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Risk Pooling, Precautionary Saving and Consumption Growth

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In this paper we model the evolution of income risk and consumption growth. We decompose the time series innovation of the income process into its common and cohort-specific components. From these we compute conditional variances which are used as separate risk terms in a consumption growth equation. Using a long series of British household data we exploit the time-series variation to identify precautionary saving effects and find strong evidence of their importance. Specifically, after allowing for demographic and labour market status, there is an independent role for income risk in explaining consumption growth. Rather than the component that is common across cohorts, however, it is the cohort-specific element that is important in determining changes in consumption growth. This result points to a failure of between-cohort insurance mechanisms.

1. INTRODUCTION

Over the last twenty years there has been a well-documented increase in cross-sectional income inequality in the U.K. and, although this may be due to rises in permanent inequality or uncertainty, popular economic commentators have suggested that households are now exposed to more income risk than they were. In the period 1984 to 1990, for example, real incomes for the households in our sample grew by 9% whereas real consumption increased by only 3%. These figures suggest that precautionary saving motives associated with an increase in income risk could have become more important. Interest in the extent to which an increase in income uncertainty can cause a delay in the recovery of consumer spending in the upturn of the business cycle has also meant that the effect of income risk on consumption growth has become an increasingly important policy issue. This paper considers a formal model of consumption smoothing and precautionary saving in which we estimate these effects.

In the presence of complete insurance, either formal or informal, it should only be the component of risk that is common to all individuals in an economy that affects consumption. We find that it is not the common component of risk, but instead the cohort-specific risks which dominate consumption growth, suggesting a failure of between cohort risk-pooling mechanisms akin to that found by Attanasio and Davis (1996) in their study of wage inequality and consumption in the United States. Our results corroborate the notion that if income uncertainty has been growing over the recent past, as the data

suggest, then the failure of insurance between agents makes the precautionary motive for saving an increasingly important self-insurance mechanism.

Our analysis differs from previous work in this field in a number of important respects. Firstly, we provide a framework in which risks can be decomposed into common and cohort-specific components, which are allowed to enter the consumption model with different effects. Second, we use a long time-series of cross-sectional information on income and expenditure to estimate parameters of the income process and construct terms to measure the conditional variance of income risk. This allows us to control for cohort-specific fixed effects and consequently rely on the time series evolution of risk terms to identify precautionary saving effects. As made clear by Hayashi (1987), a long time series on consumption growth is essential for the estimation of the consumption growth model. Finally, we use income from all sources as opposed to wages or earnings, thus capturing, to some extent, changes in unemployment risk as well as changes in uncertainty relating to earnings or wages.

There are good reasons to break down aggregate risk into separate components—for a single group of households the estimate of overall risk will encompass shocks to the macro-economy and also shocks specific to individuals in the group (like, for instance, pension reform changes). In our empirical application we use generations or cohorts, *i.e.* groups defined according to the date of birth of the head of the household. One might expect various insurance mechanisms to operate between different generations, for example through Trade Unions, Pay-As-You-Go state pension schemes, or *inter-vivos* transfers (see the discussion in Deaton and Paxson (1994), for example).¹ This is another motivation for our separation of risk into cohort and aggregate components—if both correctly measure uninsurable risk they should have the same effect on consumption growth. If not, this will be indicated through the relative size of the separate coefficients. We use an income measure that includes all sources of non-asset income to the household in an attempt to account for various mechanisms that households have for pooling risk. In contrast to the use of earnings of the head, our measure therefore includes earnings of other family members and social security receipts.

The results of this paper provide direct evidence on the importance of the precautionary motive for saving in response to income risk, which has been the focus of substantial recent research. Much of this work has highlighted the role played by income risk in deriving consumption-saving rules over the life cycle.² The age-consumption profile, in the presence of precautionary savings, is tilted toward future consumption, *i.e.* consumers postpone consumption when income becomes risky.³ Dynan (1993), using the approximation to optimal consumption under uncertainty, considers the importance of the precautionary motive using panel data on expenditures and finds estimates of the importance of precautionary saving that are “too low to be consistent with widely accepted beliefs about risk aversion”. That study relied exclusively on the use of consumption data and had the attraction of using the variance of consumption to capture all forms of risk.

The distinguishing feature of our work is to use the time-series characteristics of both expenditure and income at the micro level to identify the importance of precautionary saving over a period in which there were important systematic changes to income risk. We

1. Recent literature in this area has addressed these issues with respect to informal, as opposed to formal, insurance mechanisms. See, for example, Udry (1994) or Townsend, (1994).

2. See Deaton (1992) for a survey of these issues in standard life-cycle models, or Weil (1993) for an application in the non-standard case where the link is broken between the elasticity of substitution and individuals' preferences over risk.

3. See, Blanchard and Mankiw, 1988 or Kimball, 1990, for example, or Deaton, 1990 for a survey.

are able to exploit the changing nature of income risk over the long time series of expenditure and income data available for the 1970s and 1980's.⁴ We separate individuals according to their date-of-birth cohort and allow for interactions with demographic and labour market characteristics. We can follow a representative sample from each group through our data (see Browning, Deaton and Irish (1987)). We also allow for cohort specific effects that may capture any permanent unobservable differences in uncertainty, or more general unobservable permanent differences in consumption growth across cohorts.

The plan of the paper is as follows. In the next section we present the framework for analysing risk pooling in a consumption growth model with precautionary savings. Section 3 describes the model we use for identifying changes in disaggregated income risks and the method of estimating the income processes from synthetic panel data on cohort groups. In Section 4 we describe the data used in the empirical analysis and Section 5 presents the results from the estimation of income processes. In Section 6, we evaluate the importance of the risk terms for consumption growth. To anticipate, we find the cohort specific risk terms to be significant, pointing to strong evidence against risk pooling across cohorts. These cohort specific risk terms also imply significant changes in precautionary saving over the period of study. In contrast, there is no evidence of changes in common risk terms leading to changes in precautionary saving over this period. Finally, Section 7 concludes.

2. CONSUMPTION GROWTH AND RISK POOLING

Individual preferences are assumed to display Constant Relative Risk Aversion so that within period utility has the form

$$U(C_t) = \left(1 - \frac{1}{\rho}\right)^{-1} e^{\phi_t} C_t^{1-(1/\rho)}, \quad (2.1)$$

where ρ is the intertemporal elasticity and where the preference parameter ϕ_t will be allowed to vary across types of consumers. Allowing borrowing at real interest rate r_t , these preferences imply that optimal consumption growth can be expressed as

$$\Delta \ln C_t = \rho \ln(r_t - \delta_t) - \rho \Delta \phi_t + m_t + v_t, \quad (2.2)$$

in which δ_t is the personal discount rate, m_t captures the impact of risk and v_t is the innovation to consumption growth such that $E_{t-1}(v_t) = 0$ (see Deaton (1992), for example)⁵. Of course, it may be that preferences and discount rates contain unobservable components and, in our empirical implementation, we will allow for additional unobserved transitory and permanent effects in the consumption growth equation. In this section, however, we wish to motivate the specification of the risk term m_t .

4. In a related study, Carroll (1994) combines information from one wave of the U.S. Consumer's Expenditure Survey with income data from the PSID to examine the impact of predictable components of income on consumption levels. He finds no evidence of consumers adjusting to differences between the predictable components of current vs. future income. However, he does find evidence of reduced consumption levels for individuals who face higher level of future income variability. Our use of both consumption and income, uniquely available in the long series of repeated cross-sections of the U.K. Family Expenditure Survey, allows us to avoid constructing an expected income profile for each individual.

5. In this paper we work within the framework of the life-cycle model with no liquidity constraints. However, one could potentially extend our analysis to a liquidity constraint model such as Zeldes (1989) and use the time-series information in risk terms to separately identify the effect of liquidity constraints from precautionary saving.

The risk term m_t tilts the consumption growth profile and can be directly related to the predictable components of income risk. For example, suppose income is log normal and follows the simple random walk specification

$$\ln Y_t = \ln Y_{t-1} + e_t, \quad (2.3)$$

with

$$E_{t-1}(e_t) = 0, \quad (2.4)$$

and conditional variance

$$E_{t-1} \text{Var}(e_t) = \sigma_t^2, \quad (2.5)$$

where E_{t-1} denotes the expectations operator conditional on information at time $t - 1$. The risk term m_t is related to the conditional variance σ_t^2 according to

$$m_t = k\pi_t\sigma_t^2, \quad (2.6)$$

where k is a positive coefficient and π_t is a scaling factor. The scaling factor π_t can be expressed as the square of the ratio of period $t - 1$ income to period $t - 1$ consumption C_{t-1} (see Appendix A for further details). It is the time series variation in the conditional variance $E_{t-1} \text{Var}(\eta_t)$ that identifies the impact of precautionary savings. This also motivates our use of an ARCH framework for modelling the income risk process σ_t^2 .

