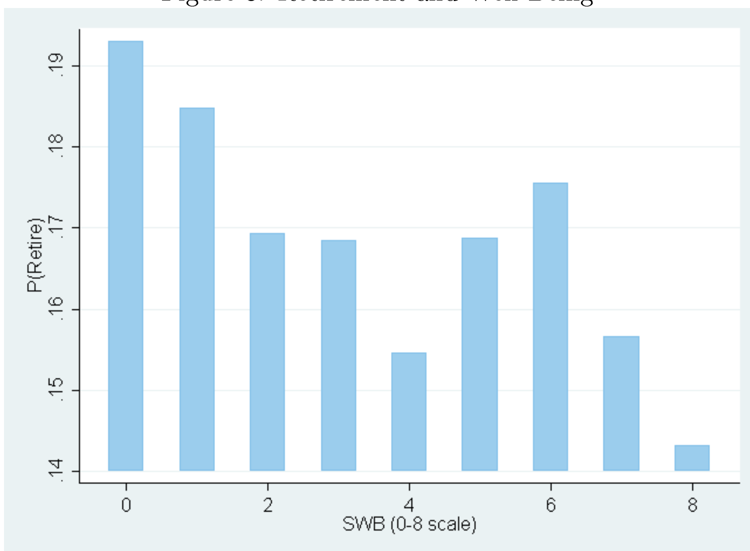

Figure 4: Predicted Means of WB by FMM Component Groups

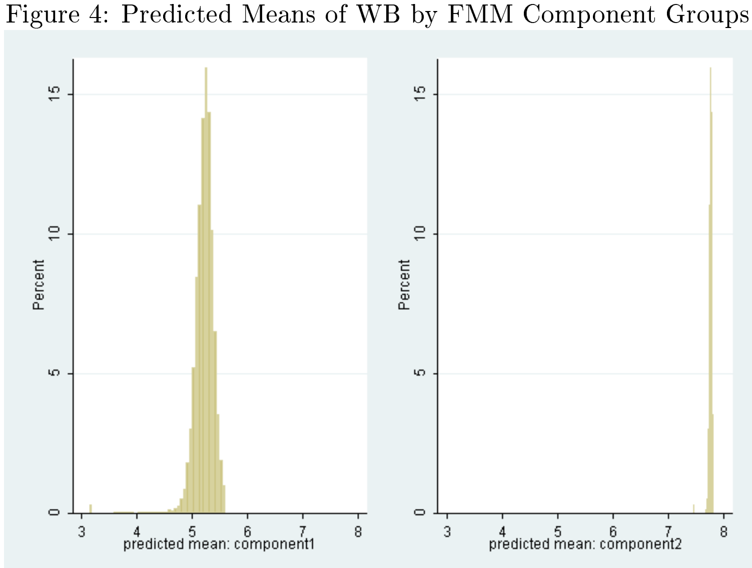

Figure 5: Prior and posterior probabilities (component 1)

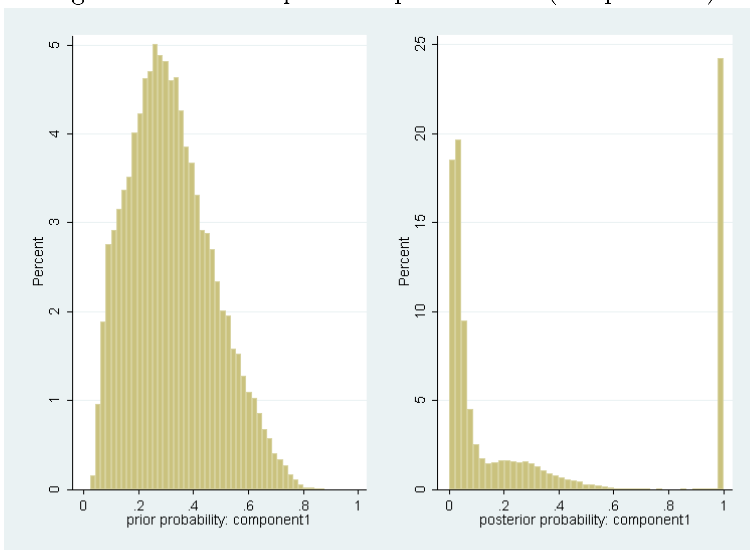

Figure 6: Density of the Marginal Utility of Income

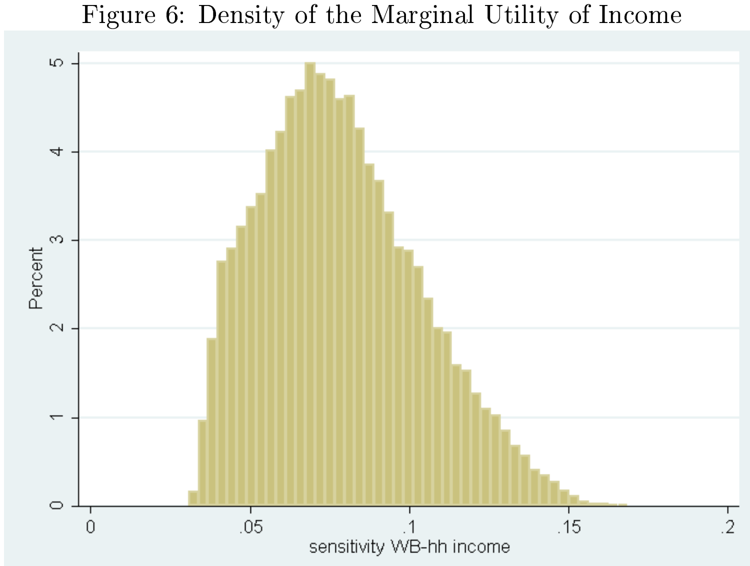

Figure 7: Marginal Utility of Income, by income quantiles

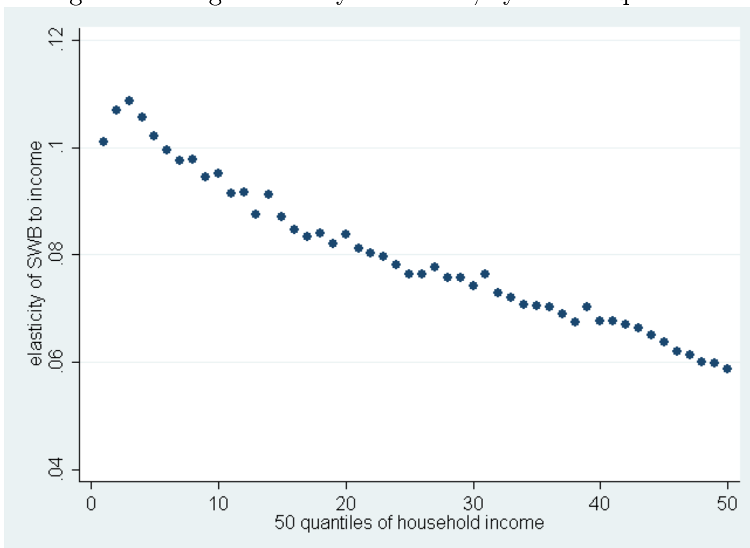

Table 7: OLS vs FMM-Between Results

	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 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			

These are the controls of the regressions presented in Table 2. Marginal effects; t statistics in parentheses;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: 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 10: Determinants of Probability of Retiring- Using specification (2) from Table 9

	(1)	(2)	(3)	(4)	(5)	(6)
Estimated marginal utility of 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 **??** for controls

Table 11: 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)
Estimated marginal utility of 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