*The Economic Journal*, **113** (*March*), C140–C152.  Published by Blackwell Publishing, 9600 Garsington Road, Oxford OX4 2DQ, UK and 350 Main Street, Malden, MA 02148, USA.

# HYPOTHETICAL INTERTEMPORAL CONSUMPTION CHOICES*

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The paper extends and replicates part of the analysis by Barsky *et al.* (1997), which exploits hypothetical choices among different consumption streams to infer intertemporal substitution elasticities and rates of time preference. We use a new and much larger dataset than Barsky *et al.* Furthermore, we estimate structural models of intertemporal choice, while parameterising the parameters of interest as a function of relevant individual characteristics. We also consider 'behavioural' extensions, like habit formation. Models with habit formation appear to be superior to models with intertemporally additive preferences.

Time preference has been extensively measured through survey techniques. In general, respondents face a hypothetical situation involving different amounts of money (or some other desirable good) at different points in time and are asked to either express a preference for one of the alternatives or to provide a trade-off (how much money does one require to postpone the receipt of a certain amount for instance). Discount rates measured in this way were found to be negatively correlated with future time orientation and positively correlated with big spending (Thomas and Ward, 1979). Kurz *et al.* (1973) asked a sample of participants in the Seattle and Denver Income Maintenance Experiments a series of hypothetical questions such as: 'What size bonus would you demand today rather than collect a bonus of \$100 in 1 year?'. They found a mean rate of time preference between 0.36 and 0.76, and between 0.40 and 1.22 for whites and for blacks, respectively.

Although these rates of time preference may seem implausibly high, high rates are also found in revealed preference studies. In a well-known study, Hausman (1979) used individual household data on the purchase and utilisation of room air conditioners to estimate the intertemporal discount rates used by consumers in order to evaluate the trade-off between present and future costs. He found an estimated average annual discount rate of 26.4% (clearly above any relevant interest rate) and an inverse relation with income. Loewenstein and Thaler (1989) cite a number of other studies that find even larger discount rates. Explanations that have been offered include information barriers and liquidity constraints. Further explanations have been provided by Kooreman (1995), whose main conclusion is that if risk-neutral consumers anticipate a random lifetime of a durable, the assumption of a deterministic lifetime results in an upward bias, as large as 35%, of estimated discount rates.

* We thank Rob Alessie, Bas Donkers, Angelika Eymann, Peter Kooreman and two anonymous referees for helpful comments. An earlier version of this paper used a different dataset, as described in the paper. We should note that we have found a programming error in the earlier version of the paper, which affected the reported results. Thus the results in the earlier version should no longer be taken to be valid.

Donkers and van Soest (1999) and Donkers *et al.* (1999) used data from the VSB panel survey[1] of Dutch households in order to elicit information about subjective measures of time preference, financial decisions and risk attitudes. Their main results are that the rate of time preference is negatively related to age and that women are more patient than men; the subjective time preference rate is furthermore positively related to the decision to hold risky assets.

In models of dynamic choice increasing attention is given to the concept of self-control. This has been investigated by means of models where the agent is assumed to be both a farsighted planner and a myopic doer. The individual is seen as an organisation, so that the problem of self-control is basically the same as the agency conflict between the owner and the manager of a firm. It is therefore not surprising that most of the work done in this field of research is based on a game-theoretic analysis. Some of the applications of the principal-agent model has been investigated by Thaler and Shefrin (1981), particularly in the study of individual saving behaviour. The work by Laibson (1997) squarely falls into this category.

Our study follows Barsky *et al.* (1997) (BJKS from now on) in using observed hypothetical choices between different consumption patterns to estimate both the rate of time preference and the elasticity of intertemporal substitution. As a theoretical framework we take the conventional intertemporally additive utility model as a starting point. We then extend the model by allowing for habit formation. By using hypothetical questions, the issue of self-control does not arise. The hypothetical nature of the questions allows the respondent to our questions to be a planner rather than a doer. Also, uncertainty is not part of the framework in which questions are asked. So, when we speak of relative risk aversion this refers to nothing else than the curvature of the intratemporal utility function. The goal of the paper is to investigate the structure of intertemporal preferences over consumption streams in as clean an environment as possible. Thus we abstract from uncertainty and present respondents in a survey with straightforward choices that do not involve complicated utility maximisation tasks.