Note that the presence of the scaling factor π_t in (2.6) demonstrates that, under CRRA preferences, it is not sufficient to enter the income risk term alone—a scaling term is required by which “poorer” individuals are more responsive to changes in income risk (see the discussion in Browning and Lusardi (1997)). This term implies that it is the conditional variance of income innovations *relative* to expected wealth that matters in generating precautionary saving and this may be thought of as capturing the impact of the target wealth–income ratio that drives buffer-stock saving behaviour (see, Carroll, 1997).

Of course, the random walk process for income (2.3) is too simple. In our empirical application we consider two generalizations. First, we allow for a permanent–transitory error structure to income⁶ and second we allow for seasonal and demographic effects on income.

In the permanent–transitory formulation, income decomposes according to

$$\ln Y_t = \ln Y_t^P + \varepsilon_t, \quad (2.7)$$

where ε_t is the transitory shock to income and permanent income, $\ln Y_t^P$, follows a random walk

$$\ln Y_t^P = \ln Y_{t-1}^P + \eta_t, \quad (2.8)$$

with $E_{t-1}(\eta_t) = 0$. The $\ln Y_t$ process then has the following ARMA generalization of (2.3) with a unit autoregressive coefficient

$$\ln Y_t = \ln Y_{t-1} + \eta_t + \varepsilon_t - \varepsilon_{t-1} \quad (2.9)$$

$$= \ln Y_{t-1} + \xi_t - \theta\xi_{t-1}, \quad (2.10)$$

6. See Moffitt and Gottschalk (1995) and Blundell and Preston (1998), for example.

with $E_{t-1}\xi_t = 0$ is the pure innovation to income (see Hamilton, 1995, for example).

In Appendix A it is shown that the expression for the risk term m_t in (2.6) may now be written

$$m_t = \tilde{k}\pi_t\sigma_t^2, \quad (2.11)$$

with \tilde{k} given by

$$\tilde{k} = k \left[(1 - \theta) + \frac{r}{1 + r} \theta \right]^2, \quad (2.12)$$

where θ is the MA coefficient. Note that for small r , the term k in the original risk term (2.6) is simply adjusted by $(1 - \theta)^2$. Further note that if innovations are purely transitory then $\theta = 1$. Thus for purely transitory processes and small r there is no impact of income risk on consumption growth; the impact grows as the process becomes more persistent.⁷

To adjust the income process for demographic and seasonal factors we write

$$\ln Y_t^* = \ln Y_{t-1}^* + \xi_t - \theta\xi_{t-1}, \quad (2.13)$$

with $Y_t^* = Y_t/f(Z_{it})$. In Appendix A we show that the risk term continues to have the form $\tilde{k}\pi_t\sigma_t^2$ but with σ_t^2 measuring the conditional variance from the demographically and seasonally adjusted income process.

3. DISAGGREGATED INCOME RISKS

The identification of the common and cohort-specific components of innovations to income is carried out within an autoregressive moving-average structure for log income in which the conditional variances of the innovations in the process are allowed to change over time. Here we consider the estimation of these disaggregated risk terms and their inclusion in the consumption growth equation.

3.1. A dynamic model of income and income risk

The impact of risk on consumption growth acts through changes in the *expected* variance of innovations to income or wealth, not to changes in the variance itself. To derive an estimate of the time-series evolution in expected variance requires two steps. We first need to remove the persistent or predictable components of income. Then we need to model the conditional variance of the resulting innovations—that is, to derive a dynamic model for the “one-step ahead” prediction of the variance of innovations which are relevant for consumption growth.

To strip out persistent features of the income process we consider the following model for each individual i of a particular cohort c at time t :

$$\ln Y_{it} = \alpha_c \ln Y_{it-1} + Z'_{it}\beta_{c1} + Z'_{it-1}\beta_{c2} + u_{it}, \quad (3.1)$$

7. We thank one of the referees for pointing out this way of adjusting the scaling factors to take account of the degree of permanence of income shocks.

where $\ln Y_{it}$ is the natural log of total after-tax income, Z_{it} and Z_{it-1} are vectors of exogenous variables and β_{c1} and β_{c2} are cohort specific parameter vectors. Aggregating (3.1) over $i \in c$ we have

$$\ln Y_{ct} = \alpha_c \ln Y_{ct-1} + Z'_{ct} \beta_{c1} + Z'_{ct-1} \beta_{c2} + u_{ct}, \quad (3.2)$$

where Y_{ct} now refers to the geometric mean of Y_{it} . Even though, without panel data, Y_{it} and Y_{it-1} cannot be observed for the same individual, the geometric averages Y_{ct} and Y_{ct-1} can be estimated from repeated cross-sections on the same cohort in periods t and $t-1$.

The error term for the cohort level model (3.2) is assumed to have three components

$$u_{ct} = \varepsilon_c + \varepsilon_{at} + \varepsilon_{ct}, \quad (3.3)$$

where ε_c is a cohort specific fixed effect, ε_{at} is the common aggregate component of the error term and ε_{ct} is a (orthogonal) cohort specific error term. To complete the stochastic specification of the income process, ε_{at} and ε_{ct} are allowed to follow MA processes, e.g.

$$\varepsilon_{at} = \xi_{at} - \theta_a \xi_{at-1}, \quad (3.4)$$

and

$$\varepsilon_{ct} = \xi_{ct} - \theta_c \xi_{ct-1}, \quad (3.5)$$

where ξ_{at} and ξ_{ct} are white noise innovations. It is the predictable components of the variances of these innovations that are the determinants of precautionary saving. This requires a conditional heteroscedastic model for the variance of income innovations across time for each cohort.

The model for income is designed to capture persistence at the individual level and that this can be estimated controlling for other observable characteristics which vary across individuals. We assume the α , θ and β parameters to be time-invariant and common to all individuals in the cohort. In the empirical application below we allow a slightly richer dynamic structure but (3.2) is sufficient to capture all the modelling issues we wish to deal with in this section.⁸ This form corresponds to the stochastic process for income underlying the MaCurdy (1982) and Carroll (1994) studies.

The income process (3.2) with $\alpha_c = 1$ and $\beta_{c1} = \beta_{c2} = 0$ can also be thought of as a rearrangement of the permanent-transitory decomposition for income described in Section 2. In this formulation income decomposes according to

$$\ln Y_{ct} = \ln Y_{ct}^P + \varepsilon_{ct}, \quad (3.6)$$

where ε_{ct} is the transitory shock to income and permanent income $\ln Y_{ct}^P$, follows a random walk

$$\ln Y_{ct}^P = \ln Y_{ct-1}^P + \eta_{ct}, \quad (3.7)$$

8. Note that (3.2) includes the "common factor" model with the specification $\ln Y_{ct} = Z'_{ct} \beta_{c1} + \zeta_{ct}$ in which the error process has the form $\zeta_{ct} = \alpha_c \zeta_{ct-1} + \varsigma_{ct} - \theta_c \varsigma_{ct-1}$ giving $\ln Y_{ct} = \alpha_c \ln Y_{ct-1} + Z'_{ct} \beta_{c1} - Z'_{ct-1} \alpha_c \beta_{c1} + \varepsilon_{ct}$, where $\varepsilon_{ct} = \varsigma_{ct} - \theta_c \varsigma_{ct-1}$.

with $E_{t-1}(\eta_{ct}) = 0$. The $\ln Y_{ct}$ process has the following ARMA representation with a unit autoregressive coefficient

$$\ln Y_{ct} = \ln Y_{ct-1} + \eta_{ct} + \varepsilon_{ct} - \varepsilon_{ct-1} \quad (3.8)$$

$$= \ln Y_{ct-1} + \xi_{ct} - \theta_c \xi_{ct-1}, \quad (3.9)$$

where the moving average coefficient θ_c is related uniquely to the ratio of the variances of permanent to transitory shocks (see Hamilton, 1995, for example). Provided these variances move in proportion to one another, the conditional variance of the income innovations will capture the terms important for precautionary saving.

