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Perception and Retrospection:

The dynamic consistency of responses to survey questions on wellbeing

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Abstract

Implementation of broad approaches to welfare analysis usually entails the use of 'subjective' welfare indicators. We analyse BHPS data on financial wellbeing to determine whether reported current and retrospective perceptions are consistent with each other and with the existence of a common underlying wellbeing concept. We allow for adjustment of perceptions in a vector ARMA model for panel data, with dependent variables observed ordinally and find that current perceptions exhibit slow adjustment to changing circumstances and retrospective assessments of past wellbeing are heavily contaminated by current circumstances, causing significant bias in measures of the level and change in welfare.

Keywords: Financial wellbeing, perceptions, dynamic adjustment, BHPS.

JEL codes: C23, C25, C33, C35, D84

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1 Introduction

'Objective' measures like income and consumption expenditure are questionable empirical indicators of wellbeing. As Sen (1982 chapter 4, 1985, 1999) and others have argued, measures of opulence like income and expenditure represent only partial intermediate stages in the chain linking fundamental entitlements and endowments to final welfare outcomes. They may not be satisfactory as welfare measures in themselves and an exclusive focus on them obscures the underlying physical, social and economic conditions that ultimately generate welfare outcomes. Because income and expenditure are limited to the monetised components of economic activity, their relevance to wellbeing depends critically on the degree to which the economy is market-based and on the system of regulation used to control market failures. A further important problem is measurement error, which affects the extremes of the income and expenditure distributions in particular (Meyer and Sullivan 2003, Nicoletti et al 2010, Pudney and Francavilla 2006). Recognition of the shortcomings of income and expenditure as welfare measures leads naturally to empirical approaches with broader scope and there is now a large applied literature that attempts to make wider views of welfare operational, both empirically and in policy terms (Sen 1985, UNDP 1990, Ravallion and Lokshin 2001, Clark 2006, Dolan and White 2007, Anand et al 2009). Nevertheless, there remains scepticism about the difficulties of making the approach operational (Sugden 1993).

Increased conceptual scope generally brings with it a move from the 'objectivity' of cash measures like income and expenditure to the 'subjectivity' of self-reported personal assessments of specific aspects of wellbeing. It is important not to over-emphasise the distinction between 'objective' and 'subjective' measures, since responses to survey questions about income and expenditure involve cognitive and behavioural processes on the part of the respondent which introduce considerable subjectivity. Nevertheless, survey questions on income and expenditure embody a clear cash metric and fairly definite accounting principles, which give respondents a tangible framework for dealing with the question. This also exists for some 'subjective' questions, such as those eliciting expectations using the concept of probability to guide responses (Dominitz and Manski 1997). In contrast, requests for personal assessments of happiness, satisfaction and many other aspects of wellbeing are potentially more problematic because the associated response scales lack the clarity provided by the conceptual frameworks of income accounting and probability theory. The accuracy and internal consistency of the process by which perceptions are formed and expressed is therefore likely to be a bigger concern for 'subjective' wellbeing variables than for 'objective' ones, although it is clearly important for both.

Retrospection is often an important component of empirical analysis. The wellbeing literature suggests some systematic biases in the differences between experienced utility as recorded continuously in experimental settings and remembered utility defined as retrospective evaluations of the same reference period (Kahneman et al 1993). However, for policy purposes, we are more interested in how welfare changes over time in response to a changing socio-economic environment than in assessments of the average level of past welfare during some past period, and memory may operate in a different way when evaluating change than it does when evaluating average past welfare. For the analyst, there are two obvious ways of measuring welfare change: either by comparing current wellbeing measured in successive periods, or by using survey questions which invite respondents to make their own comparisons of the current and past state. Let ${}_tz_s$ be the individual's perception, formed at time t, of the level of wellbeing at time s. If $s = t$, then ${}_tz_s$ is the current perception of current wellbeing and if $t > s$, ${}_tz_s$ is a current perception of past wellbeing. A comparison of successive current measures looks at ${}_tz_t - {}_{t-1}z_{t-1}$, while the respondent's own retrospective comparison looks at ${}_tz_t - {}_tz_{t-1}$. The choice between these two measures is not clear-cut. The former approach requires longitudinal data, which are expensive and relatively scarce, while the latter can be used in both longitudinal and cross-sectional surveys. Even when longitudinal data are available, there is a case for using retrospective questions to reveal change over time, since evidence suggests that assessments of current wellbeing and attitudes are strongly influenced by transient changes of mood, emotion and survey context (Smallwood and Schooler 2006, Kaheneman and Krueger 2006, Conti and Pudney 2008). This is a problem for comparison of successive current measures, ${}_t z_t - {}_{t-1} z_{t-1}$, since each term in the difference is subject to a different injection of noise, and the variance of the measured difference is consequently inflated. Retrospective comparisons of the present and the past may be less affected: if measurement noise is a fixed effect specific to the time of interview but common to the current perception of both the present (${}_t z_t$) and the past (${}_t z_{t-1}$), then the respondent's comparison of the two eliminates noise completely.

Examples of econometric analysis of attitudinal variables have proliferated with the development of the economic literature on happiness and satisfaction (Van Praag and Ferrer-i-Carbonell, 2004, Layard 2006). This body of applied work analyses responses to survey questions of the Likert (1932) type, where respondents are offered a pre-specified numerical scale of responses. There has been important work on econometric methodology in this area but, so far, little systematic discussion of the dynamics of perceptions, the intertemporal consistency of responses, or the type of dynamic analysis most appropriate for the evolution of attitudes and perceptions over time. There are difficult technical issues involved in econometric modelling of categorical variables. Discrete data may be either inherently discrete (for example, an individual either has a job or not) or observationally discrete: when the variables of interest are naturally continuous, but the survey instrument uses an ordinal scale of permitted responses to impose discreteness artificially. The state dependence model (Heckman 1978) and models of latent dynamics (Pudney 2008) are examples of econometric approaches in these two cases. Perceptions of wellbeing are not inherently discrete and so the more usual state dependence model is questionable. If the discrete nature of the dependent variable is only an artificial construct imposed by the questionnaire designer, then behaviour centres on the continuous latent perception of wellbeing which underlies the responses to survey questions, rather than the responses themselves. The econometric approach developed and applied here is intended to uncover this underlying welfare variable and determine whether respondents' reporting of it displays the properties of temporal consistency that we require of a good empirical welfare measure.

2 Panel evidence on perceptions of financial wellbeing

We use data from the British Household Panel Survey (BHPS), which is the principal source of household- and individual-level panel data in the UK. Starting in 1991, it has followed all original members of the sample annually, providing individual interviews with all over-15s in the household. We use observations on 3768 individuals who were household reference persons in the year 1992. The resulting panel dataset is unbalanced but has a common initial period t = 0 in 1993. The year 1992 is lost through the need to construct certain differenced variables and our sample period ends in 2003 to allow use of the housing equity variables constructed by Henley (1998) and updated by him to 2003.

2.1 Question design

Each year, BHPS participants are asked a series of questions about their attitudes and perceptions. For one of these domains, relating to a general concept of financial wellbeing (FWB), we also have an additional retrospective question and a follow-up on the reasons for the perceived change over time. The principal question relating to current FWB is:[1]

FWB1 *How well would you say you yourself are managing financially these days?* [(1) *finding it very difficult*; (2) *finding it quite difficult*; (3) *just about getting by*; (4) *doing alright*; (5) *living comfortably.*]

In addition to the questions on FWB, there is also a group of BHPS satisfaction questions which invites respondents to rate, on a 1-7 scale, their satisfaction with various aspects of life, including satisfaction with income (SI) and with life overall (SLO).

[1] The item non-response/don't know rate is only 0.14% for the full pooled sample covering the 1992-2003 waves and we drop these few cases in the analysis that follows.

Sen's (1982, 1985) capabilities analysis provides a possible framework for locating survey questions like FWB1 and SLO in the spectrum of wellbeing concepts. In Sen's approach, an individual has command over economic resources ("entitlements") represented by the set X of possible choices for his or her commodity vector x.[2] With a given vector of commodities, the individual achieves a vector of "functionings" b via a utilisation function $b = f(x)$. The particular pattern of commodity utilisation is chosen from a set F of possible utilisation functions. Sen (1985) equates the idea of "wellbeing" with an evaluation $v(b)$ of the achieved level of functionings[3] and Anand et al (2009) take this further empirically by associating the BHPS-type SLO variable with this concept of achieved wellbeing. Sen then contrasts wellbeing with the broader concept of "advantage", which introduces notions of freedom and opportunity, through the capabilities set $Q(X)$ defined as the set of life opportunities open to the individual:

$$Q(X) = \{b : b = f(x), f(.) \in F, x \in X\} \tag{1}$$

Personal advantage can then be thought of as an evaluation $V(Q)$ of the set of possible capabilities rather than the particular element of Q which is realised as an outcome. This broader evaluation allows the possibility that freedom matters, in the sense that a given outcome chosen from a restricted set of capabilities may be less rewarding[4] than the same outcome chosen from a wider set of possibilities.

However, the responses to survey questions on life satisfaction, financial wellbeing, etc. are determined in practice by survey respondents, not by theoretical debate about the concepts of wellbeing and advantage. So how do real people understand and interpret such questions? It is not possible to be sure about this but it seems possible that survey respondents, when asked about their life satisfaction or financial wellbeing in questions like SLO

[2]Commodities here include labour supplies, so X encompasses the trade-off between work and consumption. Sen also makes a distinction between commodities and their Gorman-Lancaster characteristics, which we leave implicit.