Section 1 describes the dataset we used for the experiment and presents the most relevant summary statistics. The basic model (with intertemporally additive utility) is presented in Section 2. In the same Section we also present estimation results for this model. Habit formation is introduced in Section 3, where two model specifications are described, as well as the estimation outcomes for these two models. One of the distinguishing features of the conventional intertemporally additive utility model is the inverse relationship between the IES and the relative risk aversion parameter (in our context without uncertainty merely interpreted as a measure of the concavity of the utility function). Introduction of habit formation breaks this relation. Section 3 presents the IES in the model with habit formation. Section 4 concludes.

[1] Now called the CentER Savings Survey (CSS).

## 1. The Dataset

In the empirical analysis we use data from the *CentERpanel*. The CentERpanel comprises some 2,000 households in the Netherlands. The members of those households answer a questionnaire at their home computers every week. These computers may either be their own computer or a set-top box provided by CentERdata, the agency running the panel. The CentERpanel is representative of the Dutch population. In the weekends of August 7–10 and August 14–7 of 1998 a questionnaire was fielded with a large number of subjective questions on hypothetical choices. The questionnaire was repeated in the weekends of November 20–3 and November 27–30 of 1998 for those panel members who had not responded yet. For reasons that will become clear below a very similar questionnaire was fielded among the members of the CentERpanel in late January of 2002. The questions we use present respondents with five different hypothetical consumption paths and then ask them to choose one of them. A typical question reads as follows:

*Now imagine that you (and your partner) decide to take financial advice and set up an expenditure plan, starting now and ending when you are 65 years old. The financial advisor tells you that, in your situation, there are a number of options. These options will be presented on the screen below. Please indicate by selecting a number, which expenditure pattern you would prefer. When making this choice, please consider your family situation to remain unchanged. Please indicate your preferred expenditure pattern by selecting a number.*

| Age/Pattern | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 52 | 7,691 | 7,017 | 6,409 | 5,659 | 4,768 |
| 54 | 7,295 | 6,803 | 6,409 | 5,853 | 5,226 |
| 55 | 7,105 | 6,699 | 6,409 | 5,953 | 5,472 |
| 57 | 6,739 | 6,495 | 6,409 | 6,157 | 5,999 |
| 59 | 6,392 | 6,297 | 6,409 | 6,368 | 6,576 |
| 60 | 6,225 | 6,201 | 6,409 | 6,476 | 6,885 |
| 62 | 5,904 | 6,012 | 6,409 | 6,698 | 7,547 |
| 63 | 5,750 | 5,920 | 6,409 | 6,812 | 7,902 |
| 65 | 5,454 | 5,740 | 6,409 | 7,045 | 8,662 |

*Select expenditure pattern 1, 2, 3, 4 or 5.*

After this question, three more, similar, questions are asked. The ages listed in the first column vary depending on the respondent's characteristics. In particular, the final age (denoted by $L$) is equal to 65, if the respondent is currently younger than 56 (as in the example reported above); $L$ is equal to 75, if the respondent is currently between 56 and 65; $L$ is equal to 85, if the respondent is currently between 66 and 75. The questions are not posed to respondents older than 75. The interval between the respondent's own age and $L$ is divided in (almost) equal parts. Respondents only see numbers and not a picture of consumption profiles.

### 1.1. *The Data Generating Process*

The various consumption patterns have been generated as follows. Let $y$ denote the respondent's self-reported after-tax household's monthly income. It is the sum of the net income of each household member, based on information that was provided by the respondent in earlier questionnaires. Let $\epsilon$ be a uniformly distributed random variable on [0.8,1.2]. For each respondent we draw one value from the distribution of $\epsilon$ and compute $C = 0.9y\epsilon$. $C$ is the flat consumption path that is given to the respondent as one of the possible choices (the middle column in the question cited above). The remaining consumption paths are derived from $C$ as follows.