The empirical counterpart of the aggregate error component in (3.4) is

$$\hat{\varepsilon}_{at} = \frac{1}{N} \sum_c \hat{u}_{ct}, \quad (3.10)$$

where \hat{u}_{ct} is the residual from the estimated cohort level log income equation (3.2) in which cohort specific dummies have been included to capture the ε_c terms. The estimate of ε_{ct} in (3.5) is simply the remaining cohort specific error component

$$\hat{\varepsilon}_{ct} = \hat{u}_{ct} - \hat{\varepsilon}_{at}. \quad (3.11)$$

From these residuals the MA specification, (3.4) and (3.5), can be estimated by maximum likelihood. Further computational details are presented in the discussion of the empirical results in Section 5.

The income innovations ξ_{at} and ξ_{ct} are assumed to be ARCH processes in which the conditional means equal zero

$$E_{t-1}\xi_{at} = E_{t-1}\xi_{ct} = 0, \quad (3.12)$$

but the conditional variances are allowed to depend non-trivially on the information set generated from past observations of ξ_{at} and ξ_{ct} , the squares of these terms and the set of weakly exogenous variables in the model.⁹ In particular, we write

$$\begin{aligned} \sigma_{at}^2 \equiv E_{t-1}(\xi_{at}^2) &= \gamma_1 \xi_{a,t-1}^2 + \gamma_2 \xi_{ct-1}^2 + \gamma_3 \xi_{a,t-1} \\ &+ \gamma_4 \xi_{ct-1} + \gamma_5 \ln Y_{ct-1} + \gamma_6 \ln C_{ct-1} + \gamma_7 Z_{ct}, \end{aligned} \quad (3.13)$$

and

$$\begin{aligned} \sigma_{ct}^2 \equiv E_{t-1}(\xi_{ct}^2) &= \gamma_{c1} \xi_{a,t-1}^2 + \gamma_{c2} \xi_{ct-1}^2 + \gamma_{c3} \xi_{a,t-1} \\ &+ \gamma_{c4} \xi_{ct-1} + \gamma_{c5} \ln Y_{ct-1} + \gamma_{c6} \ln C_{ct-1} + \gamma_{c7} Z_{ct}, \end{aligned} \quad (3.14)$$

where Z_{ct} contains an exhaustive list of cohort specific and aggregate variables which we define in Section 4 below.¹⁰ To estimate we first compute the innovations ξ_{at} and ξ_{ct} from the MA processes for income and then use these to form the conditional heteroscedasticity terms (3.13) and (3.14).

9. See Bollerslev, Engle and Nelson (1994).

10. Note that the model for the aggregate variance contains cohort level as well as aggregate level variables since there is no reason that cohort specific terms should be restricted from the common information set. This also ensures the information set is common across all equations.

Notice that the measure of income risk for each cohort is based purely on the time-series residuals from the dynamic income estimation and does not contain any cross-section variation. This emphasizes the need for a long time series of income and consumption on each cohort.

3.2. Consumption growth and cohort level risk

To set out the precise specification by which the conditional variances of these income innovations enter the consumption growth model we assume CRRA preferences (2.1) for each individual i and write $\phi_{it} = \phi'Z_{it}$. This implies a consumption growth relationship given by

$$\Delta \ln C_{it} = \rho r_t - \rho \phi' \Delta Z_{it} - \rho \delta_i + m_{it} + v_{it}, \quad (3.15)$$

with $E_{t-1}v_{it} = 0$. The risk term m_{it} now captures the disaggregation of income risk into the common aggregate component and the cohort specific component

$$m_{it} = \tilde{k}_a[\pi_{it}\sigma_{at}^2] + \tilde{k}_c[\pi_{it}\sigma_{ct}^2] + \kappa_{it}. \quad (3.16)$$

The two risk terms, $\pi_{it}\sigma_{at}^2$ and $\pi_{it}\sigma_{ct}^2$, simply arise from the separation of the income innovation into aggregate and cohort level shocks. The \tilde{k}_a and \tilde{k}_c coefficients take the form

$$\tilde{k}_a = k_a(1 - \theta_a)^2 \quad \text{and} \quad \tilde{k}_c = k_c(1 - \theta_c)^2,$$

reflecting the aggregate and cohort level MA coefficient adjustments to the coefficients k_a and k_c (see (3.4) and (3.5)). These follow from (2.12) assuming r is small. Note that since θ_c differs across cohorts the \tilde{k}_c parameter will be cohort specific. The κ_{it} term in (3.16) captures the impact of idiosyncratic risk, and π_{it} is given by

$$\pi_{it} = \left[\frac{Y_{it-1}}{C_{it-1}} \right]^2, \quad (3.17)$$

as before. Cohort aggregation of (3.15) yields

$$\Delta \ln C_{ct} = \rho r_t - \rho \phi' \Delta Z_{ct} - \rho \delta_c + m_{ct} + v_{ct}, \quad (3.18)$$

where C_{ct} refers to the within cohort geometric average of C_{it} for period t . The risk term m_{ct} is the cohort average of (3.16) given by

$$m_{ct} = \tilde{k}_a[\pi_{ct}\sigma_{at}^2] + \tilde{k}_c[\pi_{ct}\sigma_{ct}^2] + \kappa_{ct}, \quad (3.19)$$

where π_{ct} and κ_{ct} are the within cohort averages for each period t of the individual factors in (3.17) and (3.16). Although π_{it} depends on lagged consumption and income, panel data is not required and π_{ct} is still fully identified in the cohort averages for repeated cross section data.¹¹

11. Note that without panel data the within cohort idiosyncratic risk term κ_{ct} is not fully identified. In this study we assume κ_{ct} is captured by cohort, regional and seasonal effects as well as the included ΔZ_{ct} terms. Banks, Blundell and Brugiavini (1997) show that identification of idiosyncratic risk terms is possible in pseudo panel data provided prior information is available on the MA and autoregressive coefficients. In that paper identification was achieved by assuming the same MA and autoregressive coefficients as at the cohort level. However, this did not change the results for the common and cohort specific risk effects reported here and, as it was based on a rather weak form of identification, we have chosen not to include these terms in this study.

Given estimates of the MA coefficients θ_a and θ_c , the underlying k_a and k_c parameters can be recovered. A positive k_a or k_c parameter implies that risk induces a delay in spending and current consumption is therefore reduced. It is interesting to note that these parameters should be equal under the assumption that the terms $\pi_{ct}\sigma_{at}^2$ and $\pi_{ct}\sigma_{ct}^2$ both capture uninsurable risk. As a result we can assess the degree to which the measured conditional variance reflects uncertainty. Further, the difference between k_a and k_c reflects the relative degree to which each component of income risk is insurable.

4. THE PSEUDO PANEL DATA

To estimate our model we make use of 25 consecutive years of the Family Expenditure Survey (FES) running from 1968 to 1992. This Survey contains detailed information on expenditure, income and demographic characteristics of British households as well as data on earnings of the individual family members. We select seven “cohorts” of households—all those in which the head is born between 1923 and 1950—and from these we exclude the self-employed, primarily because income from self-employment is widely recognized as suffering from mis-reporting in the FES.¹² This leaves a sample of 71,055 households of which the youngest cohort in the sample is aged 18 in 1968 and 45 in 1992, and the oldest is aged 42 in 1968 and 69 in 1992. We choose this age group because each cohort is observed at working ages throughout the sample period. In addition we need a long time-series on each cohort individually, since our income processes will be estimated for each cohort separately and will require long T . Table 1 presents summary statistics relating to the cohort decomposition we use.

TABLE 1
Cohort definition, FES, 1968q1–1992q4

Cohort number	Date of Birth	Min. age in sample	Max. age in sample	Average cellsize	10th percentile	90th percentile
1	1923–26	42	69	111	96	125
2	1927–30	38	65	98	85	114
3	1931–34	34	61	96	78	118
4	1935–38	30	57	98	81	114
5	1939–42	26	53	99	83	115
6	1943–46	22	49	111	90	131
7	1947–50	18	45	120	92	146

We split each year of data into quarterly time periods and include seasonal dummies in all the estimation that follows. The sample divides equally over the year so the resulting cell sizes are sufficiently large. Our aim is to investigate the resolution of income uncertainty over the life cycle and how this is reflected in consumption growth. All variables and interaction terms in the consumption growth equation are exactly aggregated from the micro-level data on a quarterly basis giving a balanced panel of 100 time-series observations for each of the seven cohorts. As described in the next section, we control for the endogeneity of labour supply and demographic variables by using lags as instruments in all estimation equations.

