The Econometrics of Income Dynamics and Rotating Panels, with an Application to Precautionary Saving*

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Abstract

This paper is concerned with modelling the stochastic process of income, when its dynamics are given by an aggregate and an individual specific factor. A two-stage methodology is proposed to estimate the parameters of each component. The properties of different estimators are discussed in a rotating panel context, that is, given the number of individuals in each cross-section, the number of periods that an specific individual is observed and the total the number of waves (of the survey). I use this framework to model income dynamics in a Spanish household rotating panel with information on family expenditure. I obtain measures of idiosyncratic and aggregate income risks, which are then used as explanatory variables in a consumption growth equation. This allows me to assess the importance of precautionary saving in response to different sources of income uncertainty.

Keywords: income dynamics, income risk, rotating panel, precautionary saving
JEL classification: C23, D12, D91

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1 Introduction

In this paper, I try to model household income as a dynamic process subject to both idiosyncratic and common shocks. In the literature, earnings processes are estimated for many purposes;[1] the objective is to identify the statistical parameters in the stochastic process of income: say, the persistence of income, the (conditional) variance of income, etc... These parameters [2] are later used to test between different models of the determinants of income distribution, to analyse the time series variation in the earnings distribution, to model labour supply (see Abowd and Card, 1989), to check the impact of anticipated earnings growth in consumption Euler equations (see Browning and Lusardi, 1996) or to determine the earnings risk faced by individuals. As an illustration, in my empirical application, I will analysis if individuals save in order to protect their future consumption against bad outcomes in income: that is, if they make a precautionary demand for saving so as to smooth consumption across states of nature. Therefore, I have to compute the conditional variances of shocks to income and, then, check if these measures of earnings risk have a significant effect on consumption growth.

As a significant point of departure from most of the existing literature, I discuss how to estimate the statistical process of both aggregate *and* idiosyncratic factors in income. In previous work with micro data, the earnings process facing individuals was estimated given the aggregate business-cycle conditions, but without explicitly modelling them.[3] Nevertheless, it is important to separately identify common and idiosyncratic stochastic factors in income when studying precautionary saving. Aggregate shocks to income can only be smoothed (across state of nature) through the self-insurance that precautionary saving provides, whereas individuals can more easily get insured against idiosyncratic shocks because these can be "shared" with other individuals (to the extent that they are not perfectly correlated). Therefore, different dynamics needs estimating for idiosyncratic and for aggregate shocks; then, the conditional variances of each shock can be used as suitable measures of income risk, which have different key roles for decision making.

Just recently, a few papers have paid attention to the issue of estimating panel data models with serial correlation in the time effects as well as in the idiosyncratic errors. In Skoglund and Karlsson (2001a, 2001b), some asymptotic results are presented for random effects models, and Raknerud (2001) suggests a state space approach. It is worth noting that separate identification of parameters referred to idiosyncratic and common components is only possible if both the number of individuals and the number of time periods are large.

For my empirical application, I am using a special kind of data, a long rotating panel of households: the Spanish family expenditure survey (ECPF). This data has a number of

[1] See Álvarez, Browning and Ejrnæs (2001) for a brief survey.

[2] These *are not* behavioural parameters, although individuals may make their decisions taking into account such features of earnings.

[3] Indeed, there are good reasons to follow such an approach. For instance, when analysing earnings mobility (see Álvarez, 1999), one wants to focus on individual transition probabilities: i.e., the chance that an individual changes her relative position in the income distribution of two consecutive periods, but controlling for the different aggregate conditions in each period. On the other hand, aggregate dynamics can be analysed by its side, either neglecting or accounting for heterogeneity; see Blundell and Stoker (2000) for further discussion.

interesting features itself and has recently attracted international attention (see Browning and Collado, 2001). In particular, each household is followed, at most, eight consecutive quarters: this makes the ECPF comparable to an standard short panel. This is crucial to identify idiosyncratic dynamics, as compared to, say, the time series of repeated cross-sections available to Banks, Blundell and Brugiavini (1999), who also study precautionary saving.[4] Moreover, the ECPF is available for a long time period: twelve years in a quarterly basis. Thus, the aggregate (i.e., common to all individuals) dynamics can be studied, although different individuals are observed in each round of the survey.

The case of rotating panels is a convenient general framework, because some interesting questions are raised. Identification and inference of the different components are discussed given three dimensions: the number of individuals in each cross-section (say N), the number of periods that an specific individual is observed until she is replaced (say T_i), and the total number of periods available in the data set (that is, the number of rounds, say T). Thus, these results can be straightforwardly applied to genuine panels and to time series of repeated cross-sections as particular cases: in the former case, an individual is followed (unless there is attrition) for all periods ($T_i = T$ and N is also the total number of individuals ever observed) and, in the latter case, each individual is surveyed only once ($T_i = 1$).

I propose a methodology in which estimation of the parameters in the dynamic process of each component is carried out in two steps. First, the parameters in the individual component are estimated conditioning on the aggregate component (that is, capturing its effect by time-dummies). Then, this aggregate component is recovered (based upon an estimate of the individual process) and I proceed to estimate the aggregate process. This procedure is shown to be as efficient as joint estimation for the aggregate component.

Finally, in the empirical section, the rotating nature of the Spanish data is exploited to identify idiosyncratic and aggregate income risks. These conditional variances of idiosyncratic and aggregate shocks to income are then used as explanatory variables in a consumption growth equation. Hence, I assess the importance of precautionary saving in response to different sources of income uncertainty. Moreover, cohort-specific (rather than aggregate) risk is found to be significant; this fact implies a failure of between-cohort insurance mechanisms.

The rest of the paper is organised as follows. Section 2 presents the ingredients of the econometric problem I am interested in: the econometric modelling of individual and aggregate income dynamics from rotating panels; later, I propose a methodology of estimation and discuss its properties. In section 3, I move to the empirical application; results are shown and discussed in section 4. Finally, section 5 concludes.

[4]Even a similar rotating panel as the Consumer Expenditure Survey in the US is not as good in this respect as the Spanish survey.

2 Econometric Framework

2.1 Econometric Model of Income Dynamics

Now, I will consider a variable y_{it} which is determined by two mutually independent components:

$$y_{it} = z_t + u_{it}, \qquad i = 1, ..., I; \quad t = 1, ..., T \tag{1}$$

The component z_t could be regarded as an aggregate effect (at a cohort level or at the economy level) and u_{it} as an idiosyncratic component. Here, I am interested in estimating the parameters governing the statistical process of both z_t and u_{it}. For simplicity, let me consider that each one follows a simple AR(1) process:

$$u_{it} - \eta_i = \alpha \left(u_{i(t-1)} - \eta_i \right) + v_{it} \tag{2}$$

$$z_t = \beta z_{t-1} + \varepsilon_t \tag{3}$$

where $E\left[v_{it}\varepsilon_{t-k}\right] = 0, \quad \forall i, t, k$. I will assume that are both mean independent of their own past, that is, $E\left[\left. v_{it} \right| I_{t-1}^{v}\right] = 0$ and $E\left[\left. v_{it} \right| I_{t-1}^{\varepsilon}\right] = 0$, where I_{t-1}^{v} and I_{t-1}^{ε} represent, respectively, the information set at time $t-1$. I also regard v_{it} as statistically independent of v_{js} for $i \neq j$ and for any t and s. Furthermore, I consider that individual specific and common shocks are conditionally heteroskedastic:

$$\begin{aligned} E\left[\left. v_{it}^2 \right| I_{t-1}^{v}\right] &= \phi_0 + \phi_1 v_{i(t-1)}^2 \\ E\left[\left. \varepsilon_t^2 \right| I_{t-1}^{\varepsilon}\right] &= \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 \end{aligned}$$

These conditional variances capture the one period ahead expected volatility in income; as previously commented, these statistical features of the household income process might be very relevant for consumption decisions. I will also assume that the unconditional variances of v_{it} and ε_t are finite: $E\left[v_{it}^2\right] = \sigma_v^2 < \infty$ and $E\left[\varepsilon_t^2\right] = \sigma_\varepsilon^2 < \infty$.

Indeed, y_{it} admits a reduced form representation as an ARMA(2,1) process:

$$y_{it} = (\alpha + \beta)\, y_{i,t-1} - \alpha\beta y_{i,t-2} + (1-\alpha)(1-\beta)\,\eta_i + v_{it} - \beta v_{i,t-1} + \varepsilon_t - \alpha\varepsilon_{t-1}$$

But this formulation has an important disadvantage: aggregate dynamics (parameters β, ϕ_0 and ϕ_1) cannot be distinguished from individual dynamics (parameters α, γ_0 and γ_1). On the other hand, focusing on y_{it} as define in $(2)-(3)$, the dynamics depends upon three latent unobservable factors: the aggregate component (z_t), the idiosyncratic component (u_{it}) and the individual-specific mean of the latter component (η_i). Skoglund and Karlsson (2001a, 2001b) write down a joint log-likelihood for all these latent components. This "random effects" strategy allows to integrate out all the unobservable components. However, this joint approach may be computationally costly. Moreover, it is not clear how robust the results are to some distributional assumptions (specially, those concerning with the statistical relationship of η_i and the initial condition of u_{it}).

The way in which I proceed is the following. First, all my analysis is conditional on η_i (that is, a "fixed effect" approach). The idea is to focus on a transformation of the original data y_{it} (the within-group transformed data, the first differenced data, etc.), such that the transformed data does not depend on η_i; thus, the information about the parameters of interest contained in the distribution of η_i will not be considered.Next, I have to distinguish aggregate and idiosyncratic dynamics. Similarly, the original data y_{it}, $i = 1, ..., I; \quad t = 1, ..., T$ can be transformed as follows: one the one hand, I compute each cross-sectional mean of the data $\overline{y}_{\cdot t} = \frac{1}{N}\sum_{i=1}^{N} y_{it}, \quad t = 1, ..., T$ and, on the other hand, one can work with the data in deviation from these cross-sectional means: $\widetilde{y}_{it} = y_{it} - \overline{y}_{\cdot t}$, $i = 1, ..., I; \quad t = 1, ..., T$. It is worth noting that the same information is contained in the original and in the transformed data.[5] Looking at the original formulation of the model in $(1) - (3)$, it is easy to see that:

$$
\begin{aligned}
\widetilde{y}_{it} &= \widetilde{u}_{it}, \qquad i = 1, ..., I; \quad t = 1, ..., T \\
\overline{y}_{\cdot t} &= z_t + \overline{u}_{\cdot t}, \qquad t = 1, ..., T
\end{aligned}
$$

subject to $(2) - (3)$. So, one can finally work with a re-formulation of the model which only depends on observables

$$
\begin{aligned}
\widetilde{y}_{it} - \widetilde{\eta}_i &= \alpha \left(\widetilde{y}_{it} - \widetilde{\eta}_i\right) + \widetilde{v}_{it}, \qquad i = 1, ..., I; \quad t = 1, ..., T \qquad (4) \\
\overline{y}_{\cdot t} &= \beta \overline{y}_{\cdot t-1} + \varepsilon_t + \overline{u}_{\cdot t} - \beta \overline{u}_{\cdot t-1}, \qquad t = 1, ..., T \qquad (5)
\end{aligned}
$$

with $\widetilde{y}_{it}$ following an AR(1) process[6] and $\overline{y}_{\cdot t}$ expressed as an ARMA(1,1), since the error term includes not only ε_t but also $\overline{u}_{\cdot t}$ and $\overline{u}_{\cdot t-1}$. The interesting point here is that, similarly to the transformation used to remove η_i, equation (4) contains information only about individual specific dynamics, whereas (5) captures both idiosyncratic and aggregate dynamics. Again, one could focus just on (4) to learn about α (also ϕ_0 and ϕ_1), neglecting (5) at some cost of efficiency. Marshall (1992), in a related context, uses this procedure to distinguish individual specific and aggregate dynamics. As previously commented, I will not work directly with (4), which still contains η_i, but with its first differenced version.