Draw four random variables: $\alpha_1$ from $U\,[-0.05,-0.025]$, $\alpha_2$ from $U\,[-0.025,0]$, $\alpha_3$ from $U\,[0,0.025]$, and $\alpha_4$ from $U\,[0.025,0.05]$. These random variables are *consumption growth rates.* Let the current age of a respondent be $l$ (i.e. *52* in the question). Furthermore let $c_l^i$ be the consumption level at age $l$ in path $i = 1,...,4$ (the construction of $c_l^i$ is described below). Then the consumption level in path $i$ at any given age $\tau$ between $l$ and $L$ is given by $c_\tau^i = c_l^i.(1+\alpha_i)^{\tau-l}$. In other words, a consumption pattern is completely characterised by its initial value $c_l^i$ and the growth rate $\alpha_i$. It remains to describe the way the initial values $c_l^i$ are generated.

The following somewhat artificial procedure has been adopted. Let $r_i$ be a random *interest rate* drawn from a uniform distribution on [−5, 5]. Also the $r_i$ are respondent specific. Given the interest rate $r_i$ and the growth rate $\alpha_i$ we choose $c_l^i$ in such a way that the present discounted value of the consumption stream $\{c_\tau^i = c_l^i(1+\alpha_i)^{\tau-l}\}_{\tau=l}^{L}$ is equal to the present discounted value of the constant consumption pattern $C$. In other words we impose:

$$c_l^i + c_l^i\frac{(1+\alpha_i)}{1+\dfrac{r_i}{100}} + \cdots + c_l^i\frac{(1+\alpha_i)^{\tau-l}}{\left(1+\dfrac{r_i}{100}\right)^{\tau-l}} + \cdots c_l^i\frac{(1+\alpha_i)^{L-l}}{\left(1+\dfrac{r_i}{100}\right)^{L-l}} \tag{1}$$

$$= C\left[1+\frac{1}{1+\dfrac{r_i}{100}} + \cdots + \frac{1}{\left(1+\dfrac{r_i}{100}\right)^{\tau-l}} + \cdots \frac{1}{\left(1+\dfrac{r_i}{100}\right)^{L-l}}\right]. \tag{2}$$

Define $A_i \equiv 1{+}\alpha_i$ and $R_i \equiv \dfrac{1}{1+\dfrac{r_i}{100}}$. Then the equality can be written as

$$c_l^i[1 + A_iR_i + \cdots + (A_iR_i)^{\tau-l} + \cdots + (A_iR_i)^{L-l}] = C(1 + R_i + \cdots + R_i^{\tau-l} + \cdots R_i^{L-l}). \tag{3}$$

Solving for $c_l^i$ yields

$$c_l^i = C\frac{1-A_iR_i}{1-R_i}\frac{1-R_i^{L-l+1}}{1-(A_iR_i)^{L-l+1}}. \tag{4}$$

The procedure followed ensures that respondents are faced with choices that do not deviate wildly from their own consumption level. We should note that since the respondents are not told the values of $\alpha_i$ and $r_i$, these values are in themselves irrelevant for the way in which the respondents perform the task of selecting consumption paths. They can in principle infer the value of $\alpha_i$ directly from the consumption paths shown to them, but the value of $r_i$ is only of use if for some reason a respondent wanted to engage in the exercise of calculating the internal rate of return of each of the consumption paths that equates the PDV of the the paths. There is no obvious reason why a respondent would want to do that, since the task itself does not allow for borrowing or lending.

Respondents are asked to perform the task illustrated above four times. The tasks refer to different realisations of consumption paths generated by different draws from the distributions of $\alpha_i$ and $r_i$. To be sure, the growth rates and interest rates that generate the consumption paths vary across respondents and across the four tasks. The same is true of the parameter $\epsilon$ which determines the constant consumption path $C$. Finally, respondents are explicitly told that the questions are asked in a zero-inflation setting.