[3]The evaluation $v(.)$ may or may not represent a complete ordering of the set $\{b\}$ and it need not coincide with happiness or utility.

[4]Or possibly more rewarding in some settings, since freedom of choice is not necessarily always a positive attribute (Schwartz 2004).

and FWB1, take a broad view of what is wanted by the survey designer and give an answer that evaluates not just the realised value of the functionings vector b or the commodity vector x, but also some aspects of the sets Q and X from which they are generated – in other words, evaluations of feasible potential outcomes as well as actual outcomes.

If it is true that FWB1 is answered partly on the basis of command over resources rather than the realised income-consumption position, we would expect FWB1 to have greater predictive power for SLO than do conventional measures of income. To explore this, we estimate random effects ordered probit models for the two satisfaction variables SLO and SI, using 1992-2003 BHPS waves.[5] These models have a wide range of covariates covering personal and household characteristics and circumstances, together with three income variables (current per capita gross income, the respondent's share in household income, and the change in household income since the previous year) and also four dummy variables representing the response given to the financial wellbeing question FWB1. Table 1 reports Wald tests for the hypotheses that: (i) the FWB dummies are irrelevant; and (ii) the income variables are irrelevant. For comparison, Table 1 also gives results for the same model applied to the responses from a third BHPS question, asking for an evaluation of satisfaction with income.

Table 1 Random effects ordered probit models of satisfaction with life overall and income (BHPS): Wald tests of FWB and income coefficients

Dependent variable	$H_0^{(1)}$: FWB irrelevant	$H_0^{(2)}$: Income irrelevant
Satisfaction with life overall	$\chi^2(4) = 629.48$	$\chi^2(3) = 3.16$
	(P = *0.000*)	(P = *0.367*)
Satisfaction with income	$\chi^2(4) = 4160.6$	$\chi^2(3) = 206.12$
	(P = *0.000*)	(P = *0.000*)

See Appendix 2, Table A1, for full details of the model and coefficient estimates.

The response to FWB1 has much greater explanatory power as a predictor of the broad SLO measure of wellbeing than income: the FWB1 dummies are highly significant, while

[5] Other modelling approaches, such as random effects and consitional logit for SLO converted into binary form, give essentially the same conclusions.

the coefficients of the three income variables are not significantly different from zero in a joint test. This is suggestive rather than conclusive, but it is consistent with the idea that survey questions like FWB1 give an assessment of command over market resources that is broader than income itself and includes some element of evaluation of the set X of consumption/income possibilities rather than adequacy of current realised income alone. Unsurprisingly, analysis of responses to the question on satisfaction with income does succeed in finding significant income coefficients but, even there, they are dominated by FWB1 as a predictor of income satisfaction.

2.2 Retrospective questions

The retrospective BHPS question on FWB is:[6]

FWB2 *Would you say you yourself are better off or worse off financially than you were a year ago?* [(1) *worse off*; (2) *about the same*; (3) *better off*.]

Those who report some change at FWB2 are then asked:

FWB3 *Why is that?*

The free text responses are coded *ex post* into eighteen specific categories and six "other"/ inapplicable/non-response categories.[7]

Just over half the responses to question FWB2 over the 1992-2003 period indicated no change in wellbeing, a quarter indicated a deterioration and slightly fewer (23%) suggested an improvement. Table 2 shows the distribution of reasons given by those reporting retrospectively an improvement or deterioration in wellbeing. Increased earnings and increased expenditure commitments are the dominant reasons given by these two groups respectively.

[6] The item non-response/don't know rate is 0.3% for the pooled 1992-2003 sample.

[7] In our sample, of the 18,873 observations where this question is applicable, there was a 0.58% non-response/don't know rate.

However, the benefit system also plays an important role, since 11% of people reporting an improvement attribute it primarily to the effect of social security benefits.

Table 2 Reasons specified for retrospective change in wellbeing

Retrospective assessment of change since last year	Earnings changed	Benefits changed	Investment income changed	Expenses changed	One-off payment or receipt	Other
Improved *(n=9,086)*	50.5	11.3	3.6	15.3	3.5	15.9
Worse *(n=9,771)*	25.1	3.8	5.5	49.8	1.2	14.7

Note: Row percentages; BHPS sample of individuals who were household reference persons in 1992, using waves from 1992-2003

What is the 'objective' basis for these retrospective assessments? Table 3 compares the stated reasons for change with the corresponding change in reported income over the two years concerned. Five concepts of real gross income are used: the respondent's personal earnings, benefits, investment income and total income, together with total household income expressed in per capita form. On average, the responses to FWB3 match actual change in economic circumstances quite well: for example, those reporting diminished wellbeing on grounds of a fall in earnings report a current level of annual earnings averaging almost £2,000 below the level reported in the previous year.

Table 3 Comparison of mean actual real income changes with retrospective assessments of the change in wellbeing (standard errors in parentheses)

Retrospective assessment of change in wellbeing & reported cause	*Actual income change (£per year)* Respondent's personal income: Earnings	Benefits	Investment income	Total income	Per capita household income
Increased earnings	1,613	-87	50	1,535	1,814
	(169)	(17)	(35)	(182)	(136)
Increased benefits	-181	1,001	89	1,082	1,024
	(69)	(65)	(59)	(132)	(115)
Increased investment income	155	19	321	592	455
	(242)	(49)	(247)	(362)	(411)
No change	142	177	9	413	380
	(52)	(11)	(13)	(55)	(39)
Reduced earnings	-1,990	346	22	-1,312	-2,003
	(251)	(35)	(37)	(253)	(125)
Reduced benefits	-402	-653	12	-1128	294
	(184)	(187)	(55)	(266)	(200)
Reduced investment income	-139	116	-81	-86	258
	(131)	(46)	(127)	(206)	(167)

Note: Full BHPS sample of individuals who were household reference persons in 1992, using waves from 1992-2003, various row sample sizes; standard errors in parentheses

Although Table 3 shows what one might expect for the relationship between retrospective assessments and mean income change, it conceals numerous conflicts at the individual level. Table 4 shows that, among respondents who report an increased level of FWB by virtue of an earnings change, over a quarter in fact reported no increase in either their own personal earnings or total household earnings when answering detailed income questions. Larger degrees of dissonance are evident for other income components, particularly investment income. Part of this apparent conflict might be attributable to the broad scope of the FWB variable, which may be capturing changes in the individual's economic situation not reflected in short-term income movements, and some of the conflicts are undoubtedly due to income measurement error.[8] Nevertheless, this evidence casts some doubt on the validity of retrospective FWB comparisons.

[8]It should be noted that income measurement error may also have the opposite effect of making some actual conflicts appear non-conflicting.

Table 4 Sample proportions of contradictions between retrospective direction and reason for change and 'objective' change in household income

Retrospective direction of change in FWB	*Reported reason for FWB change*		
	Earnings	Benefit income	Investment income
Reported increase	25.3	27.7	52.9
	(0.7)	(1.4)	(2.8)
Reported decrease	28.3	30.7	35.7
	(0.9)	(2.5)	(1.8)

BHPS 1992-2003 sample percentages of contradictions. Standard errors in parentheses.

2.3 Perceived current wellbeing

The sequence of current assessments given in response to FWB1 is summarised in Table A2 of Appendix 2, which shows the transition rates between FWB1 response states in successive years. Higher states are more persistent than lower states: only a third of respondents remain in the "very difficult" state in successive years, whereas two-thirds of people in the "living comfortably" state remain there in the following year. Large transitions are quite rare, but more frequent in an upward than a downward direction. Table 5 examines the incidence of conflicts between the current and retrospective assessments of wellbeing. Given the coarser classification used for FWB2 than for FWB1, one would expect to see some of the cases of change in the current assessment to be reported as no change in the retrospective question, because of the presumably wider "no change" interval used by respondents when answering FWB2. This could account for the non-zero proportions in cells (1,2) and (3,2) of Table 5, but the large entries in cells (1,3), (2,1), (2,3) and (3,1) are definitely contrary to expectations. In particular, of those whose current assessment declines from year to year, almost one in eight reports a contradictory improvement in the retrospective assessment and, among those whose current assessment improves, one in six retrospectively reports a worsening of their financial situation.

Table 5 Conflicts between current and retrospective responses

Change in current level of wellbeing	*Retrospective assessment of change in wellbeing*			*% of total*
	Worse	Same	Better	
Decrease	43.7	44.4	11.9	*20.3*
No change	22.4	54.9	22.7	*56.2*
Increase	16.2	49.0	34.9	*23.5*
% of total	*25.3*	*51.4*	*23.3*	*100.0*

Note: Row percentages; BHPS sample of individuals who were household reference persons in 1992, using waves from 1992-2003, $n = 37,943$*)*

3 Adjustment, adaptation and dynamic consistency of perceptions

Two points emerge from the preceding descriptive analysis. One is that responses to the retrospective questions FWB2 and FWB3 are coherent in an average sense, but with significant conflict at the individual level between the changes in reported incomes and retrospective assessments. The second is that there is substantial conflict between retrospective assessments (FWB2) and the sequence of current assessments of wellbeing (FWB1). These conclusions support the idea that some systematic revision of perceptions may happen over time, disrupting the relationship between self-reports and the underlying actual change in circumstances. We investigate the issue using a latent perceptions model to investigate more formally the temporal consistency of reported perceptions and consequently to determine whether there exists a single underlying concept of financial wellbeing recoverable from longitudinal survey data. We view the responses to questions FWB1 and FWB2 as ordinal indicators of underlying perceptions of wellbeing, where those perceptions are essentially continuous variables. To capture this idea, we specify a dynamic model, permitting substantial deviations from temporal consistency, and then examine the validity of the restrictions necessary to impose consistency on that structure.