Now, I stop discussing for a moment how to estimate the parameters of interest in the transformed model. In the next subsection, I will consider the specific challenges that one faces when working with rotating panels as I do in my empirical application.

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[5] Actually, the transformation has more than full rank if one uses all the individuals in deviation from means.

[6] In this formulation, a minor problem remains: even after assuming that v_{it} and v_{jt} for $i \neq j$ are independent, $\widetilde{v}_{it}$ and $\widetilde{v}_{jt}$ are cross-sectionally correlated (due to the presence of $\overline{v}_{\cdot t}$) as opposed to the standard dynamic model for panel data without time effects.

2.2 Dynamic Modelling in Rotating Panels

Genuine panel data (where all individuals are observed every period) is still relatively rare.[7] Instead, researchers may find repeated surveys. Most of these surveys are just repeated cross-sections (for instance, the British Family Expenditure Survey, FES), where a new large random sample is drawn for each round. There also exists rotating panels, where a given individual is just observed for several consecutive periods (and afterwards a new individual is interviewed in her place). Nonetheless, the originally design of the latter was also more concerned with having a cross-sectionally representative samples than with overcoming the problems of genuine panels.

Deaton (1985) suggested to construct a "pseudo-panel" or "synthetic panel" from a time series of repeated cross-sections. The idea is to take means of variables for individuals in a group of fixed membership (defined by year of birth or education); then these means are treated as a panel data observation for this group or "cohort" (which can be tracked over time). This technique has important advantages itself, because one can get long panels without attrition and measurement errors are averaged out. Collado (1997) extended the work of Deaton to dynamic models. Moffitt (1993) provides a discussion of grouping as an instrumental variable estimator for repeated cross-section.[8]

Deaton proved that his procedure provides consistent estimates of the parameters in the "cohort population version of the model". Thus, this technique assumes that the relevant relationship holds at the cohort level; then, either the relationship at the individual level only differs by an individual disturbance from that or it is not regarded as of interest. Put in terms of the model discussed in the previous subsection, they are looking at (1) with interest just in (3) and assuming that the individual deviation u_{it} from z_t are just white noise disturbances. However, one could be interested in the individual process of the data; furthermore, identifying both an aggregate and an individual process would be crucial in some economic applications as the one I am interesting in.

Thus, the econometric analysis of rotating panels (as the Spanish family expenditure survey, ECPF) raises a number of interesting questions. Similarities are expected to be found with the "fixed T" micro panels when analysing the individual process and with the "long T" synthetic panels when analysing the aggregate one. The crucial point is to know the extent to which the survey design allows to identify either of them. When working with rotating panels, one has to pay attention to three dimensions.

1. First, how many individuals are interviewed each period, that is, the size of each cross-section. Without loss of generality, I assume that the size of the cross-section remains constant from one period to another: let me say in each cross-section N individuals are observed.

[7] The PSID has a long history in the US; in Europe, just recently, a new survey (the European Community Household Panel, ECHP), is been carrying out in many countries of the European Union. However, only four waves (1994, 1995, 1996 and 1997) are available so far, and information on some areas (including consumption) is very limited.

[8] Deaton (1985) and Collado (1997) use an error-in.variables estimator, as the observed cohort aggregates are error-ridden measurements of the true cohort population values. Moffitt (1993), as customary in empirical applications, neglects this issue appealing to large within cohort size.

2. Second, how long a specific individual is followed by the survey. Let me say that an individual is interviewed by T_i periods; put into other words, the fraction of individuals dropped from the sample from one period to another is $1/T_i$.

   This two dimensions are given by the design of the survey.

3. Finally, how many rounds of the survey have been carried out up to the moment (when the researcher use the data set).

As an illustration, about 3200 households are interviewed each period (each quarter in this case) in the ECPF and a given household is observed for (at most) eight periods; here, I have use forty-eight periods. So, $N = 3200$, $T_i = 8$ and $T = 48$. However, after filtering the data set and as I will later consider two aggregate factors in household income (one at the cohort level and other at the economy level), the cross-sectional dimension which is relevant for me is N between 30 and 150.

In general, T_i can be regarded as fixed (ie, a short T_i framework) as in the standard micro-panels literature; but unless T_i is long enough, no dynamic individual component could be identified (for instance, with $T_i = 1$ as in the repeated cross-sections). On the other hand, the time dimension T can be viewed as quite long, similarly to the synthetic panels approach. Note that a genuine panel is characterised by $T_i = T$: the most distinctive feature of a rotating panel is that T_i and T can be different.

In the Figure I, I graphically describe the structure of a rotating panel. After T waves, the total number of individuals that have been interviewed is $I = N + (T-1)\,N/T_i$. The rotating panel can be also viewed as an incomplete panel of I individuals potentially observed for T periods. So, a variable y_{it} could be observed for $i = 1, ..., I$ and $t = 1, ..., T$, but it is actually observed $(y_{it} \cdot S_i^t)$, where S_i^t takes on one if the individual i is observed in period t and zero otherwise. It is easy to see that

$$S_i^t = 1\left((t-1)\frac{N}{T_i} + 1 \leq i \leq (t-1)\frac{N}{T_i} + N\right)$$

where $1(\bullet)$ is the indicator function, which takes on one if the expression inside the brackets holds and zero otherwise.

Variables $(y_{it} \cdot S_i^t)$ observed in the rotating panel are selected from the underlying variable y_{it} in the complete panel. This "selection" S_i^t is determined by an exogenous deterministic rule: that given by the survey design. Therefore, it is reasonable to assume that:

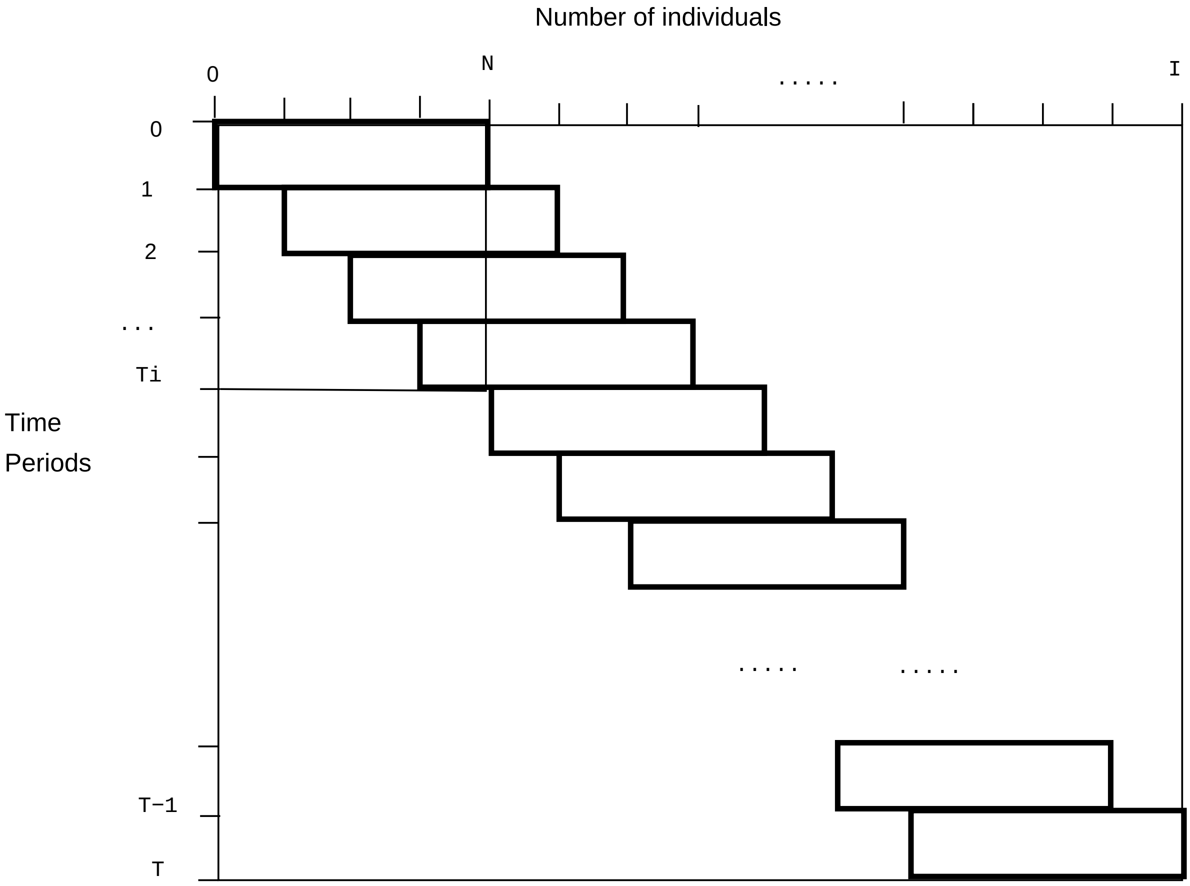
$$E\left[y_{it}^* \middle| X_{it}, S_i^t\right] = E\left[y_{it}^* \middle| X_{it}\right] \tag{6}$$

This implies directly that $E\left[y_{it} \middle| X_{it}, S_i^t\right] = E\left[y_{it}^* \middle| X_{it}\right] \cdot S_i^t$; so, provided that $E\left[y_{it}^* \middle| X_{it}\right]$ is identified in the data, any conditional inference is not affected by S_i^t.

2.3 Identification of the Parameters of Interest

So, I want to identify the parameter in the model

Figure I: Structure of Rotating Panels



$$\begin{aligned} \widetilde{y}_{it} - \widetilde{\eta}_i &= \alpha\left(\widetilde{y}_{it} - \widetilde{\eta}_i\right) + \widetilde{v}_{it}, \qquad i = 1, ..., I; \quad t = 1, ..., T \\ \overline{y}_{\cdot t} &= \beta \overline{y}_{\cdot t-1} + \varepsilon_t + \overline{u}_{\cdot t} - \beta \overline{u}_{\cdot t-1}, \qquad t = 1, ..., T \end{aligned}$$

where the data y_{it} comes from a rotating panel so I only observed $(y_{it} \cdot S_i^t)$. This does not pose any special problem if one wants to identify α. It is easy to see that y_{it-2} is uncorrelated with $\Delta\widetilde{v}_{it}$ since $E\left[v_{it} \middle| I_{t-1}^v\right] = 0$ and v_{it} and v_{jt}, for $i \neq j$, are independent; this directly implies that the following moment condition holds:

$$\underset{N,T\to\infty}{\text{plim}} \frac{1}{NT} \sum_{i,t} \left(\prod_{k=1}^{3} S_i^k \cdot y_{it-2}\right) \left[\Delta\left(y_{it} - \overline{y}_{\cdot t}\right) - \alpha\Delta\left(y_{it-1} - \overline{y}_{\cdot t-1}\right)\right] = 0 \qquad (7)$$

where $\prod_{k=1}^{3} S_i^k$ accounts for the rotating nature of data. Another important point here is that $\overline{y}_{\cdot t} = \frac{1}{N}\sum_{i=1}^{I} S_i^t y_{it}$.