### 1.2. *Descriptive Statistics*

We will use the data from the 2002 experiment. An earlier version of this paper used the 1998 data. As one can see from the description of the way in which the tasks were generated, the first two consumption patterns presented are always downward sloping, whereas consumption patterns 4 and 5 are always upward sloping. One should probably suspect that not all respondents are equally conscientious in carrying out the task of selecting the optimal consumption path. One way in which this may show up is in 'routine selection'. For instance, respondents may always pick the first consumption path or always the middle one, etc. This may systematically bias parameter estimates. If for instance many respondents would tend to pick the first consumption path this would show up in our analysis as a preference for downward sloping consumption profiles. The obvious remedy is to randomise the order in which the patterns are presented. In the 1998 data, no randomisation took place. The motivation for collecting the 2002 data was precisely to correct this omission. Hence in the 2002 data the order in which consumption paths are presented is randomised across each task.

The sample consists of 1,545 observations. Households may have multiple respondents, namely the head of household and the spouse. We constructed three levels of education: the 'low level of education' consists of primary school, low-level high school, junior high school, junior vocational training, special low-level education and apprentice system; the 'middle level of education' consists of senior high school and senior vocational training; the 'high level of education' consists of vocational colleges and university education. There are 857 males and 688 females and their ages range from 21 to 76. More than 75% of the sample respondents have a partner. The distribution across the three education levels is fairly uniform (Table 1).

When considering the possibility of 'routine selection', we find that 31 out of the 1,545 respondents choose the first column across all four tasks. In no other case do we find that a respondent always chooses the same column across the four tasks. This can be contrasted with the results of the 1998 data when we found that almost half of the respondents chose the same column across the four tasks.

## 2. The Basic Model

As a starting point we model the choice of consumption path as the result of maximising an intertemporally additive utility function. That is, a respondent

Table 1

*Distribution of Sample Respondents across Age Classes*

| Age classes (years) | Gender | | Level of Education | | | Marital status | |
|---|---|---|---|---|---|---|---|
| | Fem. | Males | Low | Middle | High | Single | Married |
| 22-32 | 121 | 89 | 25 | 85 | 100 | 76 | 134 |
| 33-43 | 227 | 231 | 108 | 189 | 161 | 103 | 355 |
| 44-55 | 185 | 268 | 123 | 154 | 176 | 95 | 358 |
| 56-66 | 99 | 155 | 91 | 65 | 98 | 48 | 206 |
| 67-75 | 56 | 114 | 64 | 47 | 59 | 37 | 133 |
| Total | 688 | 857 | 411 | 540 | 594 | 359 | 1,186 |

prefers a sequence of consumption levels, $(c_1,\ldots,c_T)$ to an alternative sequence, $\left(c'_1,\ldots,c'_T\right)$, if and only if

$$\sum_{t=l}^{L}\phi_t u(c_t) > \sum_{t=l}^{L}\phi_t u(c'_t), \tag{5}$$

where $u(c)$ is a concave utility function and $\phi_t$ is the weight given to utility in period $t$. Given that $l$ is equal to the respondent's own age, we can interpret period $l$ as being the present, whereas $L$ is the period in which the respondent either turns 65, or 75, or 85. Thus, depending on a respondent's age, the time period over which the consumption path is defined will vary. For instance, if a respondent is 40, the time period will cover 25 years: 40–65. If a respondent is 75 years of age, the time period will cover only 10 years: 75–85. The wording of the question does not specify the consumption level in years in between the ages specified. We will interpret the consumption levels in the questions as representative of a smooth path from $l$ to $L$. Given the data generating process, the utility of a consumption path can be written as a function of the parameters of the data generating process, as we will see below. In order to arrive at an estimable model, we make a number of additional assumptions. To begin with we assume exponential discounting; that is, the utility of a consumption path is written as:[2]

$$\bar{u} \equiv \sum_{t=l}^{L}(1+\delta)^{-t+1}u(c_t), \tag{6}$$

where $\delta$ denotes the discount rate. To allow for random variation in choices (for instance due to non-observable variation in preferences), we add an i.i.d. extreme value distributed error term to the utility function:

$$u_i^* = \bar{u}_i + \varepsilon_i \qquad p = 1,\ldots,5 \tag{7}$$

[2] Although we will later generalise this model to allow for habit formation, we will maintain the assumption of exponential discounting throughout. The motivation for this is that in the hypothetical and long term planning context that we study here, issues of self-control are much less likely to arise. In that sense the results presented do indeed refer to dynamic choices over a long horizon and not to short term intertemporal trade offs.

