# A panel data model for subjective information on household income growth

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# A Panel Data Model for Subjective Information on Household Income Growth

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**Abstract**

Subjective expectations about future income changes are analyzed, using household panel data. The models used are extensions of existing binary choice panel data models to the case of ordered response. We consider static models with random and fixed individual effects. We also look at a dynamic random effects model which includes a measure for permanent and transitory income. We find that income change expectations strongly depend on realized income changes in the past: those whose income fell, are more pessimistic than others, while those whose income rose are more optimistic. Expected income changes are also significantly affected by employment status, family composition, permanent income, and past expectations. Expectations are then compared to the head of household's *ex post* perception of the realized income change for the same period. The main finding is that rational expectations are rejected, and that in particular, households whose income has decreased in the past underestimate their future income growth.

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# 1 Introduction

In life cycle models of household behavior, future expectations play a central role. Decisions on consumption, savings, portfolio choice, labor supply, etc., not only depend on current variables, but also on the subjective distribution of future income, prices, etc. [see, for example, Deaton (1992)]. In empirical studies of life cycle models, direct information on households' future expectations is rarely used. Instead, the standard approach is to infer expectations from panel data on realizations. [1] This leads to the assumption of rational expectations, or to some alternative explicit model of expectation formation. [2]

Exceptions are Guiso et al. (1992, 1996), Lusardi (1997), and Alessie and Lusardi (1997), who use characteristics of subjective income distributions directly derived from survey data as explanatory variables to explain consumption, savings or portfolio choice. These studies have led to an increasing interest in data on and the modelling of income expectations. Guiso et al. (1992) and Dominitz and Manski (1997) analyze data on subjective income distributions on the basis of one cross-section. Alessie et al. (1997) use panel data and show that expected changes in income are significantly correlated with actual income changes. Das and Van Soest (1997) explain expected income changes from previous income changes. They also analyze differences between income expectations and realizations over the same time period, and find that many people underestimate their future income, particularly those whose income has fallen in the past.

To our knowledge, this is the only survey in which information on income expectations for the same households are available for a number of consecutive years. We focus on income expectations and realizations and use the same survey questions on actual and expected income changes as Alessie et al. (1997) and Das and Van Soest (1997), drawn from the Dutch Socio-Economic Panel (SEP). While Das and Van Soest (1997) focus on

[1] See the discussion in Dominitz and Manski (1997) and the references there.

[2] See, for example, Carroll (1994).

one panel wave, this paper uses an unbalanced panel of Dutch households for the period 1984 – 1989. This enables us to enrich the analysis in Das and Van Soest (1997) in four ways. First, we can analyze the robustness of the results over time. This is necessary if macro-economic shocks play a role, which may imply that results are time specific. Second, the use of more waves allows for the use of fixed household specific effects. Third, we are able to construct a measure for permanent income and can distinguish the effect of permanent and transitory income on income expectations. Fourth, we can look at dynamic panel data models, in which past expectations are included.

The survey questions refer to categories and do not provide information on exact realized or expected income changes. Our dependent variables are therefore of an ordered discrete nature. Although the literature on panel data has expanded rapidly, economic applications of panel data models for discrete data are rather scarce. Examples can be found in Chamberlain (1984) and Pfeiffer and Pohlmeier (1992). [3] Most applications for discrete data consider binary choice. We extend the binary choice model to the case of ordered response.

We consider static models with random and fixed individual effects. The extension in the random effects case is straightforward. In the fixed effects case, we use the conditional logit approach by Chamberlain (1980), aggregating all categories to two categories. The estimates for the ordered response model are then obtained by combining the estimates for separate combinations of categories with minimum distance. For the dynamic random effects model, we use the estimator suggested by Heckman (1981).

We basically aim at answering two questions: *Is the use of our type of subjective data feasible and is it useful?* The first boils down to: *do the answers make sense?* We claim that they do, by describing them for the six years and by showing that their relation to various background variables is rather robust over time and of the expected

[3] More applications exist in the fields of biology, psychology and biomedicine. An example of the latter is Gibbons et al. (1994).

sign. The second question can be restated as: *are the subjective data in conflict with the usual assumptions on rational expectations and (absence of) macro-economic shocks?* Our analysis of the deviations between expectations and realizations suggests that they are, and that the assumptions on rational expectations or absence of macro-economic shocks are not valid. This makes it worthwhile to replace these assumptions by information based upon the subjective information in the data.

The organization of the paper is as follows. Section 2 describes the data on income change expectations. Section 3 formulates the panel data model for the ordered responses. Section 4 uses this model to explain income change expectations. Among the explanatory variables are actual income, the realized income change during the previous year, and labour market status variables. Section 5 presents a dynamic random effects model, which uses the panel structure of the data to calculate a measure of permanent income that is included as an explanatory variable. The actual income level is then replaced by permanent and transitory income. Section 6 describes subjective information on realized income changes and shows that, on average, it relates quite well to more traditional measures of income change. In Section 7, using the model in Section 5 to correct for the discrete nature of our variables of interest, we construct a test for the null hypothesis that expectations are the best predictor of realizations – correcting for macro–economic shocks. The hypothesis is rejected, which is evidence against the assumption of rational expectations. In Section 8 we then use a fixed effects model to explain the deviations between the expectations in year $t$ and the realizations in year $t+1$ ($t = 84, \ldots, 88$). Section 9 summarizes our findings.

## 2 Data on income change expectations

Data are taken from the Dutch Socio-Economic Panel (SEP), which is a random sample from the Dutch population, excluding those living in special institutions like nursing homes.[4] Households were interviewed twice a year from October 1984 until 1989. Since 1990 the survey has been conducted only once a year in May. In the October interviews, information about income is gathered. Since 1990, the questions on income have changed completely. We therefore focus on the October waves of 1984 till 1989.