2.4 An Arellano-Bond-type Estimator for the Individual Process

I first re-write equation (1) using (2) to get

$$y_{it} - z_t - \eta_i = \alpha \left(y_{i(t-1)} - z_{t-1} - \eta_i \right) + v_{it}$$

where λ_t are regarded as parameters to be estimated. The parameter α can be identified using the following quite standard orthogonality conditions (see Arellano and Bond, 1991):

$$E\left[y^{t-2} \left(\Delta y_{it} - \alpha \Delta y_{i(t-1)} - \Delta \left(z_t - \alpha z_{t-1} \right) \right) \right] = 0, \quad t = 3, ..., T$$

In the standard literature of micro panel, the aggregate component z_t is not modelled, but treated as fixed parameter identified in $E\left[y_{it} - z_t \right] = 0$, since $u_{it} = \alpha^t u_{i0} + \sum_{k=0}^{t-1} \alpha^k v_{i(t-k)}$ and $E\left[v_{it} \right] = 0, \quad \forall t$. In this subsection, I try to understand how this conditional analysis links to my previous sections.

As an example consider, a simple case where $T_i = 4$ and $T = 6$ (and there are N individuals in each cross section), so I can write dowm the empirical counterpart of the former orthogonality conditions:

$$\begin{aligned}
\frac{1}{N} \sum y_{i1} \prod_{k=1}^{3} S_i^k \left(\Delta y_{i3} - \alpha \Delta y_{i2} - \Delta \left(z_3 - \alpha z_2 \right) \right) &= 0 \\
\frac{1}{N} \sum \begin{pmatrix} y_{i1} \prod_{k=1}^{4} S_i^k \\ y_{i2} \prod_{k=2}^{4} S_i^k \end{pmatrix} \left(\Delta y_{i4} - \alpha \Delta y_{i3} - \Delta \left(z_4 - \alpha z_3 \right) \right) &= 0 \\
\frac{1}{N} \sum \begin{pmatrix} y_{i2} \prod_{k=1}^{4} S_i^k \\ y_{i3} \prod_{k=1}^{4} S_i^k \end{pmatrix} \left(\Delta y_{i5} - \alpha \Delta y_{i4} - \Delta \left(z_5 - \alpha z_4 \right) \right) &= 0 \qquad (8) \\
\frac{1}{N} \sum \begin{pmatrix} y_{i3} \prod_{k=1}^{4} S_i^k \\ y_{i4} \prod_{k=1}^{4} S_i^k \end{pmatrix} \left(\Delta y_{i6} - \alpha \Delta y_{i5} - \Delta \left(z_6 - \alpha z_5 \right) \right) &= 0
\end{aligned}$$

$$\frac{1}{N} \sum S_i^t \left(y_{it} - z_t \right) = 0, \quad t = 1, ..., T$$

This can be more synthetically re-written in the following way:

$$\frac{1}{N} \sum_i \begin{pmatrix} S_i y_i \\ Z_i H v_i \end{pmatrix} = 0$$

where v_i (and equivalently for y_i) is the $(T \times 1)$ vector of errors v_{it}, $t = 1, ..., T$ for an individual i, $i = 1, ..., I$, and S_i is a $(T \times T)$ diagonal matrix[9] of the form $S_i = diag\left(S_i^1, S_i^2, ..., S_i^T \right)$

Moreover, H is a $(T-1) \times T$ matrix of the following form

[9]In the case of a genuine panel, $S_i = I_T$.

$$H=\begin{pmatrix} -1 & 1 & 0 & 0 & \cdots & 0 \\ 0 & -1 & 1 & 0 & & 0 \\ \vdots & & \ddots & \ddots & \cdots & \vdots \\ 0 & 0 & \cdots & -1 & 1 & 0 \\ 0 & 0 & \cdots & 0 & -1 & 1 \end{pmatrix}$$

and Z_i is a $K_T \times (T-1)$ block diagonal matrix with the (transpose) vector of instruments for each period in its main block diagonal and where K_T is the total number of moments available for estimating α.. For instance, in the example previously discussed:

$$Z_i=\begin{pmatrix} y_{i1}\prod_{k=1}^{3}S_i^k & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & y_{i1}\prod_{k=1}^{4}S_i^k & y_{i2}\prod_{k=2}^{4}S_i^k & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & y_{i2}\prod_{k=2}^{5}S_i^k & y_{i3}\prod_{k=3}^{5}S_i^k & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & y_{i3}\prod_{k=3}^{6}S_i^k & y_{i4}\prod_{k=4}^{6}S_i^k \end{pmatrix}$$

Let k_t be number of these moments in rotating panels,[10]

$$k_t=\begin{cases} (t-2)\,, & \text{if } T_i>t \\ (T_i-2)\,, & \text{if } T_i<t \end{cases}$$

then the total number of moments after T periods is:

$$\begin{aligned} K_T &= \sum_{t=3}^{T} k_t = \sum_{t=3}^{T_i} k_t + \sum_{t=I+1}^{T} k_t \\ K_T &= \frac{1}{2}(T_i-1)(T_i-2)+(T_i-2)(T-T_i) \end{aligned} \tag{9}$$

Following Arellano and Bond (1991), estimates of α and $\lambda_1,...,\lambda_T$ are obtained from the following Generalised Method of Moments (GMM) problem:

$$(\widehat{\alpha},\widehat{z}_{1,...,}\widehat{z}_T)=\arg\min_{(\alpha,z_1,...,z_T)}\left[\frac{1}{N}\sum_i\begin{pmatrix} S_iy_i \\ Z_iHv_i\end{pmatrix}\right]'\cdot\widehat{W}\cdot\left[\frac{1}{N}\sum_i\begin{pmatrix} S_iy_i \\ Z_iHv_i\end{pmatrix}\right] \tag{10}$$

where $\widehat{W}$ it is the weighting matrix.

In order to depict the asymptotic properties of $\widehat{\alpha}$, I use results from Crepon, Kramarz and Trogon (1997). These authors consider a general GMM framework. In order to get rid of a set of "nuisance parameters" (in my case, $(z_1,...,z_T)$ as compared with my parameter of interest α), I can use a subset of the moment conditions of the same dimension (in this case, $\frac{1}{N}\sum_i S_iy_i=0$). Thus, I get some $(\widehat{z}_1,...,\widehat{z}_T)$ as an *empirical* function of α. These $\widehat{z}_t$ can then substitute the original z_t in the second subset of orthogonality conditions (which

[10]Given that I am thinking on a rotating panel fo which many rounds are available, the condition $T>T_i$ is implicitly assumed.

now depends only upon α). Following Crepon *et al.* (1997), it can be proved for this case that the solution to this new GMM criterion is asymptotically equivalent to $\widehat{\alpha}$:

$$\widehat{\alpha} = \arg\min_{\alpha} \left[\frac{1}{N} \sum_i Z_i H \left(v_i - \overline{v} \right) \right]' \cdot \widehat{A} \cdot \left[\frac{1}{N} \sum_i \left(v_i - \overline{v} \right) \right]$$

where $\overline{v} = \frac{1}{N} \sum_i D_i v_i$, that is, the cross-sectional mean of v_{it}computed with all the v_{it} available at time t and the weighting matrix is such that

$$\widehat{A}^{-1} = \frac{1}{N} \sum_i \left(Z_i - \frac{1}{N} \sum_i Z_i \right) \frac{N-1}{N} H H' \left(Z_i - \frac{1}{N} \sum_i Z_i \right)'$$

It will be convenient define a variable $\widetilde{v}_i$ as the variable v_i in deviation from its cross-sectional mean: $\widetilde{v}_i = v_i - \overline{v}$. Then I can characterise $\widehat{\alpha}$ as

$$\widehat{\alpha} = \arg\max_{\alpha} \left[\frac{1}{N} \sum_i Z_i H \widetilde{v}_i \right]' \cdot \left(\frac{1}{N} \sum_i \widetilde{Z}_i H H' \widetilde{Z}_i' \right)^{-1} \cdot \left[\frac{1}{N} \sum_i Z_i H \widetilde{v}_i \right]$$

An important issue is in order here: $\widehat{\alpha}$ estimated in this "concentrated" GMM objective function is not the solution to a standard optimal GMM problem, because $\widehat{A}$ is not defined as the inverse of the estimated variance-covariance matrix of the orthogonality conditions.

Another important question is that

A Note on the Asymptotic Properties of the Estimator First, it is apparent (see Arellano and Bond, 1991, and Álvarez and Arellano, 1998) that this estimator is consistent when N goes to infinity for fixed T and T_i. In the case of rotating panel, this assumption for T_i seems appropriate because an individual is followed just for a small number of periods; nevertheless, I feel that the total number of waves is not so small.[11] Therefore, as in Álvarez and Arellano (1998), I will proceed to analyse asymptotics as both N and T goes to infinity, along the asymptotic path where the ratio of T/N goes to a constant (i.e., $N, T \rightarrow \infty$ with $T/N \rightarrow c$, $0 \leq c < \infty$).

It should be noted that, for the estimator that uses all the available lags at each period as instruments, the number of orthogonality conditions grow at a rate of T^2 in the case of genuine panels, whereas in this case the growth rate is T (see (9)). Álvarez and Arellano (1998) showed that this estimator for genuine panels displays an asymptotic bias as the number of moments is large relative to sample size: in fact, the bias vanishes when $c = 0$.(or, in other words, when $N \rightarrow \infty$, for fixed T). Therefore, practitioners in micro-panel often estimate using a fixed number of lags at each period; thus, the small sample bias is avoided, but a cost of efficiency (since all the relevant information will not be incorporated). In the case of rotating panel, the number of lags available at each period is given by the survey design: I only have information about a individual up to T_i backwards. So, I finally have a similar case to that actually applied in genuine panels, but with an important

[11]For instance, I have $T = 48$ in the ECPF, which is not negligible.

difference: here, using a fixed number of lags is optimal given the data available (which is exogenous to the researcher).