where $u_i^*$ represents the level of utility associated with consumption path $i$. Consumption pattern $i$ is chosen (which we denote as $d_i = 1$) whenever it yields a level of utility greater than the one associated with all other paths. Formally, this means that

$$d_i = \{\}1 \text{ if } u_i^* > u_q^* \ \forall q \neq i \ 0 \text{ otherwise}. \tag{8}$$

According to this model we then have the familiar logit form for the probability that consumption path $i$ is chosen:

$$\Pr(d_i = 1) = \frac{\exp(\bar{u}_i)}{\sum_{j=1}^{5} \exp(\bar{u}_j)}. \tag{9}$$

To close the model, we specify the form of the instantaneous utility function $u$ and we exploit the specifics of the data generating process. For the instantaneous utility function we adopt the CRRA-specification:

$$u(c) \equiv (1-\rho)^{-1} c^{1-\rho}. \tag{10}$$

The parameter $\rho$ is the coefficient of relative risk aversion and $1/\rho$ is the IES. As mentioned above, we can write the utility function (6) as a function of the underlying parameters of the data generating process. Recall that the consumption at age $\tau$ is equal to $c_\tau^i = c_l^i A_i^{(\tau-l)}$, where $A_i \equiv 1+\alpha_i$. Inserting this into (6) and using the CRRA specification (10) we obtain for the intertemporal utility function:

$$\begin{aligned} \overline{u} &= \sum_{\tau=l}^{L} (1+\delta)^{l-\tau} \frac{1}{1-\rho} (c_l^i A_i^{\tau-l})^{1-\rho} = \frac{(c_l^i)^{1-\rho}}{1-\rho} \sum_{\tau=l}^{L} (1+\delta)^{l-\tau} (A_i^{\tau-l})^{1-\rho} \\ &= \frac{(c_l^i)^{1-\rho}}{1-\rho} \sum_{\tau=l}^{L} \Phi_i^{\tau-l} = \frac{(c_l^i)^{1-\rho}}{1-\rho} \frac{1-\Phi_i^{L-l+1}}{1-\Phi_i} \end{aligned} \tag{11}$$

where $\Phi_i \equiv A_i^{1-\rho}/(1+\delta)$. Each respondent is asked to choose four times among five consumption patterns. Thus we observe four choices per respondent. Estimation of the underlying parameters ($\delta$, $\rho$) by maximum likelihood is straightforward.[3] It is worth mentioning that our methodology differs from the one adopted by BJKS, as these authors estimate the rate of time preference and the intertemporal elasticity of substitution by means of the Euler equation deriving from a standard formulation of the consumer's maximisation problem. We instead do not assume individuals to solve this problem.[4]

[3] In the calculation of standard errors we correct for the fact that the four choices of a respondent may be correlated due to unobserved heterogeneity.

[4] In fact it is not clear what meaning to attach to an Euler equation, as the respondents only get to choose from a discrete number of consumption paths. There is no reason to assume that the best choice out of this limited number satisfies first order equations, not in the least because the respondent is not even informed about the parameters of the budget constraint, like the interest rate.

### 2.1. *Empirical Results for the Basic Model*

Table 3 presents the estimation results for the basic model with randomisation. To allow for a preference for a certain column, we add dummies to the utility of each consumption path corresponding to the particular column corresponding to that consumption path. The choice of the first column serves as a reference category.