Questions FWB1 and FWB2 give us information relating to perceived current wellbeing, ${}_tz_t$, and a current assessment of change, ${}_tz_t - {}_tz_{t-1}$. To use these survey questions to generate indicators of wellbeing, there must exist a 'true' welfare measure for each period, ω_t and the sequences of perceptions $\{{}_tz_t\}$ and $\{{}_tz_{t-1}\}$ must satisfy the relations ${}_tz_t = \omega_t$ and ${}_tz_t - {}_tz_{t-1} = \omega_t - \omega_{t-1}$ for all t. It is axiomatic for conventional welfare analysis that wellbeing is path-independent in the sense that, given a sufficiently complete specification of current circumstances (entitlements, capabilities, etc.), the measure of welfare is independent of the path by which those circumstances have been reached. For example, the equivalised income or consumption measure used in conventional poverty and inequality analysis is path independent, given current income and family structure. A more general way of embedding path independence is to specify a static model for ω_t, such as the regression structure:

$$\omega_t = \boldsymbol{x}_t'\boldsymbol{\psi} + \upsilon + \xi_t \tag{2}$$

where $\boldsymbol{x}_t$ is a vector of observed variables describing the individual's characteristics, circumstances and embodied capitals, υ is a persistent individual-specific unobservable and ξ_t is the time-varying unobservable component of wellbeing. In the absence of perception errors, this gives the following 2-equation system with a moving average error structure for the (latent) responses to FWB1 and FWB2:

$${}_tz_t = \boldsymbol{x}_t'\boldsymbol{\psi} + \upsilon + \xi_t \tag{3}$$

$${}_tz_t - {}_tz_{t-1} = (\boldsymbol{x}_t - \boldsymbol{x}_{t-1})'\boldsymbol{\psi} + \xi_t - \xi_{t-1} \tag{4}$$

To investigate temporal consistency, we need to specify a more general model allowing the deviation of perceived from actual wellbeing. This is more complex than the specification of conventional time-series models of temporal adjustment, since there are two time dimensions here: the time at which the perception is expressed and the time to which that perception relates.

A generalised partial adjustment model relates the realised year-to-year adjustment in perceived current wellbeing, ${}_tz_t - {}_{t-1}z_{t-1}$, to the adjustment warranted by changing circumstances, $(\omega_t - {}_{t-1}z_{t-1})$:

$$ {}_tz_t - {}_{t-1}z_{t-1} = \lambda(\omega_t - {}_{t-1}z_{t-1}) + \Delta \boldsymbol{x}_{it}^{+\prime}\boldsymbol{\delta}_1 + v_1 + e_{1t} \tag{5} $$

where $0 \leq \lambda \leq 1$ is a speed-of-adjustment parameter, $\boldsymbol{x}_{it}^{+}$ is a subvector of $\boldsymbol{x}_{it}$ and $\Delta\boldsymbol{x}_{it}^{+}$ captures any change in state variables (marital or health status, for example) that might have a temporary impact on perceptions through emotional over- or under-reaction. If a coefficient in $\boldsymbol{\delta}_1$ has the opposite sign to the corresponding coefficient in $\boldsymbol{\psi}$, the model displays temporary under-reaction; if the same sign, there is temporary over-reaction. The variables v_1 and e_{1t} are respectively persistent and transient unobserved elements of the perception process and v_1 might represent the individual's idiosyncratic understanding of the meaning of the response scale for FWB1. This generalises (3) to:

$$ {}_tz_t = (1-\lambda)_{t-1}z_{t-1} + \boldsymbol{x}_t'\boldsymbol{\psi}\lambda + \lambda\upsilon + \lambda\xi_t + \Delta\boldsymbol{x}_{it}^{+\prime}\boldsymbol{\delta}_1 + v_1 + e_{1t} \tag{6} $$

Our model for the updating of perceptions relating to any fixed past period $t-1$ captures both partial adjustment of perceptions and cross-contamination between time periods:

$$ {}_tz_{t-1} - {}_{t-1}z_{t-1} = \phi(\omega_{t-1} - {}_{t-1}z_{t-1}) + \pi(\omega_t - {}_{t-1}z_{t-1}) + \Delta\boldsymbol{x}_{it}^{+\prime}\boldsymbol{\delta}_2 + v_2 + e_{2t} \tag{7} $$

where $\phi(\omega_{t-1} - {}_{t-1}z_{t-1})$ represents delayed adjustment of perceptions towards the true level ω_{t-1} and $\pi(\omega_t - {}_{t-1}z_{t-1})$ represents contamination of the perception of past FWB by current circumstances ω_t.[9] The latter effect can be interpreted in various ways. It is consistent with one form of the *adaptation hypothesis* (Diener et al 1999, Loewenstein and Ubel 2008), which holds that the meaning respondents attach to the concept of wellbeing is itself changed by experience. In (7), the term ω_t refers to experience accumulated after period $t-1$, which

[9]Equation (7) can be re-specified with the term ω_t replaced by its perceived equivalent ${}_tz_t$, the only difference to the model being that the parameter π in equation (8) below is replaced by $\lambda\pi$ throughout. The nature of our conclusions is not affected.

might change the individual's reference point. In this case, we would expect $\pi < 0$, since adaptation to high current wellbeing would make the past appear worse and vice versa. The term $\pi(\omega_t - {}_{t-1}z_{t-1})$ is also consistent with a different behavioural process which we call *memory substitution* – if past wellbeing cannot be recalled reliably, the respondent may, consciously or unconsciously, partially substitute current wellbeing, for which there is no problem of recall. This would imply $\pi > 0$. The term $\Delta \boldsymbol{x}_{it}^{+\prime}\boldsymbol{\delta}_2$ represents a temporary reaction to changes of state and υ_2 and e_{2t} are persistent and transient unobserved elements of the retrospection process.

Assumptions (5) and (7) imply the following generalisation of (4):

$$\begin{aligned}({}_tz_t - {}_tz_{t-1}) &= (\phi + \pi - \lambda)\,{}_{t-1}z_{t-1} + \boldsymbol{x}_t'\boldsymbol{\psi}(\lambda - \pi) - \boldsymbol{x}_{t-1}'\boldsymbol{\psi}\phi \\ &\quad -(\phi + \pi - \lambda)\upsilon + (\lambda - \pi)\xi_t - \phi\xi_{t-1} + e_{1t} - e_{2t} + \Delta\boldsymbol{x}_{it}^{+\prime}(\boldsymbol{\delta}_1 - \boldsymbol{\delta}_2) + \upsilon_1 - \upsilon_2 \qquad (8)\end{aligned}$$

Dynamic consistency would require the restrictions $\lambda = \phi = 1$, $\pi = 0$ and $\boldsymbol{\delta}_1 = \boldsymbol{\delta}_2 = \boldsymbol{0}$ to be imposed. Perfect consistency, with no reporting error, would further require $\text{var}(e_{1t}) = \text{var}(e_{2t}) = \text{var}(\upsilon_1) = \text{var}(\upsilon_2) = 0$, giving the degenerate model (3)-(4), but the absence of even random perception errors seems an unduly demanding requirement.

In practice, an ordinal scale is used for observation and we assume responses are generated by the conventional threshold-crossing mechanism:

$$y_{1it} = r \iff {}_tz_t \in [\Gamma_r^1, \Gamma_{r-1}^1)\,, \quad r = 1...5 \qquad (9)$$

$$y_{2it} = r \iff ({}_tz_t - {}_tz_{t-1}) \in [\Gamma_r^2, \Gamma_{r-1}^2)\,, \quad r = 1...3 \qquad (10)$$

where y_{1it} and y_{2it} are the ordinal responses to questions FWB1 and FWB2 and the Γ_r^j are threshold parameters, where $\Gamma_0^1 = \Gamma_0^2 = -\infty$ and $\Gamma_5^1 = \Gamma_3^2 = +\infty$. Since the scale and origin of ${}_tz_t$ and $({}_tz_t - {}_tz_{t-1})$ are not identifiable, normalisations are required. We renormalise the equations to give new threshold parameters Γ_r^{*j} such that $\Gamma_1^{*1} = \Gamma_1^{*2} = 0$ and $\Gamma_2^{*1} = \Gamma_2^{*2} = 1$ so that the model becomes:

$$y_{1it}^* = (1 - \theta_1)y_{1it-1}^* + \boldsymbol{x}_{it}'\boldsymbol{\theta}_4\theta_1 + \theta_1\zeta_{it} + \Delta\boldsymbol{x}_{it}^{+\prime}\boldsymbol{\theta}_5 + u_{1i} + \varepsilon_{1it} \qquad (11)$$

$$y^*_{2it} = (\theta_2 - \theta_3)y^*_{1it-1} + \boldsymbol{x}'_{it}\boldsymbol{\theta}_4\theta_3 - \boldsymbol{x}'_{it-1}\boldsymbol{\theta}_4\theta_2 + \theta_3\zeta_{it} - \theta_2\zeta_{it-1} + \Delta\boldsymbol{x}^{+'}_{it}\boldsymbol{\theta}_6 + u_{2i} + \varepsilon_{2it} \qquad (12)$$