Henceforth, I can expect that my estimators for the individual process will present good asymptotics properties although I am assuming both that N goes to infinity and also that T goes to infinity (what is essential to identify the aggregate process). As a preliminary example, let use consider a simpler estimator than above: in particular, the so-called Crude Instrumental Variables (CIV) estimator[12] , which differs from the former in its weighting matrix. In the CIV estimator the correlation induced by first-differencing is neglected in the weighting matrix, so

$$\widehat{A}_{CIV}^{-1} = \frac{1}{N}\sum_i \widetilde{Z}_i\widetilde{Z}_i'$$

Then, it is straightforward that

$$\begin{aligned}\widehat{\alpha}_{CIV} &= \frac{\sum_{t=3}^{T}\Delta y_{t-1}'\widetilde{Z}_t\left(\widetilde{Z}_t'\widetilde{Z}_t\right)^{-1}\widetilde{Z}_t'\Delta y_t}{\sum_{t=3}^{T}\Delta y_{t-1}'\widetilde{Z}_t\left(\widetilde{Z}_t'\widetilde{Z}_t\right)^{-1}\widetilde{Z}_t'\Delta y_{t-1}}\\ \widehat{\alpha}_{CIV}-\alpha &= \frac{\sum_{t=3}^{T}\Delta y_{t-1}'\widetilde{Z}_t\left(\widetilde{Z}_t'\widetilde{Z}_t\right)^{-1}\widetilde{Z}_t'\Delta v_t}{\sum_{t=3}^{T}\Delta y_{t-1}'\widetilde{Z}_t\left(\widetilde{Z}_t'\widetilde{Z}_t\right)^{-1}\widetilde{Z}_t'\Delta y_{t-1}} \qquad (11)\end{aligned}$$

I now take the expectation of the numerator in equation (11). This will allow me to figure out the order of magnitude of the asymptotic bias or even the inconsistency of the estimator: Álvarez and Arellano (1998) show that the CIV estimator is not only biased but inconsistent unless $T/N \to 0$.

$$\begin{aligned}E\left[\sum_{t=3}^{T}\Delta y_{t-1}'\widetilde{Z}_t\left(\widetilde{Z}_t'\widetilde{Z}_t\right)^{-1}\widetilde{Z}_t'\Delta v_t\right] &= \sum_{t=3}^{T}E\left[\Delta y_{t-1}'M_t\Delta v_t\right] \qquad (12a)\\ &= \sum_{t=3}^{T}E\left[tr\left[M_tE_t\left(\Delta v_t\Delta y_{t-1}'\right)\right]\right] \qquad (12b)\\ &= \sum_{t=3}^{T}E\left[tr\left[-\sigma^2M_t\right]\right] \qquad (12c)\\ &= -\sigma^2\sum_{t=3}^{T}k_t \qquad (12d)\end{aligned}$$

In (**??**) I have define the idempotent matrix $M_t = \widetilde{Z}_t\left(\widetilde{Z}_t'\widetilde{Z}_t\right)^{-1}\widetilde{Z}_t'$, which only depends on information available at period t. Then, as $\Delta y_{t-1}'M_t\Delta v_t$ is a scalar, it coincides

[12] I am using the terminology in Álvarez and Arellano (1998).

with his trace what allow me to go to (**??**). I then use the law of iterated expectation, by conditioning on the set of information available at time t. From (**??**) to (**??**), I note that $E_t\left(\Delta v_t \Delta y'_{t-1}\right) = E\left(\Delta v_t \Delta y'_{t-1}\right)$, i.e., it does not depend on t, and then, by using cross-sectionally independence $E\left(\Delta v_t \Delta y'_{t-1}\right) = E\left(\Delta v_{it} \Delta y'_{i(t-1)}\right) = -E\left(v_{it-1} y'_{i(t-1)}\right) = -\sigma_v^2$. So finally, in (**??**), I have use that $trace\left(M_t\right) = rank\left(M_t\right) = k_t$.

Therefore, I note that, since $\sum_{t=3}^{T} k_t = K_T$, is of order T, it can be concluded that. for $0 \leq c < \infty$,

$$\lim_{\substack{N,T\to\infty \\ \frac{T}{N}\to c}} E\left[\frac{1}{NT}\sum_{t=3}^{T} \Delta y'_{t-1} \widetilde{Z}_t \left(\widetilde{Z}'_t \widetilde{Z}_t\right)^{-1} \widetilde{Z}'_t \Delta v_t\right] = 0$$

Of course, this results as a consequence of truncating the number of lags used as instruments: the dimension of y^{t-2} in each moment condition defined $E\left[y^{t-2}\left(\Delta y_{it} - \alpha \Delta y_{i(t-1)} - \Delta\left(z_t - \alpha z_{t-1}\right)\right.\right.$ $0, \quad t = 3, ..., T$. As discussed by Álvarez and Arellano (1998), this is not optimal in general for a genuine panel case. However, in the rotating panel, the survey design limits the number of lags available to instruments at T_i; thus, this is the most efficient estimator given the data that one wants to use.

2.5 The Aggregate Process and Synthetic Panels

[TO BE COMPLETED]

Next, I will focus on the aggregate process to identify the parameter β:

$$\overline{y}_{\cdot t} = \beta \overline{y}_{\cdot t-1} + \varepsilon_t + \overline{u}_{\cdot t} - \beta \overline{u}_{\cdot t-1}, \qquad t = 1, ..., T$$

This is similar to the synthetic panel context. Usually, practitioner neglects the $\overline{u}_{\cdot t}$ terms appealing to large N. the classical within-group estimator. In general, one has to take into account that $\overline{y}_{\cdot t}$ is a "error-ridden measure" of z_t; so, using $\overline{y}_{\cdot t-1}$ implies that one has to compute a correction given by correlation between $\overline{y}_{\cdot t}$ and $\overline{u}_{\cdot t} - \beta \overline{u}_{\cdot t-1}$. The moment conditions is:

$$\operatorname*{plim}_{N,T\to\infty} \frac{1}{T}\sum_t \overline{y}_{\cdot t-1}\varepsilon_t + \operatorname*{plim}_{N,T\to\infty} \frac{1}{T}\sum_t \overline{y}_{\cdot t-1}\left(\overline{u}_{\cdot t} - \beta \overline{u}_{\cdot t-1}\right) = 0 \qquad (13)$$

If I had a genuine panel, $\operatorname{plim}_{N,T\to\infty} \frac{1}{T}\sum_t \overline{y}_{\cdot t-1}\left(\overline{u}_{\cdot t} - \beta \overline{u}_{\cdot t-1}\right) = (\alpha - \beta)\,\sigma_u^2/N$ where $\sigma_u^2 = Var\left(u_{it-1}\right)$. In the technical appendix is proven that a sequential estimation (first estimating α and σ_u^2, and then β) lead to an estimation of β as efficient as joint estimation. This result is mainly given by the following fact: moments conditions for α and σ_u^2 are expressed in deviation from means whereas moments for β are in terms of means. As a consequence, such conditions are orthogonal to each other. Using $\overline{y}_{\cdot t-1}$ in a rotating panel does not give too many additional complications: the main point is that for the covariance term $\operatorname{plim}_{N,T\to\infty} \frac{1}{T}\sum_t \overline{y}_{\cdot t-1}\overline{u}_{\cdot t}$ different individuals are used in computing $\overline{y}_{\cdot t-1}$ and $\overline{u}_{\cdot t}$; therefore, one does not gets $(\alpha - \beta)\,\sigma_u^2/N$ but α is multiplied by a factor given by the rotating structure of the data. An alternative could be used $\overline{y}_{\cdot t-T_i-1}$ as an instrument: in this case, as no individual observed at time t or $t-1$ was observed at time $t-T_i-1$ the second term can be neglected.

As commented before, in the synthetic panel literature, one often neglect the σ_u^2/N correction. I have proven in this context that estimator that neglect the correction has a large asymptotic mean square error, although its variance is lower.[13] The point is that its asymptotic bias vanishes as $N \to \infty$. Some simulation results are shown in the Table 1.

[13]Following the notation in the Technical Appendix, $Var\left(\theta_2^P\right) = \left[\Gamma_{22}'\Omega_{22}^{-1}\Gamma_{22}\right]^{-1} < Var\left(\theta_2^S\right)$, where θ_2^P is the estimator neglecting the variance.

Table 1: Simulation Results for Different Estimators, with true $\beta = 0.5$(1)= Neglecting $Var(u_{i,t-1}/N$.(2) = Two-Stage Estimator.

	T= 5		T= 10		T= 25		T= 50		T=100	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
N= 5	0.280	-0.807	0.316	1.541	0.346	0.473	0.356	0.481	0.366	0.492
	(0.243)	(****)	(0.097)	(****)	(0.038)	(0.132)	(0.020)	(0.032)	(0.010)	(0.015)
N= 10	0.327	0.316	0.356	0.430	0.398	0.469	0.409	0.480	0.418	0.490
	(0.252)	(43.324)	(0.093)	(4.967)	(0.036)	(0.047)	(0.018)	(0.022)	(0.009)	(0.011)
N= 25	0.353	0.472	0.395	0.426	0.434	0.465	0.451	0.482	0.458	0.489
	(0.235)	(26.981)	(0.090)	(0.110)	(0.033)	(0.036)	(0.016)	(0.018)	(0.008)	(0.009)
N= 50	0.365	0.380	0.404	0.420	0.447	0.463	0.464	0.480	0.474	0.491
	(0.247)	(1.264)	(0.088)	(0.097)	(0.033)	(0.034)	(0.016)	(0.016)	(0.008)	(0.008)
N=100	0.375	0.381	0.413	0.421	0.456	0.464	0.474	0.482	0.483	0.491
	(0.232)	(0.324)	(0.086)	(0.090)	(0.032)	(0.033)	(0.015)	(0.016)	(0.008)	(0.008)
N=250	0.383	0.388	0.420	0.423	0.461	0.464	0.477	0.480	0.488	0.491
	(0.227)	(0.248)	(0.086)	(0.088)	(0.032)	(0.032)	(0.016)	(0.016)	(0.008)	(0.008)

3 Empirical Application

In the next sections, I will analyse precautionary saving associated with income risk in Spain for the period 1985-1996. As a theoretical starting point, I consider a standard model of consumption which allows for precautionary saving; that is, consumers want to borrow and save to smooth consumption over time and across states of nature. The importance of the precautionary-saving motive is estimated through the effect of income variability on consumption growth.

This entails a proper modelisation of income dynamics, up to the second conditional moment. I use income from all labour sources (not just wages) thus capturing, to some extent, changes in unemployment risk as well as changes in earnings uncertainty. Thus, I set up a dynamic model for income in which the variances of the innovations in this process are allowed to vary over time. Following Banks, Blundell and Brugiavini (1999), the innovation to household income will be decomposed into three terms: an idiosyncratic (household-specific) risk component, a cohort-specific risk component (affecting in the same manner to every household whose head belongs to the same cohort, defined by year of birth and educational attainment), and an aggregate risk component (common to all households in an economy).

This analysis is carried out with a household rotating panel: the Spanish family expenditure survey, a rotating panel. On the one hand, forty-eight quarterly waves from which a long time series synthetic panel for cohorts can be constructed; this allows me to capture the changing nature of income risk over long time series of expenditure and income, controlling for household unobserved heterogeneity, and consequently relying on the time evolution of risk terms to elicit precautionary saving effects. But, as a fundamental point of departure from Banks, Blundell and Brugiavini (1999), I can actually observe each individual for several consecutive periods; such a fact is exploited in this paper to identify the process for idiosyncratic shock.