The attrition rate in the panel is about 25 percent on average, and falls over time. New households have entered the panel each year. After eliminating observations with item nonresponse, mainly due to missing information on one or more components of actual household income, we retained a sample of 6845 households. Only 722 of them are in the balanced subpanel (10.5%). This is the reason why we will focus on the complete unbalanced panel and not on the balanced subpanel. For 14% of all households the required information is available in five waves, for 18% in four, for 16.8% in three, and for 16.4% in two waves. The remaining households (24.3%) provided information for only one wave. Most of those who are in more than one wave, participate in consecutive waves. In the final data set used for estimation, about 24% are included in non-consecutive waves, mainly due to item nonresponse. The numbers of observations per wave are included in Table 1.

We do not address attrition and selection problems, although the numbers suggest that such problems could be serious. Attrition and nonresponse will be related to income and labour market status, but these are among our conditioning variables. Conditional upon our regressors, we see no compelling reasons to expect an attrition or selection bias, particularly since item nonresponse on our dependent variables is virtually nonexistent.

Heads of households are asked to answer the question

[4]See CBS (1991) for details about contents, setup and organization of the SEP.

*What will happen to your household's income in the next twelve months? Possible answers: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5).*

The distribution of the answers, denoted by $\text{EXP}_t$ ($t = 84, \ldots, 89$), are given in Table 1. Except for 1984, the number of households expecting a strong decrease is quite low. Aggregating the categories *strong decrease* and *decrease*, shows that the number of households expecting a fall in household income decreases over time, except in 1987.

INSERT TABLE 1 APPROXIMATELY HERE

Since the number of answers in the categories *strong decrease* and *strong increase* is quite low, we combined categories 1 and 2 and categories 4 and 5. This leaves three possible outcomes for the dependent variable $\text{EXP}_t$. Definitions and summary statistics of the explanatory variables are presented in Tables A1 and A2 in Appendix A.

# 3 Static panel data models for ordered categorical data

Our starting point is the well-known binary choice panel data model with time varying parameters and individual effects:

$$\begin{aligned} y^*_{i,t} &= \beta'_t x_{i,t} + \alpha_i + u_{i,t}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \\ y_{i,t} &= 1(y^*_{i,t} \geq 0) \end{aligned} \tag{1}$$

in which $\beta_t \in \mathbb{R}^k$ and $1(A)$ is the indicator function which is equal to 1 if A is true and 0 otherwise. The index $i$ represents the household and index $t$ represents time. $x_{i,t}$ is a $k$-dimensional vector of explanatory variables, including a constant term. Instead of observing $(y^*_{i,t}, x'_{i,t})'$ one observes $(y_{i,t}, x'_{i,t})'$.

We assume that $x_i = [x'_{i,1}, x'_{i,2}, \ldots, x'_{i,T}]'$ and $u_i = [u_{i,1}, u_{i,2}, \ldots, u_{i,T}]'$ are independent. The mutually independent disturbances $u_{i,t}$ are assumed to follow some distribution with mean 0 and variance $\sigma^2$. We both consider the normal and the logistic distribution.

It is easy to extend model (1) to allow for more than two outcomes for $y_{i,t}$. Suppose $y_{i,t}$ has $p$ possible outcomes. As in model (1), these are assumed to be determined by an underlying latent variable $y^*_{i,t}$. The relation between $y_{i,t}$ and $y^*_{i,t}$ is modelled by

$$\begin{aligned} y^*_{i,t} &= \beta'_t x_{i,t} + \alpha_i + u_{i,t}, & & i = 1, \ldots, N, \quad t = 1, \ldots, T \\ y_{i,t} &= j \quad \text{if } m_{j-1} < y^*_{i,t} \leq m_j & & j = 1, \ldots, p \end{aligned} \tag{2}$$

where $m_0 = -\infty$ and $m_p = \infty$. To identify the model, location and scale have to be fixed. For the individual effect $\alpha_i$ we will use two specifications: random effects (Section 3.1) or fixed effects (Section 3.2).

## 3.1 Random effects specification

The random effects model consists of model (2) with the additional assumption that the individual effects $\alpha_i$ are normally distributed with mean 0 and variance $\sigma^2_\alpha$.[5] Moreover, we assume that $x_i, u_i,$ and $\alpha_i$ are independent.

In general, the likelihood function for model (2) is a $T$-variate integral. Under the above assumption, however, it can be reduced to a single integral [see Butler and Moffitt (1982)]. The integrand is then a product of one normal density and $T$ differences of values of the distribution function $F_\sigma$ of $u_{i,t}$, where $\sigma$ is a scale parameter. The contribution $\text{Prob}(y_{i,1}, \ldots, y_{i,T})$ for individual $i$ to the likelihood function is given by

[5] For random effects models in which the assumed family of distributions for the individual effect adopts a variety of forms and shapes, see Crouchley (1995).

$$\int_{-\infty}^{\infty} g(\alpha_i)[\prod_{t=1}^{T}\{F_\sigma(m_{y_{i,t}} - \beta_t' x_{i,t} - \alpha_i) - F_\sigma(m_{y_{i,t}-1} - \beta_t' x_{i,t} - \alpha_i)\}]\mathrm{d}\alpha_i, \tag{3}$$

where $g(\alpha_i)$ is the density of $N(0, \sigma_\alpha^2)$. The boundaries $m_j (j = 1, \ldots, p-1)$ are assumed to be constant across individuals.

The model described so far is only applicable for balanced panels. Since we use an unbalanced panel, the notation should slightly be adapted. Define

$$c_{i,t} = \begin{cases} 1 & \text{if individual } i \text{ is in wave } t \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

We assume that $c_{i,t}$ is independent of $u_{i,t}$ and $\alpha_i$, implying that we do not allow for selection or attrition bias (see the discussion in the previous section). The likelihood contribution for individual $i$ is then given by

$$\int_{-\infty}^{\infty} g(\alpha_i)[\prod_{t=1}^{T}\{F_\sigma(m_{y_{i,t}} - \beta_t' x_{i,t} - \alpha_i) - F_\sigma(m_{y_{i,t}-1} - \beta_t' x_{i,t} - \alpha_i)\}^{c_{i,t}}]\mathrm{d}\alpha_i.$$

## 3.2 Fixed effects specification

A limitation of the random effects specification is the assumption that the individual effect $\alpha_i$ is uncorrelated with the $x_{i,t}$. This can be relaxed by treating $\alpha_i$ as a fixed effect, i.e. each $\alpha_i$ becomes an unknown parameter. In the fixed effects specification, the slope coefficients $\beta_{t,k}$ are only identified if the corresponding regressors $x_{i,t,k}$ vary over time. For time-invariant $x_{i,t,k}$, only the differences $\beta_{t,k} - \beta_{s,k}$ are identified, so that without loss of generality, the coefficients of one time period can be normalized to zero.