where $y^*_{1it} = {}_tz_{it}/S_1$ and $y^*_{2it} = ({}_tz_{it} - {}_tz_{it-1})/S_2$ are the renormalised latent perceptions underlying responses to FWB1 and FWB2, $S_j = \Gamma^j_2 - \Gamma^j_1$ is the normalising factor for the jth equation and the Γ^{*j}_r are the pre-normalisation thresholds. This normalisation is more convenient than, but observationally equivalent to, the more usual one of setting intercepts to zero and residual variances to unity. The parameter vector for this form of the model is $[\theta_1, \theta_2, \theta_3, \boldsymbol{\theta}'_4, \boldsymbol{\theta}'_5, \boldsymbol{\theta}'_6] = [\lambda, (\phi S_1/S_2), ([\lambda - \pi]S_1/S_2), (\boldsymbol{\psi}'/S_1), (\boldsymbol{\delta}'_1/S_1), (\boldsymbol{\delta}_1 - \boldsymbol{\delta}_2)'/S_2)]$, and the composite unobservables are $u_{1i} = (\lambda\upsilon + v_1)/S_1$, $u_{2i} = (v_1 - v_2 - (\phi + \pi - \lambda)\upsilon)/S_2$, $\varepsilon_{1it} = e_{1it}/S_1$, $\varepsilon_{2it} = (e_{1it} - e_{2it})/S_2$ and $\zeta_{it} = \xi_{it}/S_1$. The lagged latent variable y^*_{1it-1} appears in both equations (11) and (12) but the lag of y^*_{2it} in neither, which greatly simplifies the treatment of initial conditions. Detailed discussion of the general case of a multi-equation dynamic system of ordinal variables with moving average errors is set out in Appendix 1, where identification and estimation by maximum simulated likelihood (MSL) are explained.

4 Empirical analysis

This application is based on waves 2-13 of the BHPS, covering the years 1992-2003. We first select a sample consisting of all individuals recorded as the household reference person in the 1992 wave. Those individuals are then observed for 1993 (period 0) through all subsequent periods until 2003 (period $T = 10$) or an attrition event, whichever occurs sooner. This gives an unbalanced but compact panel, containing 3,768 individuals and 32,698 observations in total (averaging 8.7 observations per individual). The vector $\boldsymbol{x}_{it}$, which is summarised in Table A3 of Appendix A2, contains covariates representing personal and household characteristics, partnership status, education, income and housing equity, which is the dominant form of wealth for the great majority of households. The covariates are broadly representative of variables used in the empirical literature on subjective wellbeing.

4.1 Long-run effects

MSL estimates of the key parameters of the joint model (11) and (12) are set out in Tables 6-8 below and full estimates are given in Table A4 of Appendix 2. The estimated coefficient vector $\boldsymbol{\psi}/S_1$, which represents the long-run comparative statics effect of $\boldsymbol{x}$ on financial wellbeing, is reproduced in Table 6. Estimated coefficients are consistent with expectations and broadly in line with evidence from the applied literature on other measures of subjective wellbeing; in particular, there is a wide range of significant influences beyond income. Wellbeing is found to be significantly increasing in real per capita household income and also in the respondent's own share of household income. The latter conflicts with the idea of risk reduction by diversification but may reflect a subjective value placed on a sense of financial control, which is consistent with Sen's notion of the capabilities set as a basis of welfare evaluation. There are also significant positive effects for education, interpretable as an indicator of human capital, and for home ownership and housing equity, which provide a measure of real physical assets and of access (through the financial markets) to a store of potential finance for meeting future borrowing needs. Both of these are consistent with the idea that subjective financial wellbeing represents Sen's notion of "advantage", involving an evaluation of the entitlement set X rather than the current income-consumption outcome alone.

Relationship status is a very strong influence on financial wellbeing. Relative to a baseline of marriage or cohabitation, there are large, approximately equal, negative effects for single (never married) status and widow(er)hood and a much larger negative effect for divorce. There is no strongly significant evidence of an effect for household size or composition. There is significant evidence of lower financial wellbeing for members of the two main ethnic minority groups, which might be interpreted in line with Sen's approach, as representing the exclusion of minority groups from access to economic opportunity. However, the smaller but significant gender effect favouring women is not consistent with that interpretation. Cohort and year effects are captured in the model by a quadratic in year of birth and a set of year dummies and there is a significant negative cohort effect (or, equivalently, a rising age profile) and rising year effect.

Table 6 Long-run coefficients ($\boldsymbol{\psi}/S_1$)

Covariate	*Coefficient*	*Covariate*	*Coefficient*
Household income p.c.[a]	4.579***	Female	0.140**
	(0.246)		(0.055)
Share in household income	0.252***	African/Caribbean	−0.753**
	(0.086)		(0.321)
Home-owner	0.629***	South Asian	−0.446**
	(0.069)		(0.219)
Housing equity[b]	0.053***	Single (never married)	−0.398***
	(0.015)		(0.089)
Private rented home	0.096	Divorced	−0.687***
	(0.097)		(0.087)
Employed	−0.068	Widow(er)	−0.382***
	(0.083)		(0.096)
Self-employed	−0.098	(Year of birth - 1940)/10	−0.246***
	(0.105)		(0.028)
Retired	−0.130	$((\text{Year of birth - 1940})/10)^2$	0.013
	(0.123)		(0.010)
Unemployed	−0.619	1999[c]	−0.343***
	(0.185)		(0.071)
Long-term sick	−0.453***	2000[c]	−0.308***
	(0.124)		(0.054)
University degree	0.329***	2001[c]	−0.098***
	(0.080)		(0.053)
Certificate/diploma	0.0.373***	2002[c]	−0.102***
	(0.099)		(0.055)
High school qualification	0.195**	Pre-school child	0.234
(A-level)	(0.078)		(0.234)
Intermediate school qualification	0.182***	Number of pre-school children	−0.146
(O-level/GCSE)	(0.065)		(0.128)
Vocational qualification	0.034	Number of school-age children	0.001
	(0.052)		(0.029)
		Number of retired adults	0.061
			(0.074)
		Number of other adults	−0.063*
			(0.038)

[a] in £'000 per year; [b] in £00,000; [c] reference year 1999; standard errors in parentheses; Significance: * = 10%; ** = 5%; *** = 1%

4.2 Evidence on temporal consistency

Our primary interest is in temporal consistency, which concerns the three critical dynamic adjustment parameters whose estimates are reproduced in Table 7. In the equation (11) for current wellbeing, the parameter λ governs the speed of adjustment of current perceptions to changing circumstances. The estimate implies that only two-thirds of the warranted adjustment is completed within a year and the hypothesis $\lambda = 1$ is strongly rejected by an asymptotic t-test. The estimate of equation (12) for FWB2 also implies substantial deviations from temporal consistency. The normalised difference between the adjustment parameter λ and the cross-period contamination parameter π is not significantly different from zero, suggesting that π is also approximately 0.67. On its own, this term would imply that the retrospective perception of last year's wellbeing is a weighted average of current wellbeing and last year's current perception, with two-thirds of the weight given (inappropriately) to current conditions. This is offset only partially by the significantly positive adjustment parameter ϕ, which tends to push the retrospective perception towards the true value ω_{t-1}. The positive sign of π gives the important conclusion that the contamination of retrospective perceptions by current conditions arises from a process like memory substitution rather than adaptation of the individual's reference standard to more recently experienced conditions, which would require $\pi < 0$.

Table 7 Dynamic adjustment parameters

Parameter	*Estimate*
Partial adjustment λ	0.665^{***}
	(0.020)
Adjustment of perceptions $\phi S_1/S_2$	0.090^{**}
	(0.036)
Adaptation of perceptions $[\lambda - \pi]S_1/S_2$	-0.028
	(0.025)

Standard errors in parentheses; Significance: * = 10%; ** = 5%; *** = 1%

The coefficients of $\Delta \boldsymbol{x}_{it}^{+}$ in the two equations of the model are set out in Table 8, with estimates of corresponding long-run effects from $\boldsymbol{\psi}/S_1$ reproduced for comparison. A Wald test strongly rejects the hypothesis $\boldsymbol{\delta}_1 = \mathbf{0}$, with significant negative coefficients for job loss and onset of poor health, which match the negative signs of their long-run effects and imply short-term over-reaction to these events. The significant positive coefficients for the level and change in real housing equity also imply that perceptions of current financial wellbeing display very large short-term over-reaction to booms in the housing market, which is consistent with some macro-economic evidence on the influence of house prices on consumer behaviour (see Muellbauer and Murphy 2008 for a review). The only (marginally) significant evidence of under-reaction is with respect to income, where the long-run income effect is temporarily offset to some degree by a negative coefficient for income change.

The significant deviations from $\lambda = 1$ and $\boldsymbol{\delta}_1 = \mathbf{0}$ have important implications for empirical analysis, since they imply that cross-section estimates of a static model of current wellbeing will be affected by misspecification bias. Although many cross-section surveys include recall questions that allow inclusion of the term $\Delta \boldsymbol{x}^{+'} \boldsymbol{\delta}_1$ representing transient effects on perceived FWB of the arrival of a shock, $\lambda \neq 1$ implies gradual adjustment of perceptions over a long period and thus requires panel data to allow for its effects.