12. Rather than capturing true income volatility our results would be affected by measurement error with unpredictable effects on the final estimates of our assumed income error scheme. In fact, we cannot say how the mis-reporting of self-employment income varies over time and across cohorts.

The income definition is real total household income excluding any asset income but including benefit income. As we consider the dynamics of income rather than simply earnings we are in some sense including uncertainty in the employment state as well as the level of earnings. We do this deliberately since labour market participation may well account for much of observed income uncertainty and therefore precautionary saving. Therefore we include benefits in our income definition to account for the income attached to the non-participation state. The consumption growth equation is estimated using real total household non-durable non-housing expenditure deflated by a (household specific) non-durable non-housing Stone price index. We use household aggregates of income and expenditure and hence will need to control for household size by the inclusion of demographic variables in all analysis. The interest rate used is the real 3-month treasury bill interest rate. Figure 1 shows the time series' of log income and expenditure for each cohort in our sample and indicates the cross-cohort variation in the two main processes of interest. Note that it is important to allow different cohort profiles to capture the low-frequency life-cycle changes. In addition, high frequency fluctuations in income and expenditure are clearly visible. A full set of sample descriptive statistics for each cohort in our study is included in Appendix B.

The long period over which this data is available is of particular importance to the analysis of consumption growth and precautionary saving. For consumption growth the time series must be sufficient to average out macro shocks (see Hayashi, 1987, for a discussion of this point). For income the time series information must be sufficient to remove persistence from the income series. Cross-section variance in income will be dominated by permanent differences in individual incomes. Cohort level analysis on this data has the advantage of providing a long time series of information on individuals

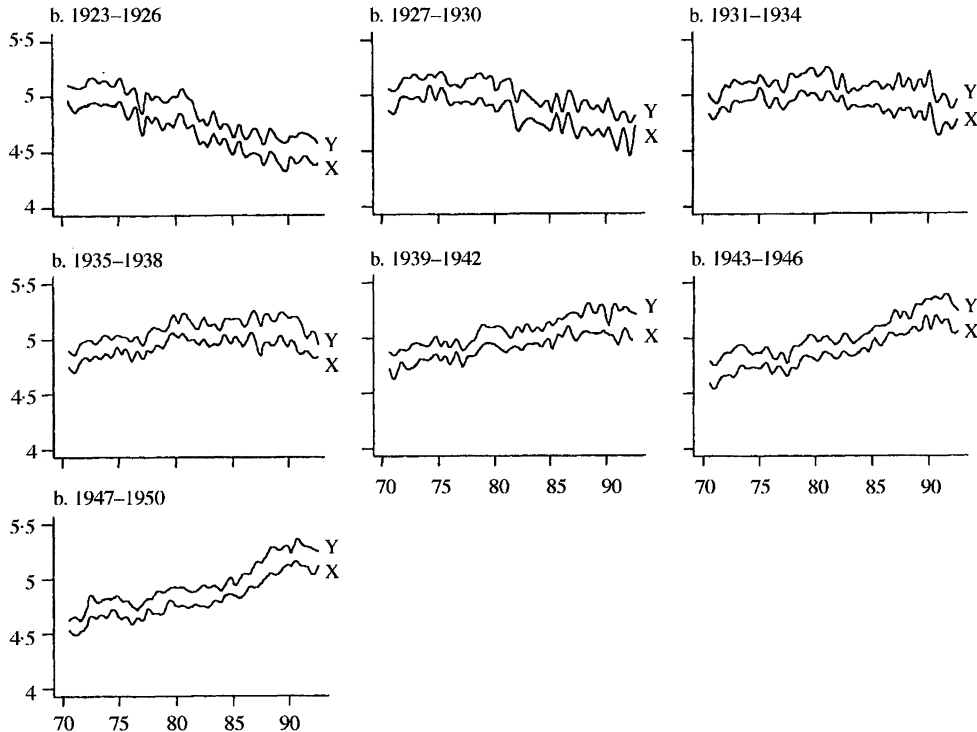


FIGURE 1

Log income (Y) and log expenditure (X) by cohort and year

drawn from the same subpopulation while avoiding the biases that result from aggregate time series analysis.

5. INCOME PERSISTENCE AND INCOME UNCERTAINTY

Many empirical studies have documented the steadily increasing income and earnings inequality in the U.K. over the last twenty years. In particular, Goodman, Johnson and Webb, 1997, provide a detailed breakdown of rising cross-sectional variances of all component of household incomes using the Family Expenditure Survey data from which we draw the sample of households used in this paper. In a related study, Blundell and Preston, 1998, identify differences between the increasing variance of income and the increasing variance of consumption in the same FES data to demonstrate that at least part of this increasing cross-sectional variance of income has been due to rising levels of income uncertainty as opposed to permanent inequality. This study also shows important differences across cohorts. Given this result we allow income risk to be cohort specific as set out in Section 3. Therefore, in this section we document estimated income processes for each of our cohorts individually. The residuals from each model are used to define an innovation process for income from which the conditional variances can be derived as described earlier.

The key results of this exercise are presented in Table 2 which gives the cohort specific AR and MA coefficients. The high AR coefficients, even after controlling for demographic and labour supply variables, coupled with well-known inference difficulties in high-persistence time-series processes lead us to focus on results using the ARIMA(0, 1, 1) specification. In Table 2 the innovation to the income process for each cohort is split into two components—the common and the cohort-specific part—as defined in (3.10) and (3.11).

TABLE 2
Income process results

Income process: $\ln Y_t = \alpha \ln Y_{t-1} + X'_t \beta_1 + Z'_{t-1} \beta_2 + u_t - \theta u_{t-1}$								
Cohort (1)	Cohort (2)	Cohort (3)	Cohort (4)	Cohort (5)	Cohort (6)	Cohort (7)	Aggregate	
(a) ARIMA(0, 1, 1)								
α	1.00	1.00	1.00	1.00	1.00	1.00	—	
S.E.	—	—	—	—	—	—	—	
θ	0.780	0.665	0.668	0.657	0.753	0.802	0.297	
S.E.	0.067	0.068	0.074	0.071	0.066	0.071	0.107	
(b) ARIMA(1, 0, 1)								
α	0.978	0.910	0.820	0.928	0.976	0.978	0.965	—
S.E.	0.024	0.042	0.070	0.036	0.043	0.028	0.030	—
θ	0.555	0.606	0.476	0.627	0.743	0.714	0.656	0.257
S.E.	0.071	0.071	0.076	0.072	0.084	0.075	0.063	0.111

Note: All income processes control for regional and seasonal effects as well as changes in labour supply and demographic structure. Full parameter estimates for each cohort are reported in Appendix A. Each column corresponds to a cohort (see Table 1 for cohort definitions).

Each innovation is allowed to follow a separate MA(1) process and hence will possess a separate conditional variance. As can be seen, the common component in each cohort's aggregate risk has an MA coefficient significantly lower in absolute value than those of each cohort's cohort-specific component and hence the common process will display higher persistence. Full results for each cohort's income equation are presented

in Appendix B. Although our final specification allows an MA(1) structure for the error terms, in our specification search we initially allow for a fifth order MA structure but could not reject that the process is simply an MA(1), which we subsequently impose.

Some guide to the magnitude and evolution of the variances of the common and cohort innovations over our sample is given in Figure 2. In this figure we plot the smoothed profile for the common (aggregate) component and the cohort-specific component of the variance, *i.e.* ξ_{at}^2 and ξ_{ct}^2 , for each cohort separately.¹³ To smooth the data we simply plot the predictions of a cohort-specific linear regression of the two variances on seasonal dummies and a fifth-order polynomial trend. As can be seen the relative magnitude of the variances is such that the variances of the cohort innovations is larger than that of the common innovations. What is striking, however, as in Figure 2, is that different cohorts do appear to have experienced different patterns of risks over the sample period. This is particularly interesting in the light of Figure 1, which shows, for some cohorts at least, similar paths of consumption and income over our time period. Cohorts 1 and 2, for example, are both close to the end of their working lives in our sample but display very different patterns for the cohort specific scaled income innovations.