In this fixed effects model, the number of parameters increases with the number of individuals $N$. ML estimates of the $\alpha_i$ and the $\beta_{t,k}$ will be inconsistent if $N$ becomes large but $T$ is finite. This is known as the incidental parameter problem [Neyman and

Scott (1948)]. For the binary choice panel data model, Chamberlain (1980) suggested an approach based upon a conditional likelihood function to estimate the $\beta_{t,k}$. The idea is to work with a conditional likelihood, conditioning on sufficient statistics for the nuisance parameters $\alpha_i$. This works if the disturbance terms $u_{i,t}$ are iid and follow a logistic distribution. Then the minimum sufficient statistic for $\alpha_i$ is $\sum_{t=1}^{T} y_{i,t}$. Given this statistic, the contribution of individual $i$ to the conditional likelihood is, for a balanced panel

$$\mathrm{Prob}(y_{i,1},\ldots,y_{i,T}|\sum_{t=1}^{T} y_{i,t}) = \frac{\exp[\sum_{t=1}^{T}(x'_{i,t}\beta_t)y_{i,t}]}{\sum_{d\in B_i}\exp[\sum_{t=1}^{T}(x'_{i,t}\beta_t)d_t]}, \tag{5}$$

where

$$B_i = \{d = (d_1,\ldots,d_T) \mid d_t = 0 \text{ or } 1, \text{ and } \sum_t d_t = \sum_t y_{i,t}\}.$$

It does not depend on the incidental parameters $\alpha_i$, and the conditional ML estimator of $\beta_t$ is, under mild regularity conditions, consistent and asymptotically normal.

This approach cannot be directly extended to an ordered response panel data model where the dependent variable has $p > 2$ possible outcomes. However, we can combine adjacent categories so that the dependent variable is summarized as a binary variable, and then use this method. If we repeat this for all the possible combinations of adjacent categories, we get $p-1$ estimates of the parameters of interest. [6] These estimates can then be combined into one final estimate of the parameters of interest by using minimum distance. Details are available upon request from the authors. It is straightforward to extend this estimation procedure to the case of an unbalanced panel, similarly as for the random effects model. The unbalanced nature of our data is also the reason why we do not consider quasi fixed effects models [see Chamberlain (1984)] in which $\alpha_i$ is allowed to be correlated with the $x_{i,t}$. The fact that $x_{i,t}$ is unobserved in some waves would then

[6] The boundaries $m_j$ are not estimated and can be seen as nuisance parameters. Moreover, in the fixed effect specification the boundaries are allowed to depend on $i$.

lead to ad hoc adjustments of the correlation pattern (or to joint modelling of the $x_{i,t}$ with the $y_{i,t}$ and the specification and computational problems involved with that).

# 4 Estimation results

First we estimate the *random effects* model described in Section 3.1. We normalize $m_1$ to $-1$. For the distribution of the error terms $u_{i,t}$, we use the (standard) logistic distribution. [7]

The total number of observations in the pooled sample is 6845. Table 2a presents the estimation results. No restrictions are imposed upon the slope coefficients across the various waves. The estimates here are similar to those obtained when estimating the cross-section model for each separate wave. The only joint elements are the boundary $m_2$, and the variance of the random effect, which picks up about 20% of the total error variance (note that $\sigma_u^2 = \pi^2/3$). Joint estimation has the advantage that stability of coefficients over time can be tested straightforwardly. The final column of Table 2a presents the test results.[8]

The 1984 estimates are similar to those in Das and Van Soest (1997). Many of these remain stable over time. However, a joint test on the stability of the coefficients AGE and AGE2 rejects the null hypothesis that the age pattern remains constant over time. This suggests that there might be some cohort effect. Households with a female head tend to be less optimistic than other one earner households: the coefficient of SEX is negative and significant in three of the six years. [9] Except for 1985 and 1988, two earner households

[7] We estimated the same model with normally distributed $u_{i,t}$. The results were similar. Vuong's (1989) model selection test suggests that the model with logistic $u_{i,t}$ fits the data significantly better than the model with normally distributed $u_{i,t}$ (test statistic 14.8, compared to 5% critical value 1.64)

[8] All tests are Wald tests, based upon imposing $T-1=5$ restrictions in the general model. The results of the tests are the same when we do not include 1984 (which seems rather different from the other years, judging from the raw data).

[9] For married couples, the head of household is by definition the husband.

have significantly lower expectations of income changes than other households headed by males.

INSERT TABLE 2a APPROXIMATELY HERE

For none of the years, retired family heads are significantly different from workers. For the dummies corresponding to unemployed and disabled family heads, stability over time is rejected. Unemployed and disabled heads are significantly more pessimistic than workers (with the same income) in the first five years, but the differences decline and have basically disappeared in the last wave. For the disabled, this may well reflect anticipation to the institutional changes in disability benefit access and levels that started in 1985 and were completed in 1987. For the unemployed, it probably reflects larger expected chances of finding a job due to the upswing of the business cycle.

Those who experienced an income fall in the past have a larger probability of expecting another income fall than others (ceteris paribus). This effect becomes smaller over time, but remains significant throughout the time period considered. On the other hand, those who experienced an income rise tend to remain less pessimistic than others, and the difference with those whose income did not change during the last twelve months (the reference group) remains stable over time.

Stability over time of the relation between income expectations and the level of actual income LOG_INC (objectively measured), is rejected at the 5% level. Still, the effect is always positive, and significant in three out of the six years. We come back to this in the next section, where we distinguish between permanent and transitory income effects.