Table 8 Transient effects of life events and changes in income and housing equity

State	LR effect $\boldsymbol{\psi}/S_1$	Transient effects $\boldsymbol{\delta}_1/S_1$	$(\boldsymbol{\delta}_1-\boldsymbol{\delta}_2)/S_2$
Divorce/separation[a]	-0.687^{***}	-0.188	-0.195^{***}
	(0.087)	(0.120)	(0.071)
Widow(er)hood[a]	-0.382^{***}	0.162	0.029
	(0.096)	(0.178)	(0.106)
Retirement	-0.130	-0.109	-0.284^{***}
	(0.123)	(0.100)	(0.054)
Unemployment	-0.619^{***}	-0.571^{***}	-0.506^{***}
	(0.185)	(0.173)	(0.075)
Ill-health	-0.453^{***}	-0.624^{***}	-0.066
	(0.124)	(0.177)	(0.103)
New-born child	-0.146	-0.090	-0.211^{***}
	(0.128)	(0.111)	(0.053)
Per capita real income[b]	0.046^{***}	-0.003^{*}	0.009^{***}
	(0.002)	(0.001)	(0.001)
Real housing equity[c]	0.053^{***}	0.099^{**}	0.158^{***}
	(0.015)	(0.050)	(0.017)
χ^2_8 Wald joint significance test		36.4^{***}	230.8^{***}

[a] Baseline category = married/cohabiting; [b] = in £'000 per annum; [c] = £'00,000; standard errors in parentheses; Significance: * = 10%; ** = 5%; *** = 1%

For equation (12) which relates to the retrospective assessment of change, the coefficients of the transient life-event variables and changes in income and housing equity should be interpreted as $\boldsymbol{\theta}_6 = (\boldsymbol{\delta}_1 - \boldsymbol{\delta}_2)/S_2$, where $\boldsymbol{\delta}_1$ and $\boldsymbol{\delta}_2$ capture their temporary effects on the adjustment processes (5) and (7). There are significant negative coefficients for the events of retirement and childbirth, for which there were no significant transient effects in the equation for FWB1, implying positive coefficients in $\boldsymbol{\delta}_2$. This means that occurrence of retirement or childbirth during the intervening period makes the past appear (temporarily) financially rosier from today's perspective than it did at the time. Conversely, the large positive income coefficient in $\boldsymbol{\theta}_6$ and the small, marginally significant effect of income change in the model for FWB1 implies that a rise in income has the temporary effect of making the past seem worse than it did at the time – which is consistent with the adaptation hypothesis, only in a transient sense.[10]

5 Conclusions

There is a widely-accepted view that the concept of welfare needs to be conceived much more broadly than than conventional income- or expenditure-based microeconomic definitions. Empirical implementation of these broader concepts generally involves the use of 'subjective' survey measures, like the two BHPS financial wellbeing variables used here: one an assessment of current wellbeing, the other an evaluation of the direction of change over the preceding year. Our findings suggest very strongly that the current variable should not be regarded as a direct observation on wellbeing and that the retrospective variable is not very reliable as an indicator of change. We have demonstrated the importance of dynamic adjustment of perceived wellbeing, in two dimensions of time.

First, perceptions of current wellbeing take time to adjust fully to changed circumstances: only around two-thirds of the year-to-year adjustment that would be required to bring perceived wellbeing in line with changed circumstances is accomplished within a year and there is evidence of a substantial transient over-reaction to major life events like unemployment, onset of long-term ill-health and booms in the housing market, in their year of occurrence.

Second, memory operates in a non-stationary way, so that perceptions of wellbeing, as experienced at some fixed time in the past, may vary depending when the perception is expressed. In particular, perceptions of past wellbeing are positively contaminated by current circumstances, suggesting a process of memory substitution: that difficulty in recall leads to some degree of substitution of the current state for the past state, when forming perceptions of the past. This is the opposite effect to that produced by the much-discussed adaptation hypothesis, which would lead to a negative influence of current wellbeing on

[10]For other coefficients in $\boldsymbol{\theta}_5$ and $\boldsymbol{\theta}_6$, where both are significant and of the same sign, it is not possible to draw definite conclusions about the sign of $\boldsymbol{\delta}_2$, since $\boldsymbol{\theta}_5$ and $\boldsymbol{\theta}_6$ have different normalisations.

today's judgement of the past. We have also found transient effects of major events on recollections of past wellbeing.

Despite these large dynamic distortions detectable in individual sequences of reported perceptions of wellbeing, it is possible to uncover an underlying wellbeing measure, using appropriately specified dynamic models. This reveals, in addition to significant income effects, important long-term roles for human capital, relationship status, housing wealth and demographic characteristics, which suggest that the financial wellbeing variables succeed in capturing a wider concept of welfare than income alone, perhaps approximating to Sen's notion of the individual's "entitlements" set.

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Appendix 1: Identification and Estimation

A1.1 A general model

In terms of the underlying continuous variables, ${}_tz_t$ and $({}_tz_{t-1} - {}_{t-1}z_{t-1})$, the model of section 3 is a multi-equation first-order vector autoregression, with a latent moving average component: a VARMA(1,1) system. Generalise this to a J-equation system for a panel of individuals indexed by $i = 1...n$, with unobservable individual effects and a non-degenerate Q-dimensional moving average component:

$$y^*_{jit} = \sum_{k=1}^{J} \alpha_{jk} y^*_{kit-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta}_j + u_{ji} + \sum_{q=1}^{Q} (\kappa_{0jq}\zeta_{qit} + \kappa_{1jq}\zeta_{qit-1}) + \varepsilon_{jit} \ , \quad j = 1...J \tag{13}$$

or, in matrix form:

$$\boldsymbol{y}^*_{it} = \boldsymbol{A}\boldsymbol{y}^*_{it-1} + \boldsymbol{B}\boldsymbol{x}_{it} + \boldsymbol{u}_i + \boldsymbol{K}_0\boldsymbol{\zeta}_{it} + \boldsymbol{K}_1\boldsymbol{\zeta}_{it-1} + \boldsymbol{\varepsilon}_{it} \tag{14}$$

where $\boldsymbol{A} = \{\alpha_{jk}\}$, $\boldsymbol{B} = \{\boldsymbol{\beta}_1...\boldsymbol{\beta}_J\}$, $\boldsymbol{K}_0 = \{\kappa_{0jk}\}$, $\boldsymbol{K}_1 = \{\kappa_{1jk}\}$. Since $\boldsymbol{K}_0$ and $\boldsymbol{K}_1$ are unrestricted in scale, $\boldsymbol{\zeta}_{it}$ can be normalised to have unit variances. The J-dimensional vectors $\boldsymbol{y}^*_{it}$ and $\boldsymbol{u}_i$ have typical jth elements y^*_{jit} and u_{ji} and $\boldsymbol{\zeta}_{it}$ is Q-dimensional, with elements $\{\zeta_{qit}\}$. Note that (11)-(12) imply nonlinear restrictions on the elements of $\boldsymbol{B}$, $\boldsymbol{K}_0$ and $\boldsymbol{K}_1$ in (14). These restrictions are imposed, rather than leaving $\boldsymbol{B}$, $\boldsymbol{K}_0$ and $\boldsymbol{K}_1$ unconstrained, to avoid an unduly high-dimensional parameter space. We assume the vectors $\{\boldsymbol{u}_i, \boldsymbol{\zeta}_{i0}, ..., \boldsymbol{\zeta}_{iT_i}\}$ are mutually independent, with Gaussian distributions:

$$\boldsymbol{u}_i \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_u) \tag{15}$$

$$\boldsymbol{\zeta}_{it} \sim N(\boldsymbol{0}, \boldsymbol{I}) \ , \quad t = 0...T_i \tag{16}$$

We only observe each element of the vector $\boldsymbol{y}^*_{it}$ according to the following grading scale:

$$y_{jit} = r \quad \text{iff} \quad y^*_{jit} \in [\Gamma_{j-1r}, \Gamma_{jr}) \ \ , \quad j = 1...J; \ r = 1...R \tag{17}$$

where each $\Gamma_{j0} = -\infty$ and $\Gamma_{jR_j} = +\infty$. Note that different variables may use scales with different numbers and types of interval: in our case, with $J = 2$ equations, we have $R_1 = 5$ and $R_2 = 3$. The thresholds Γ_{jr} may be observable in some applications (such as banded earnings variables) or specified as unknown parameters for others (such as Likert responses). We are interested in the latter case, which implies that the origin and scale of the latent vector $\boldsymbol{y}^*_{it}$ are unobservable. Consequently normalisation restrictions are required. Common practice is to drop the intercept term from the vector $\boldsymbol{x}_{it}$ and set the residual variance to unity. For our purposes, these are inconvenient and we instead make the following observationally equivalent normalisation:

$$\Gamma_{j1} = 0 \ ; \quad \Gamma_{j2} = 1 \ , \quad j = 1...J \tag{18}$$

Note that the use of this normalisation requires the inclusion of an intercept dummy variable in the covariate vector $\boldsymbol{x}_{it}$. We deal with the initial conditions problem using the following approximation, which allows for both the random effect $\boldsymbol{u}_i$ and the initial MA term $\boldsymbol{\zeta}_{i0}$ to influence $\boldsymbol{y}_{i0}$.

$$\boldsymbol{y}^*_{i0} = \boldsymbol{D}\boldsymbol{w}_i + \boldsymbol{G}\boldsymbol{u}_i + \boldsymbol{K}_0\boldsymbol{\zeta}_{i0} + \boldsymbol{\eta}_i \tag{19}$$

where $\boldsymbol{\eta}_i$ is a random vector distributed as $N(\boldsymbol{0}, \boldsymbol{\Sigma}_\eta)$, independently of $\boldsymbol{u}_i$ and $\boldsymbol{\zeta}_{it}$ for all $t \geq 0$. The unobserved $\boldsymbol{y}^*_{i0}$ is assumed to be mapped into the observable grades $\boldsymbol{y}_{i0}$ by the same mechanism (17), possibly allowing for different values of the thresholds Γ_{jr} to give additional flexibility. The covariate vector $\boldsymbol{w}_i$ should be specified sufficiently richly to give an adequate approximation and it should include an intercept dummy variable.