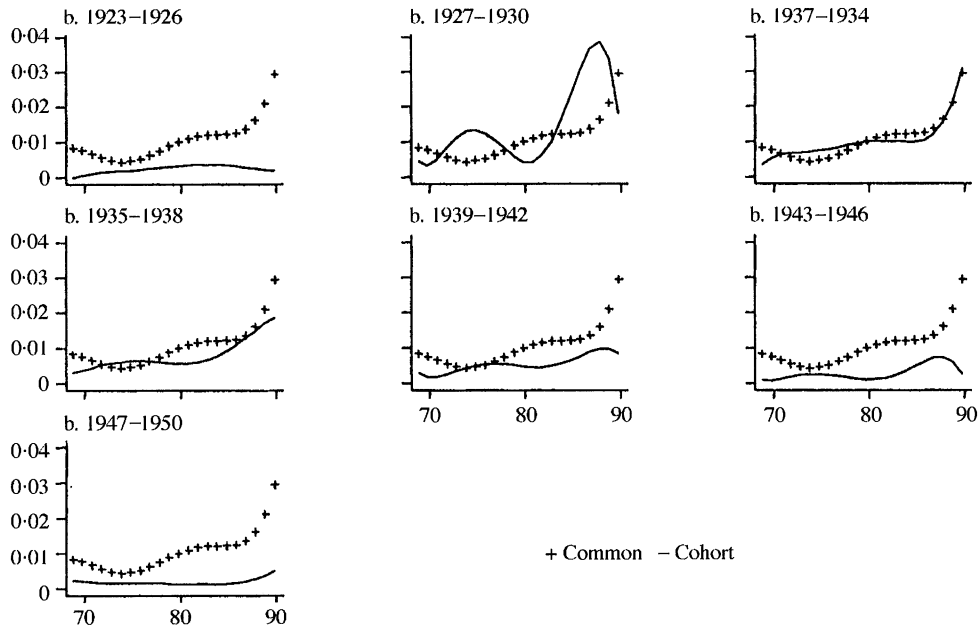


FIGURE 2

Smoothed variances of income innovations, by cohort and year

13. Since the variances enter the Euler equation with a scaling factor we plot the smoothed scaled variances in Figure 2. These variances are adjusted for the degree of permanence of the shocks as described in the Appendix. As the scaling factors are cohort specific the resulting "common" component may differ slightly across cohorts. The sample averages for each cohort's variances are 0.003, 0.012, 0.010, 0.008, 0.005, 0.002 and 0.001 respectively, compared to a sample average conditional variance for the common shocks of 0.014.

6. EVIDENCE ON RISK POOLING

To study the impact of precautionary saving on consumption growth we consider the cohort and time specific averages for (log) non-durable expenditure and make use of the conditional variance of the income innovations estimated in Section 5. We allow for cohort specific effects in consumption growth capturing differences across cohorts in subjective discount rates and idiosyncratic risk. The estimating equation for consumption growth therefore takes the form

$$\Delta \ln C_{ct} = \rho r_t - \rho \phi' \Delta Z_{ct} + \tilde{k}_a \pi_{ct} \xi_{at}^2 + \tilde{k}_c \pi_{ct} \xi_{ct}^2 + \psi' D_{ct} + \omega_{ct}, \quad (6.1)$$

where D_{ct} contains the cohort specific, regional and seasonal dummies. It may also be the case that v_{it} in the individual consumption growth equation (3.15) contains some MA(1) terms reflecting either measurement error in $\ln C_{ct}$ or transitory preferences and hence estimation will use information and instruments dated $t - 2$ and before. The moment condition

$$E_{t-2} \omega_{ct} = 0, \quad (6.2)$$

therefore defines our GMM estimator of the unknown parameters of consumption growth.

As a baseline model we estimate a conventional consumption growth equation for our sample, *i.e.* excluding the aggregate and cohort risk terms $\pi_t \xi_{at}^2$ and $\pi_{ct} \xi_{ct}^2$. In later sets of results we include these risk terms. There is strong evidence of a MA(1) process in the consumption growth residuals with coefficients of the order of -0.5 although there is little evidence of higher order MA terms. This justifies our use of instruments dated $t - 2$ in all regressions (including the conditional expectation for the variance of income shocks) as defined above and as a result we also correct all the standard errors for the presence of first-order autocorrelation. In addition we use optimally reweighted instruments taking account of this autocorrelation and also the presence of heteroscedasticity of unknown form (see Newey and West (1987)). Estimation of the intertemporal substitution elasticity from the log-linearized Euler equation using cross-section or short time series data is likely to be severely biased (see Hayashi (1987) or Deaton (1992)). However, using a long time series for each cohort and including cohort fixed effects and the risk terms explicitly, avoids these potential biases.

In all estimation results the change in employment variable is, for obvious reasons, treated as endogenous. Unlike in previous studies, however, we condition on changes in the demographic variables by treating them as exogenous in estimation of both consumption and income models. We do this because we want to examine the effect of changes in the conditional variance of income innovations controlling for the effect on consumption of all changes in demographic circumstances, whether these were predictable or not.

Table 3 presents estimates from the baseline consumption growth specification with no risk terms on the right-hand side of the model, although lagged risk terms are included in the consumers information set as we want to keep the instrument set consistent across specifications. The estimated elasticity of intertemporal substitution in this model, which allows nothing apart from household size, employment status and the real interest rate to affect consumption growth, is 0.461 implying a coefficient of relative risk aversion of -2.17 , which is in accordance with previous estimates based on cohort

analyses of the U.K. data (see, for example, Blundell, Browning and Meghir, 1994). In addition, we find important effects of demographic changes on consumption growth as in other studies (Attanasio and Weber (1993) or Banks, Blundell and Tanner (1998) for example).

TABLE 3
*Baseline consumption growth specification:
No income risk*

Coefficient		
ρ	0.461	<i>0.189</i>
Demographic factors:		
Age of head	-0.007	<i>0.004</i>
Δ Children	0.080	<i>0.015</i>
Δ Adults	0.360	<i>0.022</i>
Δ Employed	0.466	<i>0.094</i>
Sargan	153.51	
D.F.	124	
GR ²	0.536	

Notes

(1) Region, season and cohort effects included in all specifications.

(2) Standard errors (in italics) are corrected for heteroscedasticity and the presence of an MA(1) in the errors.

(3) Instruments for all equations are all lagged two periods or more. In addition to lagged values of cohort and aggregate variances, these comprise consumption, income, nominal interest rates, inflation, work status variables, age and age², aggregate GDP growth, unemployment rates, the level and variance of stock market returns and interactions of cohort dummies with demographic and work status variables.

In the first column of Table 4 we introduce the two conditional variance terms in the consumption growth model (6.1). As noted in Section 3, since the MA coefficients and the π terms are pre-estimated, the k_a and k_c coefficients are estimated directly. This specification uses the ARIMA(0, 1, 1) process for log income from Table 2 above and includes the innovations and squared innovations (both appropriately scaled as defined above and in Appendix A) at the aggregate and cohort levels. Since we include these terms suitably lagged in the instrument set, the estimator effectively replaces the squared innovations with their conditional expectations as discussed in (3.13) to (3.14) above.

A rise in the expected variance of income innovations represents an increase in income risk and should depress period t consumption hence increasing the growth of consumption between t and $t + 1$. The coefficient on the cohort variance term, k_c , is positive and significant as expected, but the coefficient on the aggregate variance term, k_a is insignificant. This suggests that the important changes in income risk for consumption growth over this period have been cohort specific.¹⁴

14. Very similar results were found for the specification that allows each cohorts income process to have $\alpha_c < 1$. As an additional sensitivity analysis we estimate consumption growth equations for the ARIMA(1, 0, 0) case where income innovations are assumed to be white noise. Whilst quantitatively similar, these results show a slightly higher degree of intertemporal substitution and increased importance for the conditional variances, as would be expected. All of these results are available on request.

TABLE 4
Common risks and consumption growth

Coefficient	(1)		(2)	
ρ	0.511	0.189	0.509	0.189
k_a	-0.088	0.134	—	—
k_c	0.927	0.358	0.876	0.357
Demographic factors:				
Age of head	-0.010	0.004	-0.011	0.004
Δ Children	0.080	0.015	0.079	0.015
Δ Adults	0.356	0.042	0.357	0.022
Δ Employed	0.473	0.097	0.475	0.096
Sargan	147.05		148.11	
D.F.	122		123	
GR ²	0.540		0.538	

Note: Instruments for all equations are as in Table 3.

If one were to have a prior estimate of the proportion of income risk which was insurable one could use our model to “back out” an alternative estimate of the coefficient of relative risk aversion. Treating our approximation in Appendix A as exact, and assuming all income risk is uninsurable, our estimate of k would imply a higher value of ρ than that which we find in Table 4. This in turn suggests that at least some of the cohort income risk is insurable.