In the fixed effects specification, the assumption of independence between the individual effect and the covariates is relaxed (see Section 3.2). We normalized the constant term. We excluded the variables SEX, AGE, and AGE2, which do not vary over time or vary over time in a deterministic way. Wald tests indicate that the hypothesis that these variables play no role cannot be rejected at the 5% level. Note that with the estimates of the fixed effects specification we essentially do not use data on the households that provided all information in just one wave.[10]

The number of categories $p$ we use is equal to 3: decrease ($\text{EXP}_t < 3$), no change ($\text{EXP}_t = 3$), and increase ($\text{EXP}_t > 3$). As mentioned in Section 3.2 we summarize the ordered categories into two categories to use conditional logit. This means that there are two possible summaries: 2 versus 3 and 4, and 2 together with 3 versus 4. With a minimum distance step we combine these two estimators to get the final estimates for the $\beta_t$'s. These are shown in Table 2b.

INSERT TABLE 2b APPROXIMATELY HERE

For the variables referring to realized income changes in the past, the results are the same as in the random effects model. Those whose income decreased in the past are significantly more pessimistic, and those whose income increased are more optimistic than those whose income remained unchanged. The results for the labor market status variables are also similar to those in Table 2a. The only exception is found for $t = 89$. In Table 2a DUNEM, DDIS, and DRET are not significantly different from zero while in Table 2b all these parameters are significantly positive. This suggests that in 1989 those heads of households who became unemployed, disabled or retired are less pessimistic about future income growth than employed heads. Only for the variable LOG_INC we find a result which is substantially different from that in the random effects model. The coefficient is negative instead of positive, and significant in three out of the six waves. An explanation is that the fixed individual effect is positively correlated with income. We will come back to this in the next section.

The fixed effects specification is a generalization of the random effects model. The two can be compared using a Hausman test. If the random effects model is correctly

[10] This cannot explain the differences between random and fixed effects estimates; random effects estimates excluding the same observations gave results similar to those in Table 2a.

specified, the random effects ML estimates for the $\beta_t$ are consistent and asymptotically efficient. The estimates of the fixed effects model are consistent as long as the fixed effects specification is correct. The Hausman test is based upon the differences of the two sets of parameter estimates. The test rejects the random effects specification at all conventional significance levels.

# 5 Permanent income and dynamics

As mentioned above, the difference between the income coefficients in the random and fixed effects models could be due to a positive correlation of the fixed individual effect and income: the positive income effect according to the random effects model could mean that those with higher 'permanent' incomes are on average more optimistic than others. It suggests that heads of households expect that differentials in incomes per year between those with high and those with low permanent income tend to increase over the life cycle. The estimates of the fixed effects model then mean that, conditional on the fixed effect (i.e. on permanent income), those whose income is unusually high in a given period often expect an income fall. In other words, this means that the expected change in transitory income is negatively related to the level of transitory income.

To verify that the above intuition is correct, we construct measures of permanent and transitory income for each household along the lines of King and Dicks-Mireaux (1982). This means that we estimate a simple random effects model for household income, and use it to construct best predictions of permanent and transitory incomes for each household.[11]

Estimates of the static random effects model with these measures for permanent and transitory income, show that the intuition is correct: the coefficient for permanent income

[11] A notable difference with King and Dicks-Mireaux (1982) is that we can use panel data while they had observations on household earnings for only one year. Thus we can replace some of their *ad hoc* assumptions by estimates. Details are available upon request from the authors.

is significantly positive for all waves and, except for the years 1988 and 1989, the coefficient for transitory income is significantly negative.[12] Estimates of the coefficients of the other variables are similar to those presented in Table 2a.

Given the availability of panel data, another natural way to extend the model is to allow today's expectations of future income to depend on yesterday's expectations. This would be the case, for example, if expectations were formed according to an adaptive mechanism. Thus we want to include lagged dummy dependent variables $1(y_{i,t-1} < 3)$ and $1(y_{i,t-1} > 3)$, indicating whether the respondent expected an income decrease or increase in the previous year.

Estimators for dynamic panel data models with qualitative dependent variables, however, are scarce. The only estimator we know of is the one of Heckman (1981), for the random effects case with time constant slope coefficients. This is a Maximum Likelihood estimator, integrating out the random effect. The initial value problem is taken into account by using a reduced form static equation for the first wave, with coefficients for the first period. The equations for respondent $i$ are given by [13]

$$
\begin{aligned}
y_{i,t}^* &= \delta' x_{i,t} + \rho \alpha_i + v_{i,t}, && t = 1, \\
y_{i,t}^* &= \beta' x_{i,t} + \gamma_1 1(y_{i,t-1} < 3) + \gamma_2 1(y_{i,t-1} > 3) + \alpha_i + u_{i,t}, && t = 2, \ldots, T.
\end{aligned}
\tag{6}
$$

We have normalized the category bounds to 0 and 1. As before, the $\alpha_i$ are assumed to be normally distributed, while the $u_{i,t}$ and $v_{i,t}$ also follow normal distributions (with variances to be estimated). [14] For the reduced form equation in period 1, this implies the same *ad hoc* approximation as Heckman (1981). His Monte Carlo experiments suggest that the estimator performs quite well in practice.

[12] The coefficients for transitory income for the waves of 1988 and 1989 are slightly positive, but far from significant.

[13] This is for the case an individual is observed in all waves. The estimator is adjusted to the unbalanced panel in the same way as in Section 3.

[14] Again, the logistic distribution gives similar results. The reason for using the normal and for the chosen normalization is given in Section 7.