Table 3 shows that the first and third column are most likely to be chosen, as was also suggested by Table 2. Although the column dummies are statistically significant it is worth mentioning that their magnitude is much less than when estimated on the 1998 data. There we find for instance that the dummy for the middle column is equal to 1.86 with a t-value of 6.39. Thus the randomisation has wiped out most of the column effects, but not all of it. Although not significant at the 5% level, the estimated value of $\delta$ ($-0.094$) is in line with the findings of BJKS, who find a preference for upward sloping consumption paths. The estimated value of $\rho$ (exp $(0.664) = 1.94$) is smaller than usually found in the literature. The implied IES $1/\rho = 0.51$ is larger than usually found. For instance, BJKS (who use the individual data to derive bounds on individual parameters) report an average upper bound on the IES equal to 0.36. Hall (1988) using a revealed preference representative agent approach estimates the IES to be around 0.1. We return to this below, when we consider more complicated models.

Table 2

*Frequency of Consumption Patterns Choice*

| | Question 1 | | Question 2 | | Question 3 | | Question 4 | |
|---|---|---|---|---|---|---|---|---|
| Cons. pattern | Freq. | % | Freq. | % | Freq. | % | Freq. | % |
| 1 | 379 | 24.53 | 340 | 22.01 | 312 | 20.19 | 294 | 19.03 |
| 2 | 281 | 18.19 | 296 | 19.16 | 305 | 19.74 | 283 | 18.32 |
| 3 | 337 | 21.81 | 341 | 22.07 | 319 | 20.65 | 340 | 22.01 |
| 4 | 259 | 16.76 | 276 | 17.86 | 310 | 20.06 | 311 | 20.13 |
| 5 | 289 | 18.71 | 292 | 18.90 | 299 | 19.35 | 317 | 20.52 |
| Total | 1,545 | 100 | 1,545 | 100 | 1,545 | 100 | 1,545 | 100 |

Table 3

*Preference Parameters for Consumption Paths (basic model)*

| Parameters | Coeff. | s.e. | t-value |
|---|---|---|---|
| delta | −0.094 | 0.051 | 1.84 |
| ln(rho) | 0.664 | 0.122 | 5.46 |
| Dummy for column 2 | −0.128 | 0.044 | 2.89 |
| Dummy for column 3 | 0.010 | 0.044 | 0.23 |
| Dummy for column 4 | −0.135 | 0.044 | 3.04 |
| Dummy for column 5 | −0.100 | 0.044 | 2.30 |
| Log likelihood | −9928.4 | | |

### 2.2. *Parameterisation of $\delta$ and $\rho$*

We allow for variation in preferences, by making both $\delta$ and $\rho$ a function of observable characteristics. One should note that the influence of characteristics on the two parameters $\delta$ and $\rho$ is probably not non-parametrically identified, so interpretation of the separate estimates has to be interpreted with care. As a reflection of the tenuous identification, we found that convergence was sometimes difficult to achieve if we included all observable characteristics in the equations for both parameters. Thus we were forced to impose rather arbitrary exclusion restrictions. The estimation results that yielded the highest likelihood value are given in Table 4. The improvement in the log-likelihood value as a result of the parameterisation is considerable as one can see from a comparison of Tables 4 and 3. The parameters of age and age squared are jointly significant at the 1% level for both $\rho$ and $\delta$. The education dummies are jointly insignificant for $\delta$. Gender does not have any significant impact on either $\rho$ or $\delta$. The effect of household income on $\delta$ is significant at the 5% level and suggests that patience rises with income, as also found by Lawrance (1991).