Although the aggregate and cohort specific income innovations are constructed to be orthogonal there is no reason why the conditional variances should not be correlated. In column (2) of Table 4, we examine a specification that only includes cohort conditional variance term. There is very little impact of this exclusion reinforcing our conclusion that the important changes in income risk for consumption growth over this period have been cohort specific.¹⁵

Our approach to the identification of precautionary saving effects requires the conditional variance of the innovations to be changing over time, and this may be why the common risk term does not enter significantly. Such an interpretation would be supported by Figure 2. To investigate this further, we estimated a simple OLS regression of the Euler equation residuals on the actual aggregate and cohort income innovations, ξ_{at} and ξ_{ct} . Both enter significantly and positively with coefficients and standard errors 0.117 (0.022) and 0.342 (0.034) respectively. This is clear evidence of important effects on consumption growth of uninsured aggregate shocks in addition to their cohort-specific counterparts. But since the risk terms in the consumption growth equations (6.1) and (6.2) are identified from changes in income risk over time, this suggests there is insufficient predictable time series variation in aggregate income risk in our sample.

Finally, to provide some idea of the order of magnitude of these effects, we can evaluate the impact of a rise in income risk. In particular, we consider an increase in the scaled conditional variance by an amount equal to the average within-cohort interquartile range (a number equal to 0.0068 over our sample period). The estimates in Table 4 suggest that, other things being equal, such an increase would depress current consumption by 0.6 of a per cent.

15. The aggregate risk term remains insignificant but becomes small and positive if included in a specification without the cohort risk terms. A full set of results are available from the authors on request.

7. SUMMARY AND CONCLUSIONS

This paper has used a twenty-five year time series of micro-data on income and consumption, uniquely available in Britain, to analyse the role of income risk in a cohort model of consumption growth. Income risk has been decomposed into two separate sources: that which is common to all cohorts and that which is specific to particular date of birth cohorts. The aim has been to evaluate the importance of income risk for consumption growth and to assess the degree to which there is evidence of income pooling, or risk sharing, across generations.

Under Constant Relative Risk Averse preferences the scaled conditional variance of uninsured innovations enters additively in consumption growth to tilt consumption towards the future. The scaling of the conditional variance is required to account for the increasing importance of risk among lower wealth households and for the degree of permanence of the income shocks. If the precautionary saving motive is important, and uninsurable income risks can be shown to have changed, then these changes in uncertainty ought to have affected consumption growth. If income risks are insured across generations then only the common risk component ought to enter.

In order to assess the importance of these precautionary savings effects, an autoregressive moving-average structure for the process of log income was estimated for each cohort using the long time series of British micro data. This dynamic model for log income also included a multitude of observable factors. The scaled conditional variances of the innovations from these regressions were then used to construct risk terms which were added to an empirical model of consumption growth. Using a decomposition of the innovations into common and cohort specific components, we found that the different components of income risk enter consumption growth in differing ways. More precisely, that it is the cohort-specific element of this risk as opposed to the part that is common across all cohorts that is important for consumption growth. These effects enter in addition to demographic and labour supply effects and it is worth emphasizing that, because we include cohort specific effects in all our analysis, these results are entirely driven by the time variation in the risk components.

In summary, the empirical work reported in this paper shows strong evidence of the importance of precautionary saving. In addition, our results agree with Attanasio and Davis (1996), who, using a different technique, find a failure of the hypothesis of between-group consumption insurance in the U.S. We would argue that the between-group insurance hypothesis is also not consistent with the evidence we present for Britain.

APPENDIX

Consumption growth and risk with CRRA preferences

If we let W_t denote the value of current financial wealth plus the present value of future incomes at period t and let $\zeta_t = W_t - E_{t-1}W_t$ denote the innovation to W_t . Suppose that optimal consumption C_t is approximately proportional to W_t

$$C_t \simeq cW_t,$$

for some c . By the Euler equation and intertemporal budget constraint

$$\begin{aligned} C_{t-1}^{-1/\rho} &\simeq E_{t-1}(cW_t)^{-1/\rho} \\ &= E_{t-1}(c\{(W_{t-1} - C_{t-1})(1+r) + \xi_t\})^{-1/\rho}. \end{aligned}$$

Taking a Taylor expansion around $E_{t-1}(\xi_t) = 0$ i.e. $E_{t-1}W_t = (W_{t-1} - C_{t-1})(1+r) \equiv \bar{W}_t$ gives

$$\begin{aligned} C_{t-1}^{-1/\rho} &\simeq (c\bar{W}_t)^{-1/\rho} \left[1 + \frac{1+\rho}{2\rho^2} \frac{Y_{t-1}^2}{(c\bar{W}_t)^2} \text{Var}_{t-1}(\xi_t) \right] \\ &\equiv (c\bar{W}_t)^{-1/\rho} [1 + k\pi_t^2\sigma_t^2], \end{aligned}$$

where the scaling factor $\pi_t = Y_{t-1}^2/(c\bar{W}_t)^2$ and the ξ_t refer to the innovations in the random walk log income process. Rearranging we have

$$C_{t-1} \simeq cE_{t-1}W_t [1 + k\pi_t^2\sigma_t^2]^{-\rho},$$

and therefore

$$\frac{C_t}{C_{t-1}} \simeq \frac{W_t}{\bar{W}_t} (1 + k\pi_t^2\sigma_t^2)^\rho.$$

Thus consumption growth depends on the conditional variance of income innovations scaled by expected wealth (squared) through the term $\pi_t^2\sigma_t^2$ as derived in Blundell and Stoker (1998). Consequently we may write

$$\Delta \ln C_t \simeq k\pi_t^2\sigma_t^2 + v_t.$$

Note that the v_t may be directly related to innovation in the income process as shown in Blundell and Preston (1998), for example. In the empirical implementation we replace the expected wealth term $c\bar{W}_t$ in the scaling factor $\pi_t = Y_{t-1}^2/(c\bar{W}_t)^2$ by C_{t-1} .

These expressions generalize for more general income processes. For example, suppose the income process has an MA(1) structure with MA coefficient θ . In this case it is straightforward to show that the new scale coefficient k becomes

$$\tilde{k} = k \left[(1 - \theta) + \frac{r}{1+r}\theta \right]^2, \tag{7.1}$$

or simply adjusted by $(1 - \theta)^2$ for small r . Thus purely transitory processes with $\theta = 1$ there is very little impact and the impact grows as the process becomes more persistent.

Finally consider the impact of adjusting income for seasonal and demographs, so that adjusted $Y_t^* = Y_t/f(Z_{it})$. The innovation ξ_t in the expression above now refers to the innovation in Y_t^* . However, note that the adjustment $f(Z_{it})$ also enters the scaling factor and consequently cancel out from the risk term.

APPENDIX B

Complete income process results

TABLE B1(a)
Estimated income processes by date of birth cohort
FES Data, 1968–1992, ARIMA(1, 0, 1) and (0, 1, 1) specifications

Variable	Dependent variable $\ln Y_t$		Dependent variable $\Delta \ln Y_t$	
	Parameter	S.E.	Parameter	S.E.
<i>Cohort born 1923–1926</i>				
$\ln Y_{t-1}$	0.978	0.024		
Spring	–0.003	0.018	–0.002	0.018
Autumn	–0.008	0.013	–0.008	0.013
South	–0.023	0.129	–0.053	0.124
Δ Employed	0.510	0.144	0.507	0.146
Δ Children	0.082	0.052	0.086	0.053
Δ Adults	0.378	0.053	0.380	0.054
Constant	0.122	0.111	0.022	0.036
<i>Cohort born 1927–1930</i>				
$\ln Y_{t-1}$	0.910	0.042		
Spring	0.019	0.016	0.019	0.016
Autumn	0.037	0.016	0.038	0.017
South	0.122	0.129	0.084	0.128
Δ Employed	1.062	0.179	1.075	0.188
Δ Children	0.050	0.049	0.060	0.050
Δ Adults	0.440	0.062	0.458	0.066
Constant	0.410	0.202	–0.030	0.039
<i>Cohort born 1931–1934</i>				
$\ln Y_{t-1}$	0.820	0.070		
Spring	0.003	0.016	–0.002	0.017
Autumn	–0.002	0.021	–0.002	0.023
South	0.218	0.105	0.183	0.109
Δ Employed	0.720	0.165	0.789	0.188
Δ Children	0.053	0.033	0.058	0.034
Δ Adults	0.340	0.046	0.326	0.051
Constant	0.865	0.346	–0.047	0.032
<i>Cohort born 1935–1938</i>				
$\ln Y_{t-1}$	0.928	0.036		
Spring	0.000	0.015	–0.000	0.016
Autumn	–0.017	0.019	–0.018	0.020
South	–0.097	0.100	–0.093	0.102
Δ Employed	0.727	0.173	0.762	0.178
Δ Children	0.040	0.035	0.044	0.036
Δ Adults	0.331	0.059	0.348	0.060
Constant	0.402	0.187	0.036	0.033

S.E. = Standard Error.