Although this model extends the static model in that it allows for lagged dependent variables, it also imposes some restrictions. First, the slope coefficients are no longer allowed to vary over time. Although this hypothesis is statistically rejected in the static models, it still seems a reasonable approximation, since most slope coefficients were similar in most waves. Second, the model does not allow for fixed effects. In the static case, the random effects model was rejected against the fixed effects model, but the main differences were the income coefficients. By incorporating separate measures for permanent and transitory income as regressors, the correlation between remaining random effects and regressors is reduced, and the assumption of random effects should become less problematic.[15]

INSERT TABLE 3 APPROXIMATELY HERE

The results are presented in Table 3. For comparison, we have estimated the same model without dynamics ($\gamma_1 = \gamma_2 = 0$). These results are in the first two columns. A likelihood ratio test comparing the two shows that the dynamics are significant. Those who expected a decrease in the past more often expect another decrease, *ceteris paribus.* The effect is significant, though not very large, compared to, for example, the effect of the actual income change in the past (DECR_1 and INCR_1). On the other hand, those who expected an income increase in the past more often expect another increase and the magnitude of the effect is comparable to magnitude of the effect of the actual income change in the past. The impact of permanent (PERMINC) and transitory (TRANSINC) income are in line with those in the static model discussed above: the first is significantly positive, and the second is negative, though insignificant at the 5% level (t-value 1.1). The effects of the other variables are also in line with the findings in the static model in

[15]Formal tests are not available since the dynamic fixed effects model cannot be estimated.

the first column of the table. As expected, the reduced form slope coefficients for the first period have the same signs as the slopes for the other periods, but tend to be larger in size. In the dynamic model, the role of the individual effects is much smaller than in the static model, as indicated by a smaller value of $\sigma_\alpha$.

## 6 Comparing expectations with realizations

Family heads also answered the question

> *Did your household's income increase, decrease, or remain unchanged during the past twelve months?*

The possible answers, which we denote by $\text{PREV}_t$ ($t = 84, \ldots, 89$), are the same as for $\text{EXP}_t$. Table 4 presents the distribution of the answers.

INSERT TABLE 4 APPROXIMATELY HERE

The dispersion in realized income changes is much larger than in expected income changes (cf. Table 1). Many households experienced a strong decrease or a strong increase. This is not surprising, since the expected income change refers to some location measure of the household's (subjective) income change distribution, while the realization is one draw from the (actual) distribution of income changes. The dispersion in the latter is not only due to variation in income growth distributions across families, but also to the uncertainty of the income change for a given household.

Figure 1 shows the relation between the answers to the subjective income change question and the objectively measured change in actual real total family income over the same time period (using the consumer price index for each year). We present the median real income change for families with given value of PREV.

INSERT FIGURE 1 APPROXIMATELY HERE

The results are fairly stable over time, except for those with a large fall. For those who reported no change (PREV = 3), the median real income change varies between 0.4% and 1.5%. For those who reported an income decrease, the median real change varies from -1.5% to -0.5%; for those who reported an increase, it varies from 4.2% to 6.0%. These numbers are more stable for real than for nominal income changes. In Das and Van Soest (1997) we already argued that the subjective answers reflect real rather than nominal changes. Figure 1 provides further evidence to support this. For those reporting a strong increase, the median varies between 12.1% and 17.1%. Only for those who reported a strong decrease, the pattern seems nonstationary, and the median falls from -5.9% to -16.8%. This group, however, is quite small in 1989 (see Table 4).

Although the questions are not very well specified, it seems reasonable to assume that the head of household has the same concept in mind while answering the questions on $\mathrm{PREV}_t$ and $\mathrm{EXP}_t$. Due to the panel nature of the data, we can compare the expectation of income change (provided in wave t-1) with the realization for the same time period (provided in wave t). If $\mathrm{PREV}_t$ is larger than $\mathrm{EXP}_{t-1}$ then the head of household has *(ex post)* underestimated household income growth. Analogously, if $\mathrm{PREV}_t$ is smaller than $\mathrm{EXP}_{t-1}$ then the income growth is overestimated.

INSERT TABLE 5 APPROXIMATELY HERE

Table 5 shows the frequencies of households who under- and overestimated their income changes. In all cases, the percentage of families underestimating exceeds the percentage of families overestimating future income growth. Except for 1986-1987, this difference is highly significant. We find it hard to believe that unanticipated macro-economic shocks explain the fact that this happens several times in a row.

A possible weakness of our way of comparing expectations with realizations might be implied by the vague wording of the question. People may have adjusted to a strong income decrease in the past, and won't use the word *strong* again (habit formation). To eliminate this problem, we performed the after combining categories 1 and 2 and categories 4 and 5, so that the difference between *strong* and *moderate* is eliminated. The values of the test-statistics for the five years are then given by $14.2, 10.3, 0.1, 12.3$, and $14.8$. The underestimation is significant in the same four years as in Table 5.

# 7 Testing for rational expectations

Let $\mathrm{EXP}^*_{i,t}$ denote the continuous variable underlying $\mathrm{EXP}_{i,t}$, and let $\mathrm{PREV}^*_{i,t+1}$ denote the continuous variable underlying next year's observed realization $\mathrm{PREV}_{i,t+1}$, $t = 84, \ldots, 88$. Under rational expectations, $\mathrm{EXP}^*_{i,t}$ can be seen as an unbiased predictor of $\mathrm{PREV}_{i,t+1}$. To test this, we consider the model

$$\mathrm{PREV}^*_{i,t+1} = \pi \mathrm{EXP}^*_{i,t} + \rho_t + \varepsilon_{i,t+1}. \tag{7}$$

Year dummies ($\rho_t$) are included to allow for macro–economic shocks. Under rational expectations we have $\pi = 1$ and $\varepsilon_{i,t+1}$ is has mean zero given the information available at time $t$ (including $\mathrm{EXP}_{i,t}$). A test for $\pi = 1$, maintaining the assumptions on $\varepsilon_{i,t+1}$, can thus be seen as a test for rational expectations.

If the continuous variables $\mathrm{PREV}^*_{i,t+1}$ and $\mathrm{EXP}^*_{i,t}$ were observed, the test could be based upon a simple regression. Since we only observe the categorical variables, we need some auxiliary assumptions. First, we need to model $\mathrm{EXP}^*_{i,t}$. Here we use the dynamic model (6) in Section 5. Second, for maximum likelihood estimation, we need to make a distributional assumption on $\varepsilon_{i,t+1}$. We assume that it is normal $N(0, \sigma^2_\varepsilon))$ and independent of everything in (6). This is somewhat stronger than the assumption of zero conditional mean implied by rational expectations.