## 3. Habit Formation

We now relax the assumption of intertemporal additivity of the utility function, so that the marginal rate of substitution between any two periods is no longer independent of the level of consumption in any two other periods. Thus, we consider life time utility functions of the following form:

$$\overline{u} = \sum_{t=l}^{L} (1+\delta)^{l-t} v(c_t, z_t) \tag{12}$$

Table 4

*Preference Parameters for Consumption Paths*

| Parameter | Coeff. | s.e. | t-value |
|---|---|---|---|
| delta | | | |
| age | 0.339 | 0.088 | 3.83 |
| age squared | 0.006 | 0.002 | 3.43 |
| gender | −0.013 | 0.023 | 0.59 |
| middle education | 0.001 | 0.014 | 0.09 |
| higher education | −0.012 | 0.011 | 1.11 |
| log(household inc.) | −0.050 | 0.009 | 5.49 |
| constant | 5.121 | 1.35 | 3.78 |
| ln(rho) | | | |
| age | −0.030 | 0.006 | 4.72 |
| age squared | 0.001 | 0.0004 | 3.11 |
| gender | 0.019 | 0.049 | 0.38 |
| constant | 0.386 | 0.123 | 3.14 |
| Dummy for column 2 | −0.125 | 0.044 | 2.83 |
| Dummy for column 3 | 0.010 | 0.044 | 0.24 |
| Dummy for column 4 | −0.135 | 0.045 | 3.01 |
| Dummy for column 5 | −0.100 | 0.044 | 2.29 |
| Log likelihood | −9879.9 | | |

where, as before, $L$ is the horizon, $\delta$ the discount rate, $t$ denotes the time period, $v$ is the intratemporal utility function, $c_t$ is consumption in period $t$, and $z_t$ now reflects the stock of habits.[5] To complete the model we have to describe the evolution of the stock of habits. We consider two alternative cases: First-order Markov (AR) habits and Moving Average (MA) habits. The former is the simplest case, where we specify the intratemporal utility function as $v[h(c_t)-\theta h(z_t)]$, $h(\cdot)$ being a monotonically increasing function. In the MA case, we let habits evolve according to $h(z_t) = \beta h(z_{t-1})+(1-\beta)h(c_{t-1})$, with $0 < \beta < 1$. In the remainder we choose the logarithm for the function $h(\cdot)$. In contrast to the previous case, habits now have an infinite memory. The detailed derivation of the utility function for both specifications are reported in Appendix A, which is available from the authors upon request.

### 3.1. *The Intertemporal Elasticity of Substitution for the Model with Habit Formation*

The introduction of habit formation breaks the tight link between the coefficient of relative risk aversion and the intertemporal elasticity of substitution.[6] Below we present the IES for the model with moving average habit formation. This also covers the AR-case, as the AR-case is a special case of MA, obtained by setting $\beta = 0$. Our derivation closely follows Carroll (2000), who provides a derivation of the Euler equation with a slightly different specification of habit formation. For reasons of space the derivation is relegated to Appendix B, which is available from the authors on request. Here we only present the IES for the steady state. This turns out to be approximately equal to:

$$\text{IES} \approx \frac{1}{\rho + \theta - \rho\theta}. \tag{13}$$

### 3.2. *Empirical Results for the Models with Habit Formation*

We estimate AR and MA specifications, both with and without parameterisation of the preference parameters. The estimation results for the AR and MA specifications without parameterisation are reported in Tables 5 and 6, respectively. For all cases, the number of observations is 1,545, as in the previous sections. In the specification of the stock of habits we face the problem that we do not know $z_0$. Somewhat arbitrarily we have set $z_0$ equal to 0.9 times household income. Experiments where the number 0.9 is replaced by respectively 0.95, 0.8, and 0.7 yield estimation results that are comparable to the results we present below.

The log-likelihood values are −9921.2 for the AR-specification and −9894.1 and for the MA-specification. The estimates of $\rho$ and $\delta$ are quite similar in both specifications. As in Table 3 we find a negative time preference rate, which is in line

[5] Notice that in this context we only deal with rational habit formation, as in Spinnewijn (1981), for example, as the respondents are assumed to consider the whole consumption path.

[6] Of course, habit formation is not the only way to break the link between risk aversion and intertemporal substitution; see Epstein and Zin (1989, 1991).