TABLE B1(b)

*Estimated income processes by date of birth cohort
FES Data, 1968–1992, ARIMA(1, 0, 1) and (0, 1, 1) specifications*

Variable	Dependent variable $\ln Y_t$		Dependent variable $\Delta \ln Y_t$	
	Parameter	S.E.	Parameter	S.E.
<i>Cohort born 1939–1942</i>				
$\ln Y_{t-1}$	0.976	0.043		
Spring	0.031	0.015	0.031	0.015
Autumn	0.035	0.015	0.035	0.015
South	0.181	0.118	0.194	0.120
Δ Employed	0.766	0.272	0.778	0.270
Δ Children	-0.014	0.034	-0.013	0.033
Δ Adults	0.315	0.068	0.320	0.068
Constant	0.055	0.224	-0.068	0.036
<i>Cohort born 1943–1946</i>				
$\ln Y_{t-1}$	0.978	0.028		
Spring	-0.011	0.015	-0.012	0.015
Autumn	-0.000	0.015	0.000	0.015
South	0.162	0.108	0.182	0.106
Δ Employed	0.629	0.190	0.657	0.180
Δ Children	0.015	0.038	0.020	0.039
Δ Adults	0.056	0.081	0.512	0.082
Constant	0.067	0.152	-0.049	0.034
<i>Cohort born 1947–1950</i>				
$\ln Y_{t-1}$	0.965	0.030		
Spring	0.033	0.019	0.033	0.019
Autumn	0.030	0.018	0.030	0.018
South	-0.015	0.097	-0.039	0.095
Δ Employed	0.786	0.169	0.804	0.173
Δ Children	0.044	0.059	0.053	0.061
Δ Adults	0.270	0.107	0.272	0.112
Constant	0.168	0.149	0.005	0.033

S.E. = Standard Error.

TABLE B2

Parameter estimates from estimation of
 $u_{ct} = \xi_{ct} + \theta_1 \xi_{ct-1} + \theta_2 \xi_{ct-2} + \theta_3 \xi_{ct-3} + \theta_4 \xi_{ct-4} + \theta_5 \xi_{ct-5}$

Parameter	Cohort 1923–1926		Cohort 1927–1930		Cohort 1931–1934	
	θ_1	-0.631	0.123	-0.683	0.114	-0.509
θ_2	0.227	0.139	-0.057	0.138	0.037	0.140
θ_3	-0.069	0.118	0.138	0.160	0.158	0.145
θ_4	-0.031	0.117	0.030	0.153	-0.005	0.126
θ_5	0.043	0.110	0.002	0.146	0.050	0.110
σ	0.038	0.003	0.043	0.002	0.042	0.003

Parameter	Cohort 1935–1938		Cohort 1939–1942		Cohort 1943–1946		Cohort 1947–1950	
	θ_1	-0.665	0.115	-0.538	0.122	-0.754	0.106	-0.736
θ_2	0.126	0.125	-0.113	0.123	-0.021	0.137	-0.019	0.155
θ_3	-0.188	0.148	0.099	0.108	0.208	0.134	0.182	0.171
θ_4	0.215	0.146	-0.045	0.126	-0.129	0.129	0.078	0.163
θ_5	-0.076	0.124	-0.057	0.111	-0.103	0.111	-0.166	0.125
σ	0.037	0.002	0.044	0.003	0.036	0.002	0.044	0.002

TABLE B3(a)
Sample statistics, by cohort

Variable	Mean	S.D.	Min	Max
<i>Cohort born 1923–1926</i>				
Age of head	1.61271	0.6888752	0.440458	2.756604
Δ No. of children	-0.0145425	0.1009654	-0.2755353	0.263262
Δ No. of adults	-0.0059729	0.1205607	-0.3376193	0.2574816
Δ Head employed	-0.0099696	0.0548619	-0.1356838	0.1441348
Log real income	4.872418	0.201158	4.49816	5.164613
Log real non-durable expenditure	4.674153	0.2064287	4.309422	5.013725
House owned outright	0.2847938	0.15543	0.0660377	0.6416667
House owned on mortgage	0.2420685	0.1016388	0.0322581	0.4227642
No. of earners	1.35133	0.6407349	0.1415094	2.149123
Head white collar or professional	0.1786713	0.0919552	0	0.3675214
ln (Y/C)	1.325876	0.0783948	1.186278	1.613826
ln (Y ² /C ²)	2.089517	0.3605322	1.51371	3.953263
<i>Cohort born 1927–1930</i>				
Age of head	1.211571	0.6896808	0.0361905	2.364444
Δ No. of children	-0.019044	0.1344274	-0.3848289	0.2510684
Δ No. of adults	-0.0040432	0.0987642	-0.2300506	0.2417295
Δ Head employed	-0.0073936	0.0445727	-0.13	0.137276
Log real income	5.014328	0.1350198	4.727927	5.259578
Log real non-durable expenditure	4.814949	0.1527544	4.397555	5.148386
House owned outright	0.2459875	0.1410971	0.0348837	0.5773196
House owned on mortgage	0.3342694	0.0922609	0.1340206	0.5104167
No. of earners	1.578783	0.470528	0.4536082	2.234043
Head white collar or professional	0.2145592	0.0739367	0.0309278	0.3604651
ln (Y/C)	1.332824	0.1030402	1.128085	1.607841
ln (Y ² /C ²)	2.134586	0.4641475	1.408804	3.794009
<i>Cohort born 1931–1934</i>				
Age of head	0.8145869	0.6899789	-0.3579832	1.958333
Δ No. of children	-0.0222589	0.1624309	-0.628355	0.8049924
Δ No. of adults	-0.0011072	0.1246724	-0.3030262	0.3216782
Δ Head employed	-0.0051619	0.0662007	-0.2288416	0.1524725
Log real income	5.075137	0.0951577	4.835866	5.280511
Log real non-durable expenditure	4.879029	0.105942	4.602036	5.106217
House owned outright	0.1765911	0.1122121	0.0111111	0.4642857
House owned on mortgage	0.4409687	0.0726028	0.2380952	0.5777778
No. of earners	1.688377	0.3074949	0.797619	2.202831
Head white collar or professional	0.2293934	0.0597984	0.0963855	0.4235294
ln (Y/C)	1.318117	0.1063681	1.111883	1.607981
ln (Y ² /C ²)	2.044539	0.4118807	1.374114	3.08416

S.D. = Standard Deviation.

TABLE B3(b)
Sample statistics, by cohort

Variable	Mean	S.D.	Min	Max
<i>Cohort born 1935–1938</i>				
Age of head	0.4114432	0.6897052	-0.7752381	1.569149
Δ No. of children	-0.0183918	0.181398	-0.4300414	0.4615386
Δ No. of adults	0.0008719	0.1251109	-0.3002267	0.3293104
Δ Head employed	-0.0036151	0.0449608	-0.1252204	0.1105769
Log real income	5.08241	0.1172763	4.828129	5.311255
Log real non-durable expenditure	4.907765	0.1014609	4.681043	5.089151
House owned outright	0.1311506	0.0836991	0.0208333	0.345679
House owned on mortgage	0.5106375	0.0557167	0.3535354	0.6517857
No. of earners	1.703327	0.2314748	1.272727	2.25
Head white collar or professional	0.2270798	0.0514249	0.3535354	0.377551
ln (Y/C)	1.288506	0.0948241	1.092258	1.513954
ln (Y ² /C ²)	1.950783	0.4116577	1.369557	3.801318
<i>Cohort born 1939–1942</i>				
Age of head	0.0116457	0.6892953	-1.151485	1.167778
Δ No. of children	-0.0118019	0.1676466	-0.3979266	0.444595
Δ No. of adults	0.0018307	0.124046	-0.3326833	-0.3501637
Δ Head employed	-0.0016164	0.0402439	-0.1171562	0.1047431
Log real income	5.061094	0.1492973	4.704373	5.419632
Log real non-durable expenditure	4.890941	0.1326101	4.606692	5.172838
House owned outright	0.0841083	0.0505225	0	0.2346939
House owned on mortgage	0.5697478	0.0625751	0.3645833	0.6904762
No. of earners	1.636477	0.188095	1.235849	2.113636
Head white collar or professional	0.2347545	0.0557086	0.0769231	0.3564357
ln (Y/C)	1.280475	0.0943688	1.139903	1.578861
ln (Y ² /C ²)	1.922666	0.3905098	1.420863	3.440877
<i>Cohort born 1943–1946</i>				
Age of head	-0.388883	0.6878119	-1.555056	0.761165
Δ No. of children	-0.0045691	0.1443992	-0.2769645	0.3557617
Δ No. of adults	-0.0028189	0.0661315	-0.1706855	0.209259
Δ Head employed	-0.002094	0.0408177	-0.0866667	0.1096552
Log real income	5.01538	0.1925508	4.630214	5.461026
Log real non-durable expenditure	4.846042	0.1846294	4.50517	5.32153
House owned outright	0.0608936	0.0415732	0	0.1949152
House owned on mortgage	0.5977622	0.0852014	0.2857143	0.74
No. of earners	1.550219	0.1674273	1.27381	2.044445
Head white collar or professional	0.2514414	0.0537192	0.0813954	0.3434343
ln (Y/C)	1.279912	0.0787228	1.114106	1.47035
ln (Y ² /C ²)	1.920279	0.3084502	1.432396	3.231714