Under full insurance, only risks common to all individuals should affect consumption; in other words, the individuals would be able to isolate the consumption distribution from shocks to the income distribution, through risk-sharing mechanisms. But there are good reasons to consider further separate components in the aggregate shock: overall risk will encompass shocks to the macro-economy and shocks specific to individuals in a group.[14]
For instance, temporary employment regulation was significantly relaxed in Spain since 1984. As those who started a job after the reform were more likely to do so under a temporary labour contract,[15] the income uncertainty associated to these contracts is expected to have a different incidence in different year-of-birth cohorts. Indeed, this distinction among aggregate, cohort-specific and idiosyncratic risks allows me to analyse the response of consumption to each component and, therefore, to study the ability of households of insuring against different sources of risk.

Recent literature has emphasised that full insurance could be not only implemented

[14]As Banks, Blundell and Brugiavini (1999) clearly point out, there exists an observational equivalence between a common shock affecting individuals differently and a genuine individual shock; thus both of them are regarded as "idiosyncratic". The same applies for cohorts.

[15]Bentolila and Dolado (1994) quote evidence showing that temporary employment is prevalent among the youth. As well, it is more frequent for less educated workers.

through "formal" mechanisms (i.e., perfect capital markets, the Welfare State, etc.), but there could also exist a wide-range of "informal" schemes open to individual, but unobservable to the econometrician. Therefore, it is important to assess, *a priori*, the size and importance of these idiosyncratic risks: these may be larger but they are also more insurable. For instance, at the household level, decisions are made jointly; thus, when one member faces with a higher employment uncertainty, other members' can optimally choose to join to the labour force or to work more, so that the household gets (partly) self-insured.[16] At the cohort level, pay-as-you-go state pension systems and *inter-vivos* transfers between extended family members of different generations could be thought of as informal insurance mechanisms.[17] my income measure includes all sources of non-asset income to the household, and social security receipts; so, contrary to the use of earnings of the head, earnings from all family members are incorporated, and, therefore, mechanisms that households have for pooling risk associated with individual components of income have been taken into account.[18]

Furthermore, if all three terms correctly measured uninsurable risk, their impact on consumption growth would be the same. Nevertheless, as individuals are able to pool idiosyncratic risks in many ways, the estimated effect for the idiosyncratic component would be expected to be lower than the other two components, due merely to the fact that the first one is not reflecting true uncertainty.

The results provide evidence on the importance of the precautionary motive for saving in response to income risks. Like Banks, Blundell and Brugiavini (1999) for United Kingdom, the common component of risk does not appear to be significant, but instead the cohort-specific does. This fact suggests a failure of between cohort risk-pooling mechanisms akin to that found by Attanasio and Davis (1996) in the US.

3.1 Precautionary Saving

Let me consider a model of consumption smoothing and precautionary saving; see Deaton (1992) and Browning and Lusardi (1996) for further details. The optimal allocation of consumption verifies the standard Euler equation $E_t\left[\frac{1+r_t}{1+\delta}\frac{U_C(C_{t+1},D_{t+1})}{U_C(C_t,D_t)}\right] = 1$, where r_t denotes the real interest rate, δ the subjective discount rate and $U_C(\bullet)$ denotes the first derivative of the within period utility function with respect to consumption C_t, and D_t is a vector of "modifiers for utility" or "taste shifters" such as family composition, labour supply or health status, usually referred to as "demographics".

[16] Sánchez (1999) analyses how employment uncertainty of the "primary earner" (or husbands) affects the likelihood of "secondary earners" (or spouses) joining to the labour force; moreover, she uses the introduction and diffusion of temporary contracts as a exogenous source of variation in employment risk to get identification.

[17] Bentolila and Ichino (2000) show evidence supporting that extended family networks, whose ties seem to be quite strong in Spain and Italy (as compared to Germany, the UK and the US), provide an essential source of insurance against unemployment in those countries.

[18] Hayashi, Altonji and Kotlikoff (1996) test for family insurance, that is, households who are insured/insurers within the extended family (not insured by the outside world). They take advantage of the fact that the PSID includes as new households those set-up by emancipated members of a family already surveyed. I can only control for pooling among family members who are still living together.

If I further assume that utility function is of the constant relative risk aversion (CRRA) form, namely, $U(C_t, D_t) = \frac{1}{1-\rho}\exp(\varphi' D_t) C_t^{1-\rho}$, (where $\rho > 0$ is the relative risk aversion coefficient)[19] , after taking logarithms and making a second order Taylor approximation, the Euler equation can be re-written as:

$$\Delta \ln(C_{t+1}) = \frac{1}{\rho}\ln(r_t - \delta) + \frac{1}{\rho}\varphi' \Delta D_{t+1} + \frac{1}{2\rho}\omega_{t+1}^2 + v_{t+1} \quad (14)$$

where ω_{t+1}^2 is a measure of the consumption shock conditional variance.

Equation (14) parsimoniously comprises the main determinants of consumer behaviour.[20] The first term accounts for the intertemporal substitution effect and the second ones considers how different periods in the life-cycle are reflected in the consumption path through changes in circumstances which are implicit in demographic variables ΔD_{t+1}. Finally, the last term captures the precautionary saving motive: an increased value of the expected variance of future consumption shocks, ω_{t+1}^2, leads to a higher expected consumption growth, since current consumption is lowered in order to raise precautionary saving.

It is worth noting that ω_{t+1}^2 reflects uncertainty about future realisations of *each* exogenous uninsured variables. In other words, besides income risk, uncertainty about future demographics (number of family members, illness,...) could cause consumption shocks against which individuals would wish to insure by means of precautionary saving. Dynan (1996) estimates an equation similar to (14), including the conditional variance of consumption growth itself to capture all forms of risk. However, I will use the income's innovation conditional variance so as to concentrate on the precautionary-saving motive due to income uncertainty.

This notwithstanding, the variance term ω_{t+1}^2 in equation (14) cannot be simply replaced by the income shock conditional variance. The response of the consumption shock variance to unexpected income changes depends on the amount of financial wealth held by the household and on the magnitude of current income relative to future income. To clarify, even if future income becomes risky, some households would not need to save so as to guarantee their future consumption, if they hold enough liquid assets or if their future income is expected to be much higher than current income.

Accordingly, I will consider an equation such as:

$$\Delta \ln(C_{t+1}) = \frac{1}{\rho}\ln(r_t - \delta) + \frac{1}{\rho}\varphi' \Delta D_{t+1} + k\pi_t^2\sigma_{t+1}^2 + v_{t+1} \quad (15)$$

where σ_{t+1}^2 is a measure of the income shock conditional variance and π_t is a scaling factor such that less wealthy individuals are more responsive to future income variance.

Following the approximate solutions derived by Blundell and Stoker (1999), the scaling factor can be written as $\pi_t = Y_t / E_t(A_{t+1})$. This could also be thought of as accounting for the impact of the wealth-income ratio target that drives buffer-stock saving behaviour in Carroll (1997). Assuming particular processes for income, Carroll shows that consumers

[19] As far as this paper is concerned, the most interesting feature of this functional form is that it allows to go beyond the certainty-equivalence model and, hence, to analyse the precautionary motive for saving.

[20] See Browning and Lusardi (1996) for a detailed explanation.

with certain *prudence* and *impatience*[21] patterns have a desired wealth-income ratio. Bellow this target, prudence dominates and consumers will save; but above, impatience will lead households to dissave, i. e., to use up their wealth surplus.

Nevertheless, financial wealth (A_t) is often not available in micro data-sets. For this reason, Banks, Blundell and Brugiavini (1999) replace it with C_t, and I will also use $\pi_t = Y_t/C_t$ as scaling factor.

3.2 Modelling Income and Income Risk Dynamics

A Dynamic Model of Income

Let Y_{ht} be the (log of) total income for household h at time t:

$$Y_{ht} = \beta' X_{ht} + \eta_h^* + \epsilon_{ht} \tag{16}$$

where η_h^* is an unobservable household effect and X_{ht} is a vector of exogenous control variables.

The error term is assumed to have three (pairwise orthogonal) components

$$\epsilon_{ht} = e_t + e_{ct} + e_{ht} \tag{17}$$

where e_t is the aggregate component (common to all individuals in an economy) of the error term, e_{ct} is the cohort-specific component (common to all individuals in a year-of-birth cohort) and e_{ht} is the idiosyncratic (household-specific) error term.

Allowing for a degree of persistence in the stochastic specification of income, each component of the error term is assumed to follow an ARMA, i. e.,

$$\Phi(L)e_t = \Theta(L)\varepsilon_t \tag{18}$$

$$\phi(L)e_{ct} = \theta\,(L)\,\varepsilon_{ct} \tag{19}$$

$$\psi\,(L)\,e_{ht} = \vartheta\,(L)\,\varepsilon_{ht} \tag{20}$$

where ε_t, ε_{ct} and ε_{ht} are white noise innovations.

The income innovations ε_t, ε_{ct} and ε_{ht} are assumed to be conditionally heteroskedastic to capture the time-changing nature of income risk:[22] $E_t\left(\varepsilon_{t+1}^2\right) = \sigma_{t+1}^2$, $E_t\left(\varepsilon_{c(t+1)}^2\right) = \sigma_{c(t+1)}^2$ and $E_t\left(\varepsilon_{h(t+1)}^2\right) = \sigma_{h(t+1)}^2$. These "one-period ahead" expected variances of income innovations are the determinants of precautionary saving. Controlling for observable and unobservable characteristics which vary across individuals (X_{ht} and η_h^*, respectively, in 16) and stripping out persistent features of income in $(18)-(20)$ allows me to rely just on the time series evolution of risk terms to identify the effect of income risk on consumption growth.

[21] Consumers display *prudence* when the third derivative of their utility function with respect to consumption is non-negative ($U_{CCC} \geqslant 0$); see Kimball (1990).

As for *impatience*, it sets bounds to the wealth accumulation, yet its definition depends on the context. For example, see Carroll (1997) and the papers referenced there.

[22] For instance, a permanent worker becoming unemployed will face, *ceteris paribus*, a higher income uncertainty.

Recovering Income Innovations

Along the lines of section 2, I will use a multi-stage procedure to estimate the different processes of income innovations. First, a separate income process is estimated for each cohort; as a consequence, all parameters are, by definition, allowed to be cohort-specific (common to all individuals in a cohort). After recovering the estimated income innovations, their conditional variances can be calculated so as to be included in the consumption equation.

Taking equations (16) and (17) together for a given cohort c, I have $Y_{ht} = (\beta^c)' X_{ht} + \eta_h^* + m_t^c + e_{ht}$, $\forall h \in c$, where $m_t^c = (e_t + e_{ct})$ and the superscript denotes that parameters are specific to cohort c. It is worth noticing that the cohort innovation (e_{ct}) and the aggregate innovation (e_t) cannot be separately distinguished, since both represent common effects across all households *within* a cohort; the parameter m_t^c reflects this (cohort-specific) time effect.