Table 5

*AR-specification*

| Parameters | Coeff. | s.e. | t-value |
|---|---|---|---|
| delta | −0.100 | 0.062 | 1.61 |
| ln(rho) | 1.57 | 0.239 | 6.54 |
| theta | 0.801 | 0.021 | 37.24 |
| Dummy for column 2 | −0.128 | 0.044 | 2.89 |
| Dummy for column 3 | 0.010 | 0.044 | 0.22 |
| Dummy for column 4 | −0.135 | 0.044 | 3.03 |
| Dummy for column 5 | −0.102 | 0.044 | 2.33 |
| log-likelihood | −9921.2 | | |

Table 6

*MA-specification*

| Parameters | Coeff. | s.e. | t-value |
|---|---|---|---|
| delta | −0.110 | 0.026 | 4.25 |
| ln(rho) | 1.60 | 0.091 | 17.57 |
| theta | 0.777 | 0.018 | 42.11 |
| beta | 0.929 | 0.007 | 123.2 |
| Dummy for column 2 | −0.127 | 0.044 | 2.88 |
| Dummy for column 3 | 0.010 | 0.044 | 0.22 |
| Dummy for column 4 | −0.134 | 0.045 | 3.01 |
| Dummy for column 5 | −0.101 | 0.044 | 2.31 |
| log-likelihood | −9894.2 | | |

with the results of BJKS, but at variance with much of the literature discussed in the Introduction. The parameters $\theta$ and $\beta$ are both between zero and one and significantly different from zero. These results indicate that (rational) habits play an important role in the choice of consumption paths. The most striking difference between the results presented in Tables 5 and 6 and the results presented in Table 3 (the specification without habit formation) lies in the value of $\rho$. The estimates in Tables 5 and 6 imply much more curvature than the estimate from Table 3. The steady state IES implied by Table 5 is 0.57, whereas the steady state IES implied by Table 6 is equal to 0.53. These values are about equal to the estimate of the IES implied by the estimate of $\rho$ in Table 3 (0.51). Thus we find that the value of the IES is quite robust with respect to the specification of habit formation. But the curvature of the utility function implied by the estimate of $\rho$ is much larger in the specification with habit formation than without.

As before, we have parameterised the parameters of interest ($\delta$, $\ln\rho$, $\theta$, and $\beta$) by making them dependent on respondent characteristics. Since, as noted above, identification of the effects of background variables on the parameters is only identified by functional form we abstain from presenting the myriad of parameter estimates. We only note that the log-likelihood for the AR model with parameterisation increases to −9775.2, which is to be compared to the log-likelihood value in Table 5 (−9921.2). Attempts to also parameterise the MA-model lead to a likelihood that is slightly higher, but convergence appeared hard to achieve. The latter indicates that making the four different parameters dependent on the same background characteristics is more than the data can bear.

## 4. Concluding Remarks

Our analysis is based on information from direct questions about hypothetical intertemporal consumption choices. In comparison with revealed preference approaches, the use of direct questioning to elicit dynamic preferences over consumption has the advantage of simplicity and the avoidance of strong assumptions on the constraints faced by an individual. On the other hand of course, it is still a major step to incorporate the preferences we have elicited in a model of actual behaviour. As BJKS, we find for instance that consumers are very patient (the time preference rate is negative) or equivalently that consumers prefer upward sloping consumption profiles. The fact that other studies appear to find large and positive time preference rates may indicate that self-control is a major problem in actual behaviour. With some exceptions, self-control is still not modelled extensively in economic models of intertemporal choice.

It is of interest to note that the estimate of the IES appears to be quite robust with respect to the different assumptions regarding habit formation. The coefficient of relative risk aversion however changes substantially across specifications. In itself, this demonstrates the importance of breaking the connection between IES and risk aversion in intertemporal models. The main finding of our empirical analysis may be the rejection of intertemporal additivity.

The set-up of the questionnaire can be further improved. The way the consumption paths have been presented by giving consumption levels at specified ages potentially leads to ambiguity. A better way to present consumption paths may be to show full graphs to respondents, or to assign all respondents the same horizon of ten years (say). We could then also systematically vary the horizon and investigate the effect of this on the elicited choices. These are experiments left for future work.

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