The process (14) and approximation (19) imply a distributed lag representation of the form:

$$\boldsymbol{y}_{it}^* = \boldsymbol{A}^t \boldsymbol{D} \boldsymbol{w}_i + \sum_{s=0}^{t-1} \boldsymbol{A}^s \boldsymbol{B} \boldsymbol{x}_{it-s} + \boldsymbol{\lambda}_{it} \tag{20}$$

where the stochastic error $\boldsymbol{\lambda}_{it}$ has the following structure:

$$\boldsymbol{\lambda}_{it} = \left[\boldsymbol{A}^t \boldsymbol{G} + \boldsymbol{S}_t\right] \boldsymbol{u}_i + \boldsymbol{K}_0 \boldsymbol{\zeta}_{it} + \sum_{s=0}^{t-1} \boldsymbol{A}^{t-s-1} \left[\boldsymbol{K}_1 + \boldsymbol{A}\boldsymbol{K}_0\right] \boldsymbol{\zeta}_{is} + \sum_{s=1}^{t} \boldsymbol{A}^{t-s} \boldsymbol{\varepsilon}_{is} + \boldsymbol{A}^t \boldsymbol{\eta}_i \tag{21}$$

where $\boldsymbol{S}_t = \sum_{s=0}^{t-1} \boldsymbol{A}^s = (\boldsymbol{I} - \boldsymbol{A})^{-1} \left(\boldsymbol{I} - \boldsymbol{A}^t\right)$.

A1.2 Identification

Consider the residual vector $\boldsymbol{\lambda}_{it}$ defined by (21) and write the initial period residual $\boldsymbol{\lambda}_{i0} = \boldsymbol{G}\boldsymbol{u}_i + \boldsymbol{\zeta}_{i0} + \boldsymbol{\eta}_i$. Under our assumptions, these random vectors are jointly normal with covariances:

$$\boldsymbol{C}_{00} = \boldsymbol{G}\boldsymbol{\Sigma}_u \boldsymbol{G}' + \boldsymbol{K}_0 \boldsymbol{K}_0' + \boldsymbol{\Sigma}_\eta \tag{22}$$

$$\boldsymbol{C}_{0t} = \boldsymbol{G}\boldsymbol{\Sigma}_u \left[\boldsymbol{A}^t \boldsymbol{G} + \boldsymbol{S}_t\right]' + \boldsymbol{\Sigma}_\eta \boldsymbol{A}^{t\prime} + \boldsymbol{K}_0 \left[\boldsymbol{K}_1 + \boldsymbol{A}\boldsymbol{K}_0\right]' \boldsymbol{A}^{t-1\prime}, \qquad t > 0 \tag{23}$$

$$\begin{aligned} \boldsymbol{C}_{st} = {} & \left[\boldsymbol{A}^s \boldsymbol{G} + \boldsymbol{S}_s\right] \boldsymbol{\Sigma}_u \left[\boldsymbol{A}^t \boldsymbol{G} + \boldsymbol{S}_t\right]' + \boldsymbol{A}^s \boldsymbol{\Sigma}_\eta \boldsymbol{A}^{t\prime} + \sum_{j=1}^{s} \boldsymbol{A}^{s-j} \boldsymbol{\Sigma}_\varepsilon \boldsymbol{A}^{t-j\prime} \\ & + \delta_{st} \boldsymbol{K}_0 \boldsymbol{K}_0' + (1 - \delta_{st}) \boldsymbol{K}_0 \left[\boldsymbol{K}_1 + \boldsymbol{A}\boldsymbol{K}_0\right]' \boldsymbol{A}^{t-s-1\prime} \\ & + \sum_{j=0}^{s-1} \boldsymbol{A}^{s-j-1} \left[\boldsymbol{K}_1 + \boldsymbol{A}\boldsymbol{K}_0\right] \left[\boldsymbol{K}_1 + \boldsymbol{A}\boldsymbol{K}_0\right]' \boldsymbol{A}^{t-j-1\prime}, \qquad 0 < s \le t \end{aligned} \tag{24}$$

where $\boldsymbol{C}_{st} = \mathrm{cov}(\boldsymbol{\lambda}_{is}, \boldsymbol{\lambda}_{it})$, δ_{st} is the Kronecker delta and we use the convention that $\boldsymbol{A}^0 = \boldsymbol{I}$ in the case of $\boldsymbol{A} = \boldsymbol{0}$.

Now consider the following identification strategy. With the normalisations $\Gamma_{j1} = 0$ and $\Gamma_{j2} = 1$, a multivariate cross-section ordered probit of $\boldsymbol{y}_{i0}$ on $\boldsymbol{w}_i$ for the initial period identifies $\boldsymbol{D}$ and $\boldsymbol{C}_{00}$. Now construct a set of variables $\tilde{\boldsymbol{y}}_{i0} = \boldsymbol{D}\boldsymbol{w}_i$ and estimate equation (20) for wave $t = 1$ by regressing $\boldsymbol{y}_{i1}$ on $\{\tilde{\boldsymbol{y}}_{i0}, \boldsymbol{x}_{i1}\}$, using multi-equation ordered probit. For this to be possible, we need the identifying assumption that $\boldsymbol{D}\boldsymbol{w}_i$ and $\boldsymbol{x}_{i1}$ are non-collinear, which requires the presence of sufficient variables in $\boldsymbol{w}_i$ which are excluded from $\boldsymbol{x}_{i1}$. Estimation of this system for wave 1 identifies $\boldsymbol{A}, \boldsymbol{B}$ and $\boldsymbol{C}_{11}$. With $\boldsymbol{A}, \boldsymbol{B}$ and $\boldsymbol{D}$ known, it is then possible to identify the covariance matrices $\boldsymbol{C}_{st}$ for all s, t from the residuals for periods s, t.

The next step is to identify $\boldsymbol{G}$ and $\boldsymbol{\Sigma}_u$ from the covariances $\boldsymbol{C}_{st}$. Note that:

$$\boldsymbol{C}_{0,t+1} - \boldsymbol{C}_{0t}\boldsymbol{A}' = \boldsymbol{G}\boldsymbol{\Sigma}_u \;, \quad \text{for any } t \ge 1 \tag{25}$$

$$\boldsymbol{C}_{1t} - \boldsymbol{C}_{1,t-1}\boldsymbol{A}' = \boldsymbol{A}\boldsymbol{G}\boldsymbol{\Sigma}_u + \boldsymbol{\Sigma}_u \;, \quad \text{for any } t \ge 3 \tag{26}$$

Consequently $\boldsymbol{\Sigma}_u$ is identifiable as $\boldsymbol{C}_{1t} - \boldsymbol{C}_{1,t-1}\boldsymbol{A}' - \boldsymbol{A}\left[\boldsymbol{C}_{0,t+1} - \boldsymbol{C}_{0t}\boldsymbol{A}'\right]$ for any $t \ge 3$. If $\boldsymbol{\Sigma}_u$ is non-singular, then $\boldsymbol{G}$ is identified as $\left[\boldsymbol{C}_{0,t+1} - \boldsymbol{C}_{0t}\boldsymbol{A}'\right] \boldsymbol{\Sigma}_u^{-1}$.

Singularity of $\boldsymbol{\Sigma}_u$ would generally only arise when we specify a low-dimensional factor structure so that $\boldsymbol{\Sigma}_u$ is expressible as $\boldsymbol{H}\boldsymbol{\Omega}_u\boldsymbol{H}'$ where $\boldsymbol{\Omega}_u$ is a $k \times k$ positive definite matrix with $k < J$ and $\boldsymbol{H}$ is a $J \times k$ matrix of rank k, subject to k^2 normalisation restrictions to give a unique pair $(\boldsymbol{H}, \boldsymbol{\Omega}_u)$. Then (25) can be rewritten as $\boldsymbol{C}_{0,t+1} - \boldsymbol{C}_{0t}\boldsymbol{A}' = [\boldsymbol{GH}][\boldsymbol{\Omega}_u\boldsymbol{H}']$ and solved for the product $\boldsymbol{GH}$, which is the $J \times k$ coefficient matrix of the k factors in the initial period.