Under these assumptions, (7) and (6) can be estimated jointly by maximum likelihood. Table 6 presents the results for the parameters in (7), both under the null and under the alternative. Under the null, the tendency to underestimate which was obvious from Table 5 has to be explained by macro–economic shocks. This explains why the year dummies are all significantly positive. But the second column shows that the null is clearly rejected: $\pi$ is significantly smaller than 1. $\mathrm{EXP}^*_{i,t}$ is far from the best prediction of $\mathrm{PREV}_{i,t+1}$. Even controlling for macro–economic shocks, rational expectations is rejected.

INSERT TABLE 6 APPROXIMATELY HERE

# 8 Deviations between realizations and predictions

The result of the test above shows that there are systematic deviations between realizations and predictions. A structural model explaining predictions and realizations and their interactions is beyond the scope of the current paper. Instead, we are less ambitious, and look at a reduced form model to analyze how the deviations between predictions and realizations relate to background variables, income levels, and past expected and realized income changes. For this purpose, we use a fixed effects model similar to that in Section 3.

Table 7 presents the estimates of a static ordered response panel data model with fixed effects explaining the deviation $\mathrm{DEVIATION}_{i,t} = \mathrm{EXP}_{i,t-1} - \mathrm{PREV}_{i,t}$ between income change expectation and income change realization for the same time period. The model and estimation strategy are those discussed in Section 3. The values of the dependent variable range from $-4$ (strong underestimation of future income) to 4 (strong overestimation). This would lead to 8 possible conditional logit estimates. Because of the low numbers of observations in the extreme categories and for computational convenience, our estimator is based on only two conditional logits: $\text{DEVIATION}_{i,t} < 0$ versus $\text{DEVIATION}_{i,t} \geq 0$ and $\text{DEVIATION}_{i,t} \leq 0$ versus $\text{DEVIATION}_{i,t} > 0$. These two are combined using minimum distance.

Again, for each variable, a Wald test is performed on stability over time of the corresponding parameter. Moreover, an additional Wald test is carried out to test whether all parameters corresponding to a specific explanatory variable are equal to zero. Except for the variables LOG_INC, DUNEM, and DTWO both hypotheses are rejected. The unemployed heads do not significantly differ from working heads and heads of two earner households do not underestimate more or less than other male family heads. Disabled heads have tended to underestimate significantly more than employed heads in 1988 and 1989. An interpretation of this is that people expected stronger consequences of the reforms of the system of disability benefits.

INSERT TABLE 7 APPROXIMATELY HERE

The effects of DECR_1 and INCR_1, the variables indicating an income decrease or increase in the past, vary over time. [16] Still, the effect of DECR_1 is significantly negative and the effect of INCR_1 is significantly positive in all years. Thus those whose income has fallen have a larger probability of underestimating than others. This was also found by Das and Van Soest (1997). We find that this result is robust over time. This casts further doubt on the argument that the low predictions would be explained by macro–economic shocks, since it would imply a negative correlation between unanticipated shocks and the income change in the past, which we find hard to interpret. The remaining explanation is that households whose income has fallen are simply too pessimistic, and tend to view negative income changes too much as permanent.

[16] No account has been taken of potential endogeneity of these variables.

# 9 Conclusions

We have analyzed subjective data on income change expectations and realizations using panel data covering the period 1984 − 1989. Comparing the subjective data on realizations with information on actual income suggests that the subjective data reflect percentage changes in real income. For all panel waves, we find that income growth expectations are strongly affected by previous income changes. Using a dynamic model, we also find an effect of past income change expectations on current expectations, but this is smaller than the effect of past actual changes. The impact of labor market status variables is less stable over time, and this can partly be explained by institutional changes in the time period considered. We find that those with higher permanent incomes generally have higher expected income growth than others, indicating that the expected income pattern over the life cycle depends on permanent income.

Comparing expected and realized income changes for the same time period, we find that, on average, future income growth was significantly underestimated. The hypothesis of rational expectations is rejected, even after controlling for macro–economic shocks. In particular, people whose income decreased in the recent past tend to be too pessimistic. Negative transitory incomes are too often considered to be permanent.

Our results thus cast doubt on using the assumption of rational expectations, a common assumption in many empirical studies of life cycle models. Moreover, our results suggest that subjective survey questions contain valuable additional information, which can be used to replace this assumption. Incorporating this in a life cycle model thus seems a promising topic of future research.

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# Appendix A

**Table A1: reference list variables.**

| | |
|---|---|
| **EXP$_t$** | Answer to the question : "What will happen to your household's income in the next twelve months ?" Possible answers are: strong decrease (1); decrease (2); no change (3); increase (4); strong increase (5). The subindex $t$ runs from 84 till 89 (where 84 corresponds to the year 1984, etc.). |
| **PREV$_t$** | Answer to the question : "Did your household's income increase, decrease, or remain unchanged during the past twelve months ?" Possible answers: see EXP$_t$. |
| **DECR_1** | Dummy variable related to PREV$_t$: DECR_1 = 1 if PREV$_t$ is equal to 1 or 2; 0 otherwise. |
| **INCR_1** | Dummy variable related to PREV$_t$: INCR_1 = 1 if PREV$_t$ is equal to 4 or 5; 0 otherwise. |
| **SEX** | Sex head of household: 1 = male; 2 = female. If husband and wife are present, the husband is by definition head of household. |
| **AGE** | Age head of household in tens of years. |
| **LOG_INC** | Natural logarithm of net household income where net household income is in tens of thousands (per year). The survey contains accurate information on income from about twenty potential sources for each individual. After tax household income was constructed by adding up all individual income components of all family members and some specific household components (such as child allowances). |

Dummy-variables corresponding to labor market status head of household:

| | |
|---|---|
| **DEMP** | 1 if head of household is employed; 0 otherwise. |
| **DUNEM** | 1 if head of household is unemployed; 0 otherwise. |
| **DDIS** | 1 if head of household is disabled; 0 otherwise. |
| **DRET** | 1 if head of household is retired; 0 otherwise. |
| **DOTH** | DOTH=1-DEMP-DUNEM-DDIS-DRET |

Dummy-variable corresponding to labor market status of spouse:

| | |
|---|---|
| **DTWO** | 1 if household is a two-earner household; 0 otherwise. |