Moreover, let me assume a simple first-order autoregressive structure for the idiosyncratic innovation:

$$e_{ht} = \alpha^c e_{h(t-1)} + \varepsilon_{ht}, \quad \forall h \in c \tag{21}$$

Thus, after some rearrangements, the income equation can be expressed as:

$$Y_{ht} = \alpha^c Y_{h(t-1)} + (\beta^c)' X_{ht} - \alpha^c (\beta^c)' X_{h(t-1)} + \eta_h + \lambda_t^c + \varepsilon_{ht}, \quad \forall h \in c \tag{22}$$

where $\eta_h = (1-\alpha^c)\eta_h^*$ is a household-specific unobservable effect and $\lambda_t^c = m_t^c - \alpha^c m_{t-1}^c$ is a time-effect, simply captured by including time-dummies.

Once the parameters α^c and β^c have been estimated, the idiosyncratic innovations $\widehat{\varepsilon}_{ht}$ are recovered as the residuals in equation (22). Thus, the conditional variance of this income innovation can be calculated as: $E_t\left(\widehat{\varepsilon}_{h(t+1)}^2\right) = \widehat{\sigma}_{h(t+1)}^2$.

Likewise, it is straightforward to obtain each $\widehat{m}_t^c = (\widehat{e}_t + \widehat{e}_{ct})$ as the sum across households of the residuals in $(16)$for each cross section, that is,

$$\widehat{m}_t^c = \frac{1}{N_c}\sum_{h\in c}\left[Y_{ht} - \left(\widehat{\beta}^c\right)' X_{ht}\right]$$

where $N_c$is the number of households belonging to cohort c.[23] Then, $\widehat{m}_t^c$ is decomposed into cohort and aggregate (common to all cohorts) income innovation. The latter can be recovered as follows:

$$\widehat{e}_t = \frac{1}{\mathfrak{C}}\sum_{c=1}^{\mathfrak{C}}\widehat{m}_t^c$$

[23] Without loss of generality, it can be assumed $E[\eta_h^*] = 0$ and $E[\varepsilon_{ht}] = 0$. Otherwise, the mean of η_h^* and ε_{ht} will be added to the mean of $\widehat{m}_t^c$, but the results will not be affected.

On the other hand, the time series for $\widehat{m}_t^c$ could be alternatively obtained from the parameters $\widehat{\Lambda}_t^c = \widehat{m}_t^c - \alpha^c \widehat{m}_{t-1}^c$, by inverting this process with $\widehat{m}_1^c = \frac{1}{N_c}\sum_{h\in c}\left[Y_{h1} - \left(\widehat{\beta}^c\right)' X_{h1}\right]$ as its initial condition.

where $\mathfrak{C}$ is the number of cohorts. The time-series for $\widehat{e}_{ct}$ are obtained by subtracting $\widehat{e}_t$ from each $\widehat{m}_t^c$ series.

Finally, the time series processes for $\widehat{e}_t$ and $\widehat{e}_{ct}$ can be estimated. Following the approach to prediction in dynamic models with time-dependent variances described in Ballie and Bollerslev (1992), I will first proceed to estimate the process for the conditional mean of $\widehat{e}_t$ and each $\widehat{e}_{ct}$ (that is, $\Phi(L)\widehat{e}_t = \Theta(L)\varepsilon_t$ and $\phi^c(L)\widehat{e}_{ct} = \theta^c(L)\,\varepsilon_{ct},\ c = 1, \ldots, \mathfrak{C}$, respectively) under the assumption of a constant variance; thus, the white noise innovations $\widehat{\varepsilon}_t$ and $\widehat{\varepsilon}_{ct}$ can be computed. Then, their conditional variances $E_t\left(\widehat{\varepsilon}^2_{t+1}\right) = \widehat{\sigma}^2_{t+1}$, $E_t\left(\widehat{\varepsilon}^2_{c(t+1)}\right) = \widehat{\sigma}^2_{c(t+1)},\ c = 1, \ldots, \mathfrak{C}$, are calculated.

3.3 Data

The data set used in this empirical application is the Spanish family expenditure survey (*Encuesta Continua de Presupuestos Familiares*, ECPF, hereafter). The ECPF is a rotating panel conducted by the National Institute of Statistics (INE) on a quarterly basis. About 3200 households are interviewed every quarter, with one eighth of the sample being renewed each quarter. This survey is highly suitable for my purpose, since it contains very detailed and comprehensive information on family expenditure and income and on several control variables (household characteristics such as employment status, demographics, etc ...).

Contrary to the data available to Banks, Blundell and Brugiavini (1999), households are followed by the ECPF for several, at most eight, consecutive periods. Thus, a true (although short and unbalanced) panel structure is available. This feature is crucial to identify a separate dynamic process for idiosyncratic innovations.

Here, I use twelve consecutive years of the ECPF running from the first quarter of 1985 to the fourth quarter of 1996. The long period over which this data is available is also an important point. On the one hand, the identification of the consumption model would require long time series panel, so that common (macro) shocks were averaged out (see Deaton, 1992, and Browning and Lusardi, 1996). Secondly, time series information must suffice to remove persistence from the income series.

As regards income, I use total household income earned by any member of the family, from any source with the exception of asset income. I do include unemployment benefits as a component of household income, since the participation variable accounts for much of observed income uncertainty (and, consequently, precautionary saving). As for consumption, I use household real expenditure on non-durable consumption goods.[24]

Likewise, household expenditures, income and nominal interest rate are deflated by the consumer retail price index (IPC), published by the INE. The nominal interest rate is a synthetic rate on deposits provided by Cuenca (1993).

Summary statistics relating to the cohort definition are shown in Table 2. I have selected seven cohorts in which the youngest individuals are 18 years old in 1985 and nobody is older than 64 years old in 1996. Thus, each household head is observed at working ages

[24] I have included Food, Drinks and Tobacco (corresponding to Group 1 in the *Clasificación de los Gastos de Consumo* provided by INE), Clothing and Footwear (Group 2) and Energy and transport (Sub-groups 32, 62, 63 and 64)

Table 2: Cohort Definition, ECPF, 1985:1-1996:4

Cohort	Date of Birth	Education Level	Observations each period		
			Median	25^{th} perc.	75^{th} perc.
1	1932-43	Illiterate	49	35	59
2	1932-43	Primary	173	105	185
3	1932-43	Second./Univ.	33	21	37
4	1944-55	Illiterate	23	18	26
5	1944-55	Primary	214	129	227
6	1944-55	Second./Univ	85	46	99
7	1956-67	Primary	110	65	128
8	1956-67	Second./Univ	65	36	100

throughout the sample period.[25] In the Data Appendix, additional details are given on how to obtain the final sample; other variables used in the estimation are described as well.

4 Empirical Results

4.1 Income Equation

To get the predicted conditional variance of the income innovations, the income equation (22) have first to be estimated. This constitutes a dynamic model with common factor restrictions on certain coefficients:

$$Y_{ht} = \pi_0^c Y_{h(t-1)} + (\pi_1^c)' X_{ht} + (\pi_2^c)' X_{h(t-1)} + \eta_h + \lambda_t^c + \varepsilon_{ht}, \quad \forall h \in c \tag{23}$$

with

$$\pi_0^c = \alpha^c; \quad \pi_1^c = \beta^c; \quad \pi_2^c = -\alpha^c \beta^c \tag{24}$$

As suggested by Chamberlain (1984), I initially carry out the estimation of the parameters in the reduced form (23), namely, $\widehat{\pi}_0^c$, $\widehat{\pi}_1^c$ and $\widehat{\pi}_2^c$ (without imposing any restriction). From these results, I then estimate the parameters α^c and β^c using a minimum distance technique:

$$\begin{pmatrix} \widehat{\alpha}_{MDE}^c \\ \widehat{\beta}_{MDE}^c \end{pmatrix} = \arg\min_{\alpha^c, \beta^c} \begin{pmatrix} \widehat{\pi}_0^c - \alpha^c \\ \widehat{\pi}_1^c - \beta^c \\ \widehat{\pi}_2^c - (-\alpha^c \beta^c) \end{pmatrix}' \widehat{V}^{-1} \begin{pmatrix} \widehat{\pi}_0^c - \alpha^c \\ \widehat{\pi}_1^c - \beta^c \\ \widehat{\pi}_2^c - (-\alpha^c \beta^c) \end{pmatrix}$$

[25] This choice excludes from this study households headed by young and elderly people; however, both of them are likely to exhibit a precautionary saving behaviour. On the one hand, labour income uncertainty is expected to be higher at the earlier stages of the life-cycle. On the other hand, as people age, uncertainty arises from new sources such as medical expenses, the timing of death or assets returns.

where $\widehat{V} = \widehat{Var}\left[\left(\ \widehat{\pi}_0^c,\ \ (\widehat{\pi}_1^c)',\ \ (\widehat{\pi}_2^c)'\ \right)'\right]$.

Another issue I must also address is the seasonality of labour income in Spain. The Spanish pay system presents a particular institutional feature: many workers receive extra payments in the Summer (June or July) and in the Winter (December) of each year; that is, the same annual value can be paid through either twelve equal monthly payments or twelve unequal monthly payments which include these two extra payments. The payment scheme for a worker is determined by her job and can reasonably be taken as exogenous to workers' choices. Hence, the seasonal pattern of income varies randomly from one individual to another: i. e., the income equation includes a seasonal-individual random effect. This issue is discussed by Álvarez (1999).

Consider the income equation re-written as:

$$Y_{ht} = (\pi^c)' W_{ht} + u_{ht}, \quad \forall h \in c \tag{25}$$

where $\pi^c = \left[\ \widehat{\pi}_0^c,\ \ (\widehat{\pi}_1^c)',\ \ (\widehat{\pi}_2^c)'\ \right]'$ and $W_{ht} = \left[\ Y_{h(t-1)},\ \ X'_{ht},\ \ X'_{h(t-1)}\ \right]'$. The error component u_{ht} was given in (23) by $u_{ht} = \eta_h + \lambda_t^c + \varepsilon_{ht}$ (again, η_h is the household fixed effect and λ_t^c is the time effect). In this case, Generalised Method of Moments (GMM) estimators for π^c are available from the following moment conditions in the first-differenced equation: $E\left[W_h^{t-2}\Delta u_{ht}\right] = 0, \quad t = 3, ..., T$, with $W_h^{t-2} = \left(W'_{h1}, W'_{h2}, ..., W'_{h(t-2)}\right)'$; see Arellano and Bond (1991) and Arellano and Honoré (1999).

But, taking into account the discussion two paragraphs above, I will have:

$$\begin{aligned} u_{ht} &= \eta_h + \sum_{s=1}^{4} \tau_{sh} d_{st} + \lambda_t^c + \varepsilon_{ht} \\ &= \sum_{s=1}^{4} (\eta_h + \tau_{sh})\, d_{st} + \lambda_t^c + \varepsilon_{ht} \end{aligned} \tag{26}$$

where d_{st} are seasonal dummy variables and τ_{sh} are seasonal individual effects.