The compound process $\boldsymbol{v}_{it} = \boldsymbol{K}_0\boldsymbol{\zeta}_{it} + \boldsymbol{K}_1\boldsymbol{\zeta}_{it-1} + \boldsymbol{\varepsilon}_{it}$ is characterised fully by its variance and 1st-order autocovariance matrices:

$$Var\left(\boldsymbol{v}_{it}\right) = \boldsymbol{K}_0\boldsymbol{K}_0' + \boldsymbol{K}_1\boldsymbol{K}_1' + \boldsymbol{\Sigma}_\varepsilon \tag{27}$$

$$Cov\left(\boldsymbol{v}_{it}, \boldsymbol{v}_{it-1}\right) = \boldsymbol{K}_1\boldsymbol{K}_0' \tag{28}$$

When the MA process is unrestricted, $\boldsymbol{K}_0, \boldsymbol{K}_1$ and $\boldsymbol{\Sigma}_\varepsilon$ cannot be identified from (27) and (28), since alternative values $\left\{\boldsymbol{K}_0^+, \boldsymbol{K}_1^+, \boldsymbol{\Sigma}_\varepsilon^+\right\}$ give exactly the same autocovariances, where $\boldsymbol{K}_0^+ = c\boldsymbol{K}_0, \boldsymbol{K}_1^+ = c^{-1}\boldsymbol{K}_1$ and $\boldsymbol{\Sigma}_\varepsilon^+ = \boldsymbol{\Sigma}_\varepsilon + (1-c^2)\boldsymbol{K}_0\boldsymbol{K}_0' + (1-c^{-2})\boldsymbol{K}_1\boldsymbol{K}_1'$, for any positive constant c such that $\boldsymbol{\Sigma}_\varepsilon^+$ is positive definite. In our two-equation application based on (11)-(12), we resolve this by using the normalisation $\kappa_{01} = 1$, leaving κ_{02}, κ_{11} and κ_{12} unrestricted. The parameters κ_{02}, κ_{11} and κ_{12} can be derived uniquely from knowledge of $\boldsymbol{K}_0\boldsymbol{K}_1'$ (provided either $\kappa_{11} \neq 0$ or $\kappa_{12} \neq 0$), which can be constructed as $\boldsymbol{C}_{01} - \boldsymbol{G}\boldsymbol{\Sigma}_u\left(\boldsymbol{I} + \boldsymbol{AG}\right)' - \left[\boldsymbol{C}_{00} - \boldsymbol{G}\boldsymbol{\Sigma}_u\boldsymbol{G}\right]\boldsymbol{A}'$

The final step is to recover $\boldsymbol{\Sigma}_\eta$ and $\boldsymbol{\Sigma}_\varepsilon$. The former can be constructed, using (22), as $\boldsymbol{C}_{00} - \boldsymbol{G}\boldsymbol{\Sigma}_u\boldsymbol{G}' - \boldsymbol{K}_0\boldsymbol{\Sigma}_\zeta\boldsymbol{K}_0{}'$. The latter is given directly by (24) for $s = t = 1$ as:

$$\boldsymbol{\Sigma}_\varepsilon = \boldsymbol{C}_{11} - \left[\boldsymbol{I} + \boldsymbol{AG}\right]\boldsymbol{\Sigma}_u\left[\boldsymbol{I} + \boldsymbol{AG}\right]' - \boldsymbol{K}_0\boldsymbol{\Sigma}_\zeta\boldsymbol{K}_0' - \left[\boldsymbol{K}_1 + \boldsymbol{AK}_0\right]\left[\boldsymbol{K}_1 + \boldsymbol{AK}_0\right]' - \boldsymbol{A}\boldsymbol{\Sigma}_\eta\boldsymbol{A}' \tag{29}$$

A1.3 Maximum simulated likelihood estimation

The full model consists of equation (19) and a set of equations (20) for any collection of periods $t > 0$. In practice, the initial conditions model (19) is only an approximation and is a potential source of specification error. However, if $\boldsymbol{A}$ has stable roots so that $\boldsymbol{A}^t \rightarrow 0$ as t increases, then the influence of the initial conditions declines as we consider later periods. There is, therefore, a case for leaving a gap (of S periods) between the initial period 0 and the subsequent periods used to estimate the model (20). Thus we work with a system of $J(T-S+1)$ equations consisting of (19) and (20) for $t = S+1...T$. Data on $\{y_{i1}...y_{iS}\}$ are not used but we do require observations on $\{\boldsymbol{x}_{i1}...\boldsymbol{x}_{iS}\}$ spanning the omitted periods. The choice of S involves a trade-off between possible misspecification bias and efficiency, since increasing S reduces the influence of initial conditions but also reduces the number of observations used for estimation. Increasing S also reduces the dimensionality of the computational problem.

Let the observed outcome for y_{jit} be r_{jit}, implying $y_{jit}^* \in \left[\Gamma_{j,r_{jit}-1}, \Gamma_{j,r_{jit}}\right)$. The likelihood for this set of events is:

$$\begin{aligned} &\Pr\left(y_{jit} = r_{jit},\ \ j = 1...J; t \in \mathbf{T} | \boldsymbol{w}_i, \boldsymbol{x}_{i1}...\boldsymbol{x}_{iT}\right) \\ &\qquad = \Pr\left(\lambda_{jit} \in \left[\Gamma_{j,r_{jit}-1} - \mu_{jit}, \Gamma_{j,r_{jit}} - \mu_{jit}\right),\ \ j = 1...J; t \in \mathbf{T}\right) \end{aligned} \tag{30}$$

where $\mathbf{T}$ is the index set $\{0, S+1...T\}$, λ_{jit} is the residual for equation j at individual i and time t and μ_{jit} is the jth element of the vector $\boldsymbol{\mu}_{it} = \boldsymbol{A}^t\boldsymbol{D}\boldsymbol{w}_i + \sum_{s=0}^{t-1}\boldsymbol{A}^s\boldsymbol{B}\boldsymbol{x}_{it-s}$. The covariance matrix of the residual vector for individual i) has a block structure, with blocks given by expressions of the form (22)-(24). The probability (30) is a $J(T-S+1)$-dimensional rectangle probability. Under normality, probabilities of this kind can be approximated using the GHK simulator (Hajivassiliou and Ruud, 1994), leading to a simulated log-likelihood function:

$$\ln L\left(\boldsymbol{\theta}, R\right) = \sum_{i=1}^{n}\ln\hat{P}\left(\boldsymbol{\theta}, R\right) \tag{31}$$

where $\hat{P}(\boldsymbol{\theta}, R)$ is the predicted probability (30) for individual i, estimated using the GHK algorithm with R replications. Note that, since y^*_{2it-1} does not appear in (11)-(12), y^*_{2i0} is not required, so only a single initial condition has to be modelled.

Techniques such as antithetic acceleration or Halton sequences can be used to improve simulation precision. We use a three-stage computational scheme. First, an initial approximation to the ML estimate is calculated, using crude Monte Carlo simulation with $R = 20$ replications to construct the likelihood (31), which is maximised numerically with respect to the parameters $\boldsymbol{\theta}$. At the second stage, the number of replications is increased to 200: 100 pseudo-random draws and their antithetics.[11] The resulting simulated likelihood is maximised numerically. At the third stage, a final evaluation of the log likelihood and its gradient vector is made with $R = 1000$ replications to check on simulation error and make a 1-iteration update on the converged point. In the application reported below, we use a skip rate of $S = 5$, giving a maximum dimension of 11 for the rectangle probabilities to be simulated. For optimisation, we use the simulated annealing algorithm (Goffe et al 1994) as implemented in a Gauss routine written by E.G.Tsionas to produce a starting point for a quasi-Newton algorithm implemented in the Gauss MAXLIK routine.

[11] The 100 antithetics are replaced by fresh pseudo random draws in the 27% of cases where antithetics produce no reduction in the simulation variance.

Appendix 2: Full parameter estimates

Table A1 Random effects ordered probit models for satisfaction with life overall (SLO) and income (SI)

Covariate	SLO	SI
Financial wellbeing level 2	0.394***	0.443***
	(0.069)	(0.073)
Financial wellbeing level 3	0.764***	1.331***
	(0.063)	(0.068)
Financial wellbeing level 4	1.039***	2.176***
	(0.065)	(0.070)
Financial wellbeing level 5	1.275***	2.805***
	(0.067)	(0.071)
Gross household income per head	-0.000	0.022***
	(0.001)	(0.002)
Personal share in household income	−0.081*	−0.104**
	(0.047)	(0.045)
Change in income in last year	-0.000	−0.007***
	(0.001)	(0.001)
Female	-0.070	0.092**
	(0.045)	(0.037)
Afro-Caribbean	0.244	0.266
	(0.198)	(0.178)
South Asian	0.203	0.023
	(0.185)	(0.167)
In relationship	0.292***	0.016
	(0.061)	(0.053)
Divorced/separated	-0.080	−0.174***
	(0.070)	(0.061)
Widowed	0.083	0.125*
	(0.077)	(0.067)
Employed	-0.016	0.179***
	(0.047)	(0.045)
Self-employed	-0.016	0.247***
	(0.060)	(0.057)
Retired	-0.042	0.001
	(0.072)	(0.068)
Unemployed	−0.252***	−0.466***
	(0.085)	(0.086)
Long-term sick	−0.666***	−0.253***
	(0.072)	(0.069)
Degree	−0.295***	-0.001
	(0.068)	(0.058)
HND/HNC	−0.132*	0.171**
	(0.079)	(0.069)
A-levels	−0.253***	-0.037
	(0.063)	(0.055)
O-levels	−0.099*	-0.003
	(0.053)	(0.044)
Vocational qualifications	0.019	−0.062*
	(0.043)	(0.036)