S.D. = Standard Deviation

TABLE B3(c)
Sample statistics, by cohort

Variable	Mean	S.D.	Min	Max
<i>Cohort born 1947–1950</i>				
Age of head	-0.7731092	0.6780047	-1.8875	0.3814516
Δ No. of children	0.0061969	0.151849	-0.3635987	0.3753881
Δ No. of adults	0.0029124	0.0689709	-0.154009	0.1925404
Δ Head employed	-0.001208	0.0466575	-0.17	0.1195652
Log real income	4.941163	0.2198016	4.470747	5.4177824
Log real non-durable expenditure	4.784351	0.1992375	4.395241	5.18839
House owned outright	0.034215	0.0229695	0	0.106383
House owned on mortgage	0.5671744	0.1555484	0.1846154	0.7910448
No. of earners	1.476156	0.1294017	1.15625	1.808511
Head white collar or professional	0.2412785	0.0541448	0.0967742	0.398374
ln (Y/C)	1.269138	0.0812858	1.11165	1.582016
ln (Y ² /C ²)	1.890615	0.2747996	1.407928	2.987186

S.D. = Standard Deviation

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REFERENCES

- ANGRIST, J. (1991), "Grouped Data Estimation and Testing in Simple Labor Supply Model", *Journal of Econometrics*, **47**, 243–265.
- ATTANASIO, O. P. and BROWNING, M. (1995), "Consumption over the Life Cycle and over the Business Cycle", *American Economic Review*, **85**, 1118–1137.
- ATTANASIO, O. P. and WEBER, G. (1993), "Consumption, the Interest Rate and Aggregation", *Review of Economic Studies*, **60**, 631–650.
- ATTANASIO, O. P. and DAVIS, S. (1996), "Relative Wage Movements and the Distribution of Consumption", *Journal of Political Economy*, **104**, 1227–1262.
- BALLIE, R. T. and BOLLERSLEV, T. (1992), "Prediction in Dynamic Models with Time Dependent Variances", *Journal of Econometrics*, **52**, 91–114.
- BANKS, J. W., BLUNDELL, R. and BRUGIAVINI, A. (1998), "Risk Pooling, Precautionary Saving and Consumption Growth", (UCL Discussion paper 97/03).
- BANKS, J. W., BLUNDELL, R. and TANNER, S. (1998), "Is There a Retirement Savings Puzzle? *American Economic Review*, **88**, 769–788.
- BLANCHARD, O. and MANKIW, N. G. (1988), "Consumption Beyond Certainty Equivalence", *American Economic Review*, **78**, 173–177.
- BLUNDELL, R., BROWNING, M. and MEGHIR, C. (1994), "Consumer Demand and the Life-Cycle Allocation of Household Expenditures", *Review of Economic Studies*, **61**, 57–80.
- BLUNDELL, R. and STOKER, T. (1998), "Consumption and the Timing of Income Risk", *European Economic Review*, March, **43**, 475–507.
- BLUNDELL, R. and PRESTON, I. (1998), "Consumption Inequality and Income Uncertainty", *Quarterly Journal of Economics*, **113**, 603–640.
- BOLLERSLEV, T., ENGLE, R. F. and NELSON, D. B. (1994), "ARCH Models", in R. F. Engle and D. L. McFadden (eds.), *Handbook of Econometrics* (Amsterdam: Elsevier Science B.V.).
- BROWNING, M., DEATON, A. and IRISH, M. (1985), "A Profitable Approach to Labour Supply and Commodity Demands over the Life-Cycle", *Econometrica*, **53**, 503–544.
- BROWNING, M. and LUSARDI, A. (1996), "Household Saving: Micro Theories and Micro-Facts", *Journal of Economic Literature*, **34**, 1795–1855.
- CABALLERO, R. J. (1990), "Consumption Puzzles and Precautionary Savings", *Journal of Monetary Economics*, **25**, 113–136.
- CABALLERO, R. J. (1991), "Earnings Uncertainty and Aggregate Wealth", *American Economic Review*, **81**, 859–871.
- CARROLL, C. D. (1994), "How Does Future Income Affect Current Consumption", *Quarterly Journal of Economics*, **109**, 111–148.
- CARROLL, C. D. (1997), "Buffer-Stock Saving and the Life-Cycle/Permanent Income Hypothesis", *Quarterly Journal of Economics* (forthcoming).
- DEATON, A. (1992) *Understanding Consumption* (Oxford: Oxford University Press).
- DEATON, A. and PAXSON, C. (1994), "Intertemporal Choice and Consumption Inequality", *Journal of Political Economy*, **102**, 437–467.
- DYNAN, K. (1993), "How Prudent are Consumers", *Journal of Political Economy*, **101**, 1104–1113.
- GOTTSCHALK, P. and MOFFITT, R. (1994), "The Growth of Earnings Instability in the U.S. Labor Market", *Brookings Papers on Economic Activity*, **II**, 217–272.
- GOODMAN, A., JOHNSON, P. and WEBB, S. (1997) *Inequality in the U.K.* (Oxford: Oxford University Press).
- HANSEN L. P. and SINGLETON, K. J. (1982), "Generalized Instrumental Variables Estimation of Non Linear Rational Expectations Models", *Econometrica*, **50**, 1269–1286.
- HAMILTON, J. (1995) *Time Series Econometrics* (London: Macmillan).
- HAYASHI, F. (1987), "Tests for Liquidity Constraints: A Critical Survey and Some New Observations", in T. Bewley (ed.), *Advances in Econometrics: Fifth World Congress*, Vol. 2 (Cambridge: Cambridge University Press), 91–120.
- KIMBALL, M. S. (1990), "Precautionary Savings in the Small and in the Large", *Econometrica*, **58**, 53–73.
- MACURDY, T. F. (1982), "The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis", *Journal of Econometrics*, **18**, 83–114.

- MODIGLIANI, F. and BRUMBERG, R. (1954), "Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data", in K. K. Kurihara (ed.), *Post-Keynesian Economics* (New Brunswick: Rutgers University Press).
- MOFFITT, R. (1993), "Identification and Estimation of Dynamic Models with a Time-Series of Repeated Cross-Sections", *Journal of Econometrics*, **59**, 99–123.
- MOFFITT, R. and GOTTSCHALK, P. (1995), "Trends in the Covariance of Earnings in the United States: 1969–1987", (Discussion Paper 1001, Institute for Research on Poverty, 1995).
- NEWKEY, W. K. and WEST, K. D. (1987). "A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix", *Econometrica*, **55**, 703–708.
- SKINNER, J. (1988), "Risky Income, Life Cycle Consumption, and Precautionary Savings", *Journal of Monetary Economics*, **22**, 237–255
- TOWNSEND, R. M. (1994), "Risk and Insurance in Village India", *Econometrica*, **62**, 539–591.
- UDRY, C. (1994), "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria", *Review of Economic Studies*, **61**, 495–526.
- WEIL, P. (1993), "Precautionary Saving and the Permanent Income Hypothesis", *Review of Economic Studies*, **60**, 367–384.
- ZELDES, S. (1989), "Consumption and Liquidity Constraints: An Empirical Analysis", *Journal of Political Economy*, **97**, 305–346.