Hence, given this error structure, the previous moment conditions do not hold, since some lagged endogenous variables (included in W_h^{t-2}) are now correlated with $\Delta u_{ht} = \sum_{s=1}^{4} \tau_{sh}\left(d_{st} - d_{s(t-1)}\right) + \Delta\left(\lambda_t^c + \varepsilon_{ht}\right)$ through the first term (the seasonal-individual effects). Nevertheless, as Álvarez (1999) points out, those can be easily generalised by using seasonal differencing (so that such effects can actually be removed): $\Delta_4 u_{ht} = \sum_{s=1}^{4} \tau_{sh}\left(d_{st} - d_{s(t-4)}\right) + \Delta_4\left(\lambda_t^c + \varepsilon_{ht}\right) = \Delta_4\left(\lambda_t^c + \varepsilon_{ht}\right)$, because $\Delta_4 d_{ts} = \left(d_{st} - d_{s(t-4)}\right) = 0, \quad \forall t, s$. Therefore, the following orthogonality conditions could be used to estimate the (unrestricted) parameters π^c:

$$E\left[W_h^{t-5}\Delta_4 u_{ht}\right] = 0, \quad t = 6, ..., T$$

with $W_h^{t-5} = \left(W'_{h1}, W'_{h2}, ..., W'_{h(t-5)}\right)'$; then, the parameters of interest α^c and β^c are recovered as explained before..[26] The estimation results of these parameters (for each

[26]Estimation was performed with the DPD98 program (written in Gauss by Arellano and Bond, 1998), using an extended procedure provided by Olympia Bover to get minimum distance estimates from DPD results.

cohort) are shown in the Appendix of Tables, Table I.

With regard to the conditional variance of idiosyncratic income shock, $\widehat{\sigma}^2_{h(t+1)} = E_t\left(\widehat{\varepsilon}^2_{h(t+1)}\right)$, it has been estimated (Appendix of Tables, Table II) allowing it to depend on:

1. The information set at time t (past observation of $\widehat{\varepsilon}_{h(t+1)}$, $\widehat{\varepsilon}^2_{h(t+1)}$ and other weakly exogenous variables: demographics, number of household members having an employment, labour status for household head, ...).

2. Control variables which account, to some extent, for permanent differences in idiosyncratic risk.

Lastly, Tables III and IV in the Appendix of Tables report the estimated ARMA processes for the conditional mean and ARCH processes for the conditional variance of the time series $\widehat{e}_{c(t+1)}$ and $\widehat{e}_{t+1}$. The main purpose of this estimation is to capture the time series dynamics, so as to get suitable forecasts of the conditional variances, $\widehat{\sigma}^2_{c(t+1)}$ and $\widehat{\sigma}^2_{(t+1)}$, to be included in the consumption growth equation. It should be noted that these estimates are purely based on time series, which emphasises the need for a long time series of income on each cohort. Along the lines of discussion in section 3, some corrections should be done in order to take into account that $\widehat{e}_{c(t+1)}$ and $\widehat{e}_{t+1}$ have been obtained from a previous stage. At this point, this has not been attempted yet (so it could be thought of as appealing to large N in my cross-sections). In the Appendix of Figures, I show the evolution of the cohort-level and aggregate variances (actually, their fitted values from regressing them on a 3^{rd} degree polynomial trend and seasonal dummies).

4.2 Consumption Growth Equation

Making use of the conditional variance of the income innovations estimated above, I finally move on to study the impact of precautionary saving on consumption growth. Thus, the estimated consumption growth equation will be:

$$\begin{aligned}\Delta \ln\left(C_{h(t+1)}\right) &= \tfrac{1}{\rho} r_t + \tfrac{1}{\rho}\varphi' \Delta D_{h(t+1)} \\ &\quad + k_1 \pi^2_{ht}\sigma^2_{t+1} + k_2 \pi^2_{ht}\sigma^2_{c(t+1)} \\ &\quad + k_3 \pi^2_{ht}\sigma^2_{h(t+1)} + \upsilon_{h(t+1)} \qquad (27)\end{aligned}$$

where the expectational error is included in $\upsilon_{h(t+1)}$. Nevertheless, in the presence of measurement errors in consumption, these extra terms will also be added to the disturbance; provided that the measurement errors are serially uncorrelated, the error term in equation (27) will have a MA(1) structure.

It follows that a GMM estimator for the parameters in (27) is defined by the moment conditions:

$$E\left[\begin{pmatrix} Z_h^{t-2} \\ \widetilde{Z}_h^t \end{pmatrix} \upsilon_{ht}\right] = 0, \quad t = 3, ..., T$$

with $Z_h^{t-2} = \left(Z'_{h1}, Z'_{h2}, ..., Z'_{h(t-2)}\right)'$, $\widetilde{Z}_h^t = \left(\widetilde{Z}'_{h1}, \widetilde{Z}'_{h2}, ..., \widetilde{Z}'_{ht}\right)'$ and where Z_{ht} is a vector of endogenous variables in the model and $\widetilde{Z}_{ht}$ is a vector of exogenous variables. Moreover, I have used optimally reweighted instruments taking into account of the autocorrelation in v_{ht}.

The results are reported in Table 3. Demographic variables are treated as exogenous[27] whereas employment variables, the interest rate, income, consumption and conditional variances are, obviously, regarded as endogenous.

Table 3: Estimates for the Consumption Growth Equation

$$\Delta \ln\left(C_{h(t+1)}\right) = \frac{1}{\rho} r_t + \frac{1}{\rho}\varphi' \Delta D_{h(t+1)} + k_1 \pi_{ht}^2 \sigma_{t+1}^2 + k_2 \pi_{ht}^2 \sigma_{c(t+1)}^2 + k_3 \pi_{ht}^2 \sigma_{h(t+1)}^2 + v_{h(t+1)}$$

	(1)	(2)	(3)	(4)
r_t	1.816	1.802	1.842	1.838
	(1.044)	(1.048)	(1.042)	(1.051)
Age of head	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Δ#children	0.002	0.003	-0.003	-0.001
	(0.004)	(0.004)	(0.005)	(0.001)
Δ#members	0.066	0.085	0.058	0.059
	(0.190)	(0.188)	(0.187)	(0.187)
Δ#employed	0.183	0.309	0.333	0.410
	(0.143)	(0.155)	(0.153)	(0.149)
$\pi_{ht}^2 \sigma_{h(t+1)}^2$		0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
$\pi_{ht}^2 \sigma_{c(t+1)}^2$		1.867		1.291
		(0.568)		(0.613)
$\pi_{ht}^2 \sigma_{t+1}^2$			15.314	11.345
			(4.083)	(4.571)

Notes:

1) See the Data Appendix regarding the variables displayed in this Table. Seasonal dummies (not reported) were also included.

2) Numbers in parentheses are standard errors.

3) The set of instruments includes: age and age squared of the household head and household head's wife,
Number of total members, children, and elderly in the household dated at t, $t-1$, $t-2$, $t-3$ and $t-4$; real interest rate, number of employees, labour status of household head and his wife, household income, consumption and conditional variances (in the columns where they appear) dated at $t-2$, $t-3$ and $t-4$.

In the first column, it is reported, as a baseline, a conventional consumption growth equation, that is, without including the risk terms in the right hand side. Several results

[27] Statistical tests cannot reject the demographics dated at t and $t-1$ as valid instruments.

are worth noting. First, the estimated coefficient for real interest rate (i.e., the elasticity of intertemporal substitution) is positive and significantly different from zero. Likewise, some demographic variables are found to have important effects: the estimated response to an increased number of household members is significantly positive. These results remain unchanged when conditional variances are introduced as explanatory variables into the consumption equation.

In columns (2) and (3), besides the idiosyncratic risk term, I have included a common-risk term: the aggregate risk term σ^2_{t+1} in (2) (common to all households) and the cohort-specific risk term $\sigma^2_{c(t+1)}$ (common to all households whose head belongs at the same cohort) in (3). Similar conclusions can be reached from both columns: the idiosyncratic component is not significant, whereas the common-risk components are positive and significantly different from zero; the latter confirms the importance of a precautionary motive for saving. It is also worth noting that the theoretical model for consumption, see equation (14), predicts that the coefficient for risk term should be one half of the coefficient for interest rate; the estimated coefficients in columns (2) and (3) seem to verify this property. On the other hand, the non-significance of the idiosyncratic term suggests that much of what is being counted as idiosyncratic risk in $\sigma^2_{h(t+1)}$ does not pose true (i. e., uninsurable) risk; as commented before, households can get insured against idiosyncratic risks through many different schemes unobservable to the econometrician.

Finally, all the three risk components have been included in column (4). As expected, fully aggregate uncertainty appears to be important for individuals saving decisions. Nevertheless; the coefficient for the variance of cohort component is still significantly different from zero (and positive).[28] Hence, these results indicate that "between groups" insurance mechanisms at the cohort level have not worked out to limit the differential impact of these risks across households, so households needed to protect themselves from uncertainty associated with cohort level income variability by means of saving.

5 Conclusions

In this paper, I started from an interesting empirical application: the analysis of precautionary saving. I have a household rotating panel with information on family expenditure. I need identify the individual and the aggregate process of income, because idiosyncratic and aggregate income risks are expected to be play different roles in household decision making. Aggregate shocks can only be smoothed (across state of nature) by using precautionary saving, whereas individuals can more easily get insured against idiosyncratic shocks, because these can be "shared" with other individuals.

In many aspects, my data set, *Encuesta Continua de Presupuestos Familiares* (ECPF), is unique. Individuals are interviewed for eight consecutive periods, so I have a short true panel for each unit which crucially allows to identify the individual process; having as many as eight periods is not so common in rotating panel. Furthermore, I can easily

[28]Notice that the cohort-specific shock has to be regarded as including some macroeconomic shocks (common to all households in an economy), which have different impacts on individuals in different generations.

applied synthetic panels technique to study the aggregate process, because I also have a quite long time series (forty-eight periods).

Undoubtedly, these features raise very interesting econometric questions. So, I have taken seriously my data set and, in a econometric section, I discuss the properties that my estimates are expected to have, given the structure of the data that I am using. Finally, in the empirical section, I present results providing evidence on the importance of precautionary motive for saving in response to income risk.

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A Technical Appendix

Let me introduce some notation. Let these moment conditions be:

$$\Psi\left(w_{it};\theta\right)=\left[\begin{array}{c}\Psi_1\left(w_{it};\theta_1\right)\\ \Psi_2\left(w_{it};\theta_1,\theta_2\right)\end{array}\right]$$

such that $(7)-(\textbf{??})$ are $\Psi_1\left(w_{it};\theta_1\right)$ with $\theta_1=\left(\begin{array}{cc}\alpha & \sigma_u^2\end{array}\right)$, and $\Psi_2\left(w_{it};\theta_1,\theta_2\right)$ are (13) with $\theta_2=\beta$. These conditions verify that its expectations evaluated at the true parameter equals zero: $\operatorname{plim}_{N,T\to\infty}\frac{1}{NT}\sum_{i,t}\Psi\left(w_{it};\theta_0\right)=E\left[\Psi\left(w_{it};\theta_0\right)\right]=0$. Let me also define

$$\begin{aligned}E\left[\frac{\delta}{\delta\theta'}\Psi_{it}\left(\theta_0\right)\right] &= \Gamma=\left[\begin{array}{cc}\Gamma_{11} & 0\\ \Gamma_{21} & \Gamma_{22}\end{array}\right]\\ E\left[\Psi_{it}\left(\theta_0\right)\Psi_{it}\left(\theta_0\right)'\right] &= \Omega=\left(\begin{array}{cc}\Omega_{11} & 0\\ 0 & \Omega_{22}\end{array}\right)\end{aligned}$$

where (given that $\Psi_1\left(w_{it};\theta_1\right)$ is independent of θ_2) and Ω is block diagonal since $\Psi_1\left(w_{it};\theta_1\right)$ depends on $\Delta\left(y_{it}-\overline{y}_{\cdot t}\right)$ and $\Psi_2\left(w_{it};\theta_1,\theta_2\right)$ depends on $\overline{y}_{\cdot t}$ which are orthogonal to each other. The point is to know whether there is an efficiency loss in proceeding in two stages. Let call θ^J the joint estimator and θ^S the sequential estimator (first estimating θ_1^S and then θ_2^S using the previous estimates).