**Table A2: Mean values (standard deviations in parentheses).**

| $t$ | 84 | 85 | 86 | 87 | 88 | 89 |
|---|---|---|---|---|---|---|
| Nr. Obs | 2683 | 2787 | 3850 | 3899 | 4059 | 4133 |
| $EXP_t$ | 2.66 | 2.95 | 3.04 | 2.98 | 3.07 | 3.17 |
| | (0.76) | (0.68) | (0.64) | (0.67) | (0.61) | (0.64) |
| $PREV_t$ | 2.67 | 2.89 | 3.13 | 3.02 | 3.14 | 3.26 |
| | (0.90) | (0.92) | (0.85) | (0.86) | (0.83) | (0.83) |
| DECR_1 | 0.36 | 0.26 | 0.16 | 0.21 | 0.14 | 0.11 |
| INCR_1 | 0.12 | 0.20 | 0.28 | 0.24 | 0.26 | 0.33 |
| SEX | 1.20 | 1.19 | 1.19 | 1.23 | 1.23 | 1.23 |
| Age head of household | 46.6 | 46.1 | 45.6 | 47.1 | 47.0 | 46.9 |
| | (17.0) | (16.4) | (16.2) | (17.0) | (16.9) | (17.0) |
| Net household income | 3.48 | 3.57 | 3.64 | 3.79 | 3.71 | 3.79 |
| (in Dfl. 10,000) | (1.98) | (2.24) | (2.12) | (2.98) | (2.32) | (2.21) |
| DEMP | 0.554 | 0.545 | 0.587 | 0.528 | 0.543 | 0.575 |
| DUNEM | 0.045 | 0.037 | 0.030 | 0.030 | 0.022 | 0.026 |
| DDIS | 0.068 | 0.075 | 0.063 | 0.069 | 0.061 | 0.063 |
| DRET | 0.158 | 0.143 | 0.183 | 0.230 | 0.229 | 0.193 |
| DTWO | 0.204 | 0.216 | 0.253 | 0.230 | 0.235 | 0.245 |

**Table 1 : Univariate frequencies (in %) of $\mathbf{EXP}_t$ ($t = 84, \ldots, 89$)**

| $\mathrm{EXP}_t$ | 84 | 85 | 86 | 87 | 88 | 89 |
|---|---|---|---|---|---|---|
| # observations | 2683 | 2787 | 3850 | 3899 | 4059 | 4133 |
| 1: strong decrease | 5.9 | 1.9 | 1.6 | 2.3 | 1.3 | 1.3 |
| 2: decrease | 33.1 | 18.9 | 12.6 | 15.8 | 10.9 | 8.2 |
| 3: no change | 50.3 | 62.4 | 66.4 | 63.9 | 68.6 | 63.2 |
| 4: increase | 10.3 | 16.0 | 18.6 | 17.4 | 18.4 | 26.5 |
| 5: strong increase | 0.4 | 0.9 | 0.8 | 0.6 | 0.9 | 0.9 |

**Table 2a : Random effects model**

| DEPENDENT VARIABLE: $EXP_t$ $(t = 84, \ldots, 89)$ | | | | | | | |
|---|---|---|---|---|---|---|---|
| Number of Observations: 6845 | | | | | | | |
| Variable | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | |
| CONSTANT | 3.91* | 4.30* | 4.45* | 3.81* | 4.23* | 3.96* | NR |
| DECR_1 | -1.79* | -1.20* | -0.76* | -1.26* | -0.76* | -0.46* | R |
| INCR_1 | 1.41* | 1.08* | 1.14* | 0.98* | 0.98* | 1.04* | NR |
| SEX | -0.21 | -0.10 | -0.30* | -0.27* | -0.25* | -0.10 | NR |
| AGE | -1.35* | -0.98* | -0.89* | -0.75* | -0.84* | -0.75* | NR |
| AGE2 | 0.12* | 0.07* | 0.05* | 0.04 | 0.05* | 0.05* | NR |
| LOG_INC | 0.30* | 0.11 | 0.09 | 0.34* | 0.26* | 0.11 | R |
| DUNEM | -1.00* | -1.27* | -1.03* | -0.68* | -0.73* | -0.04 | R |
| DDIS | -1.65* | -1.30* | -1.04* | -0.98* | -0.92* | -0.05 | R |
| DRET | -0.27 | -0.34 | -0.07 | 0.11 | -0.02 | -0.20 | NR |
| DOTH | -0.07 | -0.27* | -0.42* | -0.03 | -0.34* | -0.36* | R |
| DTWO | -0.54* | -0.21 | -0.26* | -0.32* | -0.18 | -0.27* | NR |
| $\sigma_\alpha^2$ | 0.75* | | | | | | |
| $m_2$ | 3.18* | | | | | | |

1) * = significant at 5 % level.

2) Null hypothesis: coefficient corresponding to explanatory variable does not vary over time; R = rejected, NR = not rejected (significance level: 5%).

**Table 2b : Fixed effects model**

| DEPENDENT VARIABLE: $EXP_t$ ($t = 84, \ldots, 89$) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Number of Observations: 5185 | | | | | | | |
| Variable | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | |
| DECR_1 | -1.62* | -0.71* | -0.36* | -0.89* | -0.45* | -0.35* | R |
| INCR_1 | 0.60* | 0.48* | 0.63* | 0.31* | 0.39* | 0.55* | NR |
| LOG_INC | -0.57* | -0.17* | -0.15* | -0.01 | -0.02 | -0.04 | R |
| DUNEM | -0.76* | -0.42 | -0.58* | -0.30 | 0.14 | 0.78* | R |
| DDIS | -1.66* | -0.74* | -0.55* | -0.73* | -0.33 | 0.88* | R |
| DRET | 0.22 | 0.07 | 0.46* | -2E-3 | 0.48* | 1.13* | R |
| DOTH | -0.12 | -0.06 | -0.23* | 0.15 | -0.06 | 0.84* | R |
| DTWO | -0.39* | -0.31* | -0.26* | -0.48* | -0.27 | -0.27* | NR |

1) * = significant at 5 % level.