Table A1 continued

Covariate	SLO	SI
Number pre-school children	-0.049	0.015
	(0.064)	(0.062)
Number school-age children	-0.042^{**}	0.058^{***}
	(0.018)	(0.017)
Number retired household members	-0.024	0.023
	(0.044)	(0.042)
Number working-age household members	-0.061^{***}	-0.009
	(0.021)	(0.020)
Has pre-school children	0.025	0.123
	(0.081)	(0.078)
ownocc	0.088^{**}	0.119^{***}
	(0.043)	(0.039)
Private rented housing	0.207^{***}	0.134^{**}
	(0.059)	(0.054)
Birth year	-0.013^{***}	-0.020^{***}
	(0.002)	(0.002)
Birth year squared	0.000	0.001^{***}
	(0.000)	(0.000)
Separated/divorced in last year	-0.332^{***}	0.043
	(0.088)	(0.086)
Widowed in last year	-0.592^{***}	0.106
	(0.134)	(0.129)
Retired in last year	0.239^{***}	0.060
	(0.078)	(0.073)
Entered unemployment in last year	0.014	0.100
	(0.114)	(0.117)
Became long-term sick in last year	-0.245^{*}	-0.126
	(0.139)	(0.143)
New child in last year	0.154^{**}	0.012
	(0.063)	(0.061)
Threshold 1	-2.426^{***}	-0.126
	(0.123)	(0.117)
Threshold 2	-1.882^{***}	0.553^{***}
	(0.121)	(0.118)
Threshold 3	-1.135^{***}	1.353^{***}
	(0.121)	(0.118)
Threshold 4	-0.246^{**}	2.266^{***}
	(0.120)	(0.118)
Threshold 5	1.001^{***}	3.385^{***}
	(0.121)	(0.119)
Threshold 6	2.514^{***}	4.511^{***}
	(0.121)	(0.119)
Intra-class correlation	0.541^{***}	0.426^{***}
	(0.008)	(0.009)

Table A2 Transition rates for the current state of financial wellbeing

Origin state	*Destination state* Very difficult	Quite difficult	Getting by	Doing alright	Living comfortably	*All destinations*
Very difficult	32.9	26.6	29.5	9.2	1.9	*2.8*
Quite difficult	10.6	25.5	47.5	13.3	3.1	*6.0*
Getting by	2.5	8.8	54.3	26.3	8.1	*27.9*
Doing alright	0.5	1.8	19.5	53.5	24.7	*32.2*
Living comfortably	0.2	0.5	6.3	24.0	68.9	*31.0*
All origins	*2.5*	*5.6*	*27.3*	*33.0*	*31.7*	*100.0*

Note: Row percentages: BHPS sample of individuals who were household reference persons in 1992, using waves from 1992-2003, $n = 43,594$)

Table A3 Summary statistics for covariates

Variable	*Mean 1993-2003*
Female	0.403
African/Afro-Caribbean	0.007
South Asian	0.010
Any pre-school child in household	0.107
Number of pre-school children	0.134
Number of school-age children	0.458
Number of retired household members	0.433
Number of other adults	1.468
Married or cohabiting	0.649
Divorced or separated	0.107
Widowed	0.141
Employed	0.458
Self-employed	0.085
Retired	0.308
Unemployed	0.029
Long-term sick	0.047
(Year of birth - 1940)/10	0.314
Degree	0.113
Higher diploma or certificate	0.070
Higher school qualification (A-levels)	0.141
Intermediate school qualifications (O-levels/GCSE)	0.258
Vocational qualifications	0.340
Homeowner	0.730
Private rental housing	0.066
Housing equity (£'00,000)	0.578
Per capita gross annual household income (£'000)	11.1
Respondent's share of household income	0.654
Divorced or separated in last year	0.008
Widowed in last year	0.004
Retired in last year	0.013
Lost job in last year	0.010
Onset of long-term illness in last year	0.004
Birth of child in last year	0.023
Change in real per capita household income	0.154
Change in real housing equity	0.048

Table A4 MSL estimates of joint model: adjustment parameters, long-run effects $\boldsymbol{\psi}/S_1$ and transient effects $\boldsymbol{\theta}_5$ and $\boldsymbol{\theta}_6$ (standard errors in parentheses)

Parameter	*Estimate*	*Parameter*	*Estimate*	*Parameter*	*Estimate*
λ	0.6654	A-level	0.1949	2001	-0.0979
	(0.02)		(0.0784)		(0.0528)
$\phi S_1/S_2$	0.0904	O-level	0.1819	2002	-0.1024
	(0.0359)		(0.0647)		(0.0554)
$(\lambda - \pi)S_1/S_2$	-0.028	Vocational education	0.0341	Newly-divorced	-0.1879
	(0.0252)		(0.052)		(0.1195)
Constant	1.9366	No. pre-school children	-0.1459	Newly-widowed	0.162
	(0.1762)		(0.1277)		(0.1783)
Female	0.1397	No. school-age children	0.0006	Newly-retired	-0.1086
	(0.0549)		(0.0285)		(0.0995)
Black	-0.7534	No. retired	0.0609	Job loss	-0.5711
	(0.3207)		(0.0736)		(0.1734)
South Asian	-0.446	No. other adults	-0.0632	Onset of illness	-0.6238
	(0.2187)		(0.0376)		(0.1765)
Married/cohabiting	0.3979	Any pre-school children	0.2342	New birth	-0.0897
	(0.0888)		(0.1669)		(0.1112)
Divorced/separated	-0.2887	Home-owner	0.6288	Δ income	-0.2608
	(0.097)		(0.0685)		(0.1375)
Widowed	0.016	Private rental	0.0963	Δ housing equity	0.0987
	(0.1024)		(0.0967)		(0.0495)
Employed	-0.0676	Housing equity	0.053	Newly-divorced	-0.1952
	(0.0828)		(0.0152)		(0.0705)
Self-employed	-0.0978	Annual household income	4.5794	Newly-widowed	0.029
	(0.1048)		(0.2456)		(0.1057)
Retired	-0.1302	Share in income	0.2523	Newly-retired	-0.2836
	(0.1233)		(0.0861)		(0.0539)
Unemployed	-0.619	Birth year/10	-0.2463	Job loss	-0.5059
	(0.1846)		(0.0279)		(0.0748)
Long-term sick	-0.4532	(Birth year/10)^2	0.0127	Onset of illness	-0.0662
	(0.1239)		(0.0104)		(0.103)
Degree	0.3286	1999	-0.343	New birth	-0.2105
	(0.0796)		(0.0709)		(0.0527)
Diploma/certificate	0.3734	2000	-0.3079	Δ income	0.9381
	(0.0994)		(0.0539)		(0.1449)
				Δ housing equity	0.1581
					(0.0165)

Table A4 continued MSL estimates of joint model: initial condition coefficients, covariance parameters and ordinal thresholds (standard errors in parentheses)

Parameter	*Estimate*	*Parameter*	*Estimate*	*Parameter*	*Estimate*
Constant	1.2739	No. other adults2	0.1543	$\overline{\text{No. other adults}}$	-0.2992
	(0.27250001)		(0.0634)		(0.0974)
Female	0.0748	Pre-school children	-0.0079	$\overline{\text{Home-owner}}$	0.6298
	(0.068)		(0.1782)		(0.1998)
Black	-0.8267	Home-owner	-0.1337	$\overline{\text{Private rental}}$	0.4036
	(0.26910001)		(0.1725)		(0.2242)
South Asian	-0.7811	Private rental	-0.1425	$\overline{\text{Housing equity}}$	-0.0911
	(0.2369)		(0.1737)		(0.0811)
Married/cohabiting	0.3261	Housing equity	0.2911	$\overline{\text{Household income}}$	3.446
	(0.17460001)		(0.0991)		(0.7498)
Divorced/separated	-0.0973	Household income	4.9309	$\overline{\text{Share in income}}$	-0.1106
	(0.21089999)		(0.6052)		(0.2269)
Widowed	0.2994	Share in income	0.3088	G_{11}	1.1786
	(0.26530001)		(0.1498)		(0.1042)
Employed	0.3811	(Birthyear-1940)/10	-0.1579	G_{12}	-0.7142
	(0.1224)		(0.0347)		(0.0873)
Self-employed	0.1771	((Birthyear-1940)/10)^2	0.0358	σ_{u_1}	0.633
	(0.1803)		(0.0111)		(0.0765)
Retired	0.1277	$\overline{\text{Married/cohabiting}}$	0.0648	$\rho_{u_1 u_2}$	0.3920
	(0.2045)		(0.2098)		(0.0473)
Unemployed	-0.2765	$\overline{\text{Divorced/separated}}$	-0.4439	σ_{u_2}	0.3169
	(0.1578)		(0.2452)		(0.0187)
Long-term sick	0.083	$\overline{\text{Widowed}}$	-0.2904	σ_{ε_1}	0.4988
	(0.1981)		(0.2834)		(0.1653)
Degree	0.0524	$\overline{\text{Employed}}$	-0.4121	$\rho_{\varepsilon_1 \varepsilon_2}$	0.7386
	(0.1025)		(0.1882)		(0.1756)
Diploma/certificate	0.1985	$\overline{\text{Self-employed}}$	-0.4023	σ_{ε_2}	0.3559
	(0.1135)		(0.2522)		(0.0066)
A-level	0.2664	$\overline{\text{Retired}}$	-0.2301	σ_η	0.6332
	(0.0899)		(0.2805)		(0.2071)
O-level	0.0692	$\overline{\text{Unemployed}}$	-0.5826	Γ_3^1	2.792
	(0.0707)		(0.3239)		(0.0798)
Vocational education	0.0175	$\overline{\text{Long-term sick}}$	-0.5009	Γ_4^1	4.3878
	(0.058)		(0.2585)		(0.1417)
No. pre-school children	-0.1032	$\overline{\text{No. pre-school children}}$	0.3337	Γ_3^0	2.694
	(0.1434)		(0.1326)		(0.1041)
No. school-age children	0.125	$\overline{\text{No. school-age children}}$	0.0101	Γ_4^0	3.9236
	(0.067)		(0.0869)		(0.1684)
No. retired	0.0255	$\overline{\text{No. retired}}$	-0.0125	σ_ζ	1.2418
	(0.1383)		(0.1784)		(0.3674)