Then it is easy to prove that

$$Var\left(\theta^J\right) = \left[\Gamma'\Omega^{-1}\Gamma\right]^{-1}$$

$$\begin{aligned}Var\left(\theta_2^S\right) &= \left[\Gamma_{22}'\left(\Omega^*\right)^{-1}\Gamma_{22}\right]^{-1}\\ \Omega^* &= A\Omega A' \text{ and } A=\left[\begin{array}{ccc}-\Gamma_{21}\left(\Gamma_{11}\Omega_{11}^{-1}\Gamma_{11}\right)^{-1}\Gamma_{11} & \vdots & I\end{array}\right]\end{aligned}$$

After some basic manipulation, one can show that $Var\left(\theta_2^J\right)=Var\left(\theta_2^S\right)$. Therefore, given that Ω is block diagonal and that the weighting matrix is optimally chosen in the first step (that is why Ω_{11}^{-1} appears in A), one is not doing it worse in a sequential estimation for β than in a joint estimation.

B Data Appendix

The final sample of the households has been constructed by imposing the following requirements on the original data set:

- Households having permanent guests at any interview period are dropped, since I could be dealing with some kind of rooms-for-rent business which does not fit to my purpose in this paper.
- Every household member must have fully answered the survey. When a household member does not answer the survey, his/her income and expenditure are attributed by the INE according to his/her known characteristics (age, attained education, ...); I have decided to keep only households whose information is actually reported by themselves.
- The household head must be a married male.
- The household head must have been born between 1932 and 1959 (i. e., he belongs to any cohort in Table 2).
- The household must have answered the survey for, at least, 6 consecutive periods. This allows me to use lagged variables as instruments in the seasonally differenced panel data estimates.

The following variables, used in the estimates, are easily available from ECPF records:

- Age and age squared of the household head.
- Age and age squared of the household head's wife.
- Number of household members.
- Number of females in the household.
- Number of children: calculated as those household members aged 17 or less.
- Number of members older than 65 years old.
- Number of household members having an employment, either as wage earners or as self-employed.
- Dummy variables for the labour market status of the household head: part-time employed, unemployed, and out of the labour force (dummy for fully employed[29] is omitted in estimates).
- Dummy variables for the household head's educational attendance: illiterate or no schooling, secondary schooling, and university and post-graduate studies (dummy for primary schooling is omitted in estimates).

[29]Concerning employees, an individual working less than one third of the legal shift is regarded as partly employed and, otherwise, as fully employed.

C Appendix of Tables

Table I: Estimates for the Income Equation, by Cohort

$$Y_{ht} = \alpha^c Y_{h(t-1)} + (\beta^c)' X_{ht} - \alpha^c (\beta^c)' X_{h(t-1)} + \eta_h + \lambda_t^c + \varepsilon_{ht}, \quad \forall h \in c$$

	Coh. 1	Coh. 2	Coh. 3	Coh. 4	Coh. 5	Coh. 6	Coh. 7	Coh. 8
$Y_{h(t-1)}$	0.370	0.538	0.633	0.576	0.495	0.577	0.668	0.669
	(0.193)	(0.144)	(0.125)	(0.135)	(0.124)	(0.139)	(0.140)	(0.103)
#employed	0.182	0.213	0.337	0.251	0.367	0.266	0.312	0.499
	(0.082)	(0.150)	(0.088)	(0.095)	(0.102)	(0.118)	(0.132)	(0.140)
#members	0.051	0.191	-0.205	0.416	0.354	-0.072	0.218	-0.294
	(0.172)	(0.133)	(0.090)	(0.297)	(0.156)	(0.314)	(0.223)	(0.183)

Note: Numbers in parentheses are standard errors.

Table II: Estimates for the Conditional Variance of Idiosyncratic Shock to Income, by Cohort

$$\log \varepsilon_{ht}^2 = \gamma_1^c \varepsilon_{h(t-1)}^2 + \gamma_2^c \varepsilon_{h(t-1)} + (\tau^c)' Z_{h(t-1)} + \xi_{ht}, \quad \forall h \in c$$

	Coh. 1	Coh. 2	Coh. 3	Coh. 4	Coh. 5	Coh. 6	Coh. 7	Coh. 8
$\varepsilon_{h(t-1)}^2$	6.885	1.058	-0.188	1.248	1.062	4.427	4.400	1.115
	(3.407)	(0.937)	(0.940)	(3.010)	(0.776)	(2.470)	(2.510)	(0.835)
$\varepsilon_{h(t-1)}$	0.320	0.736	-0.244	0.873	0.448	6.463	0.224	-0.932
	(1.098)	(1.859)	(0.891)	(2.958)	(1.209)	(2.535)	(1.314)	(0.832)
Consumption$_{t-1}$	-0.721	0.252	-0.337	-1.194	-0.006	-0.733	-0.389	-0.137
	(0.641)	(0.448)	(0.535)	(0.979)	(0.517)	(0.780)	(0.555)	(0.547)
$(\text{Consumption}_{t-1})^2$	-2.180	-1.403	-1.634	0.599	-1.284	-1.055	0.293	-1.524
	(1.419)	(0.832)	(1.318)	(1.613)	(2.099)	(1.839)	(0.806)	(1.232)
#employed $_{t-1}$	-0.330	-0.219	0.366	0.435	-0.355	0.319	0.918	-1.203
	(0.475)	(0.398)	(0.635)	(1.185)	(0.365)	(0.697)	(0.683)	(0.642)
#members $_{t-1}$	-1.283	0.360	0.282	1.088	1.776	-1.816	-1.152	3.075
	(1.309)	(0.694)	(0.619)	(3.615)	(1.248)	(1.928)	(0.977)	(0.469)
Age of wife	-0.738	5.602	0.378	-4.594	-2.726	2.243	1.198	-1.822
	(3.684)	(3.672)	(0.959)	(2.350)	(4.020)	(4.295)	(4.402)	(3.282)

Note: Numbers in parentheses are standard errors.

Table III: Estimates for the Conditional Mean of Cohort Specific and Aggregate Shocks to Income, by Cohort

	Coh. 1	Coh. 2	Coh. 3	Coh. 4	Coh. 5	Coh. 6	Coh. 7	Coh. 8	Aggregate
Dependent Variable	e_{1t}	e_{2t}	Δe_{3t}	Δe_{3t}	Δe_{5t}	Δe_{6t}	Δe_{7t}	e_{8t}	$\Delta\Delta_4 e_t$
Contant	0.326	-0.023						1.404	
	(0.012)	(0.009)						(0.045)	
AR(1)	0.263	0.506	-0.380	-0.363	-0.032	-0.555		0.763	0.259
	(0.092)	(0.060)	(0.122)	(0.168)	(0.003)	(0.143)		(0.054)	(0.078)
MA(1)							-0.222		
							(0.099)		
MA(4)						0.590		-0.109	-0.911
						(0.137)		(0.077)	(0.031)

Note: Numbers in parentheses are standard errors.

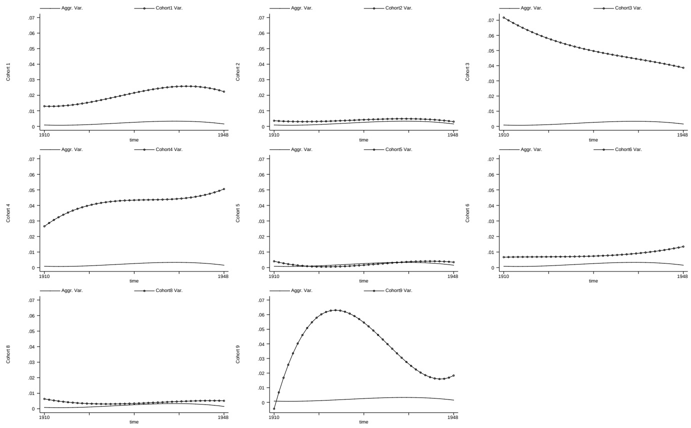
Table IV: Estimates for the Conditional Variance of Cohort Specific and Aggregate Shocks to Income, by Cohort

$$\varepsilon_{ct}^2 = \exp\left(\kappa_0 + \sum_{s=1}^{4} \kappa_{1s}\varepsilon_{c(t-s)}^2 + \sum_{l=1}^{4} \kappa_{2l}\varepsilon_{c(t-l)} + \tau\sigma_{c(t-1)}^2 + \vartheta_{ct}\right)$$

	Coh. 1	Coh. 2	Coh. 3	Coh. 4	Coh. 5	Coh. 6	Coh. 7	Coh. 8	Aggregate
Constant	-5.964	-11.012	-3.502	-9.348	-6.413	-1.209	-0.362	-2.720	-3.244
	(2.611)	(1.261)	(0.926)	(0.379)	(1.648)	(1.848)	(0.863)	(1.367)	(1.251)
$\varepsilon_{c(t-1)}^2$	-0.905	0.791	2.119	0.846	0.419	-0.350	-0.455	-0.920	-1.056
	(0.568)	(0.218)	(0.554)	(0.610)	(0.670)	(0.240)	(0.336)	(0.672)	(0.473)
$\varepsilon_{c(t-1)}$	-0.423	-0.521	-0.157	0.013	0.339	-0.090	0.067	-0.115	-0.521
	(0.292)	(0.273)	(0.340)	(0.341)	(0.178)	(0.192)	(0.117)	(0.545)	(0.306)
$\varepsilon_{c(t-2)}^2$	-1.003				0.477			0.407	
	(0.709)				(0.672)			(1.013)	
$\varepsilon_{c(t-2)}$	-0.576				0.053			0.290	
	(0.305)				(0.232)			(0.568)	
$\varepsilon_{c(t-3)}^2$					0.054			0.088	
					(0.622)			(0.887)	
$\varepsilon_{c(t-3)}$					-0.070			-0.139	
					(0.266)			(0.563)	
$\varepsilon_{c(t-4)}^2$					-2.863			-0.407	
					(0.528)			(0.854)	
$\varepsilon_{c(t-4)}$					-0.644			-0.771	
					(0.390)			(0.432)	
$\sigma_{c(t-1)}^2$	-0.331	-0.479	0.671	-0.895	-0.068	0.772	0.886	0.371	0.475
	(0.556)	(0.196)	(0.154)	(0.085)	(0.204)	(0.282)	(0.088)	(0.330)	(0.186)

Note: Numbers in parentheses are standard errors.

D Appendix of Figures



Evolution of (Fitted) Conditional Variances