2) Null hypothesis: coefficient corresponding to explanatory variable does not vary over time; R = rejected, NR = not rejected (significance level: 5%).

## Table 3 : Dynamic random effects model

| DEPENDENT VARIABLE: $EXP_t$ $(t = 84, \ldots, 89)$ | | | | |
|---|---|---|---|---|
| Number of Observations: 6805$^o$ | | | | |
| | without dynamics | | with dynamics | |
| Variable | $\delta$ | $\beta$ | $\delta$ | $\beta$ |
| CONSTANT | 1.10* | 1.11* | 1.09* | 0.95* |
| DECR_1 | -0.32* | -0.25* | -0.32* | -0.25* |
| INCR_1 | 0.31* | 0.22* | 0.32* | 0.20* |
| SEX | -0.03 | -0.06* | -0.03 | -0.05* |
| AGE | -0.22* | -0.15* | -0.22* | -0.11* |
| AGE2 | 0.02* | 0.01* | 0.02* | 0.01* |
| PERMINC | 0.15* | 0.06* | 0.14* | 0.04* |
| TRANSINC | -0.06* | -0.01 | -0.06* | -0.02 |
| DUNEM | -0.18* | -0.18* | -0.19* | -0.16* |
| DDIS | -0.32* | -0.19* | -0.32* | -0.15* |
| DRET | -0.03 | -0.05* | -0.03 | -0.04* |
| DOTH | -0.02 | -0.06* | -0.02 | -0.05* |
| DTWO | -0.04* | -0.07* | -0.04* | -0.07* |
| $\gamma_1$ | | 0 | | -0.08* |
| $\gamma_2$ | | 0 | | 0.25* |
| $\rho$ | 1.03* | | 3.35 | |
| $\sigma_u$ | 0.41* | | 0.44* | |
| $\sigma_v$ | 0.47* | | 0.46* | |
| $\sigma_\alpha$ | 0.20* | | 0.07* | |

1) * = significant at 5 % level.
2) $^o$ Some observations dropped because of the calculation of permanent and transitory income.

**Table 4 : Univariate frequencies (in %) of $\mathbf{PREV}_t$ ($t = 84, \ldots, 89$)**

| $\mathrm{PREV}_t$ | 84 | 85 | 86 | 87 | 88 | 89 |
|---|---|---|---|---|---|---|
| 1: strong decrease | 11.7 | 9.1 | 4.9 | 5.5 | 4.4 | 3.8 |
| 2: decrease | 24.6 | 16.9 | 10.7 | 15.2 | 9.1 | 6.9 |
| 3: no change | 51.6 | 53.9 | 56.3 | 55.8 | 60.2 | 56.1 |
| 4: increase | 9.0 | 15.7 | 23.1 | 19.0 | 20.4 | 26.1 |
| 5: strong increase | 3.1 | 4.3 | 5.0 | 4.5 | 5.9 | 7.0 |

**Table 5 : Frequencies (in %) of under- and overestimating future income changes**

| | underestimation | overestimation | Test-statistic |
|---|---|---|---|
| 1984-1985 | 34.9 | 15.4 | 12.8 |
| 1985-1986 | 29.3 | 15.9 | 9.9 |
| 1986-1987 | 22.5 | 21.5 | 0.9 |
| 1987-1988 | 29.2 | 14.6 | 13.1 |
| 1988-1989 | 28.9 | 12.5 | 15.6 |

Note: A conditional sign test is carried out to test whether the probability of overestimating equals the probability of underestimating future income growth. The third column displays the test-statistic that should be compared with critical values from the standard normal distribution.

**Table 6 : Estimation results for equation (7)**
**(standard errors in parentheses)**

| | $\pi$ fixed | | | |
|---|---|---|---|---|
| year dummies | $\rho$ | | $(\pi, \rho)$ | |
| 1984 | 0.23 | (0.02) | 0.35 | (0.02) |
| 1985 | 0.19 | (0.02) | 0.39 | (0.01) |
| 1986 | 0.03 | (0.01) | 0.26 | (0.01) |
| 1987 | 0.15 | (0.01) | 0.37 | (0.01) |
| 1988 | 0.19 | (0.01) | 0.42 | (0.01) |
| $\pi$ | 1 | | 0.54 | (0.01) |
| $\sigma_\varepsilon$ | 0.61 | (0.005) | 0.53 | (0.005) |

**Table 7 : Fixed effects model**

| DEPENDENT VARIABLE: $\text{DEVIATION}_t = \text{EXP}_{t-1} - \text{PREV}_t$ $(t = 85, \ldots, 89)$ | | | | | | | |
|---|---|---|---|---|---|---|---|
| Number of Observations: 4243 | | | | | | | |
| Variable | 1985 | 1986 | 1987 | 1988 | 1989 | $H_0^{(1)}$ | $H_0^{(2)}$ |
| DECR_1 | -0.60* | -0.97* | -0.78* | -1.16* | -1.09* | R | R |
| INCR_1 | 1E-3 | 0.33* | 0.73* | 0.87* | 0.70* | R | R |
| LOG_INC | 0.18* | 0.14 | 0.06 | 0.11 | 0.02 | NR | NR |
| DUNEM | -0.26 | 0.06 | 0.32 | -0.12 | -0.37 | NR | NR |
| DDIS | 0.07 | -0.20 | 0.15 | -0.70* | -0.82* | R | R |
| DRET | -0.42 | -0.24 | 0.85* | -0.05 | -0.08 | R | R |
| DOTH | -0.49* | -0.08 | 0.12 | -0.03 | -0.31* | R | R |
| DTWO | 4E-3 | 0.34* | 0.12 | 0.03 | 0.22 | NR | NR |

1) * = significant at 5 %.

2) Hypothesis $H_0^{(1)}$: coefficients corresponding to explanatory variable do not vary over time; Hypothesis $H_0^{(2)}$: all the coefficients corresponding to explanatory variable are equal to 0 (R = rejected, NR = not rejected, significance level = 0.05).

**Figure 1 : Relation between the answers to the subjective income change question and the objectively measured change in actual real total family income.**