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Abstract

This paper studies for the first time the importance of the contribution of state dependence to the explanation of self-assessed health dynamics in Spain. With this objective in mind, we estimate a series of econometric models including a new proposal for a Heckman selection model with an initial conditions equation run as an ordered probit. Evidence suggests that state dependence and unobserved heterogeneity account for much of the probability of reporting a specific health status while the significance of observed heterogeneity vanishes when controlling for both. However, state dependence looses importance once the error structure of the estimations is improved.

JEL Codes: I1, C1

Resumen

Este trabajo estudia por primera vez la importancia de la contribución de la dependencia en un estado de salud para comprender la dinàmica de la salud autopercibida en España. Teniendo en cuenta este objetivo, estimamos una serie de modelos econométricos incluyendo una nueva propuesta de un modelo de selección de Heckman con una ecuación de condiciones iniciales estimada utilizando un modelo probit ordenado. La evidencia sugiere que la dependencia en un estado de salud y la heterogeneidad no observada recogen buena parte de la probabilidad de tener un determinado estado de salud, mientras que la significatividad de la heterogeneidad observada desaparece cuando controlamos por ambas. De todas maneras, la dependencia en un estado de salud pierde importancia a medida que mejoramos la estructura de error.

1. Introduction

The relationship between socioeconomic status and health is well documented in the literature (Wilkinson, 2000; Deaton, 2003). Empirical evidence shows that low endowments of human capital or low income worsen the individual level of health. To the extent that this individual socioeconomic heterogeneity persists over time, the probability of persistence in health outcomes increases (Gravelle and Sutton, 2006; Blanco-Pérez and Ramos, 2010). On the other hand, the literature, especially in the field

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of labour market economics, has shown the importance of accounting for *scarring effects* when explaining inherently dynamic processes (Arulampalam *et al.*, 2000; Stewart, 2007; Biewen, 2009). The effect of a past value influencing *by itself* the future values of the same process is known as *genuine state dependence*.

In this paper, we aim to measure, for the first time, the degree of genuine state dependence in self-assessed health status in Spain, that is, how much *current* health is explained by *past* health experiences while controlling for observed and unobserved characteristics.[1] At the measurement level, accounting for state dependence will correct the possible overestimation of the socioeconomic factors – such as income or education. As for policy design, if the results show that the degree of state dependence is positive and significant, this will imply that policy interventions that improve health will have long-lasting consequences over time. As a result, health policies should give special emphasis to prevention.

As a matter of fact, one of the objectives of the Spanish public health agenda is to reduce health inequalities by working on the social determinants of health, as was proposed and approved during the Spanish Presidency of the European Union in 2010.[2] For this reason, Spain established a Health Commission as early as 2008 to study and monitor health determinants. Despite the preliminary results obtained, it has been suggested that more empirical evidence is required to understand the mechanisms through which social determinants affect health.[3] This paper is in line with this objective as it studies the importance of state dependence on health and its relationship with other health determinants.

Few existing studies have taken into account the importance of state dependence and unobserved heterogeneity when explaining health outcomes. Contoyannis *et al.* (2004a) and (2004b), our main references for this study, support the existence of a certain degree of self-assessed health state dependence in the United Kingdom. They show that the impact of individual heterogeneity on their model decreases when controlling for state dependence and that unobserved heterogeneity accounts for 30% of the unexplained variation in health. Halliday (2008) finds that the degree of health state dependence in the United States is modest for half of the population while very high for those suffering bad health. He concludes that many health problems should be traced back to early

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[1] For the remainder of the paper, we refer to genuine state dependence when describing state dependence.
[2] See *Council conclusions on Equity and Health in All Policies: Solidarity in health*, Council of the European Union, Brussels, 2010:

http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/lsa/114994.pdf

[3] *Análisis de situación para la elaboración de una propuesta de políticas e intervenciones para reducir las desigualdades sociales en salud en España*, Comisión para Reducir las Desigualdades Sociales en Salud en España, Ministerio de Sanidad y Política Social, Madrid, 2010:

http://www.mspsi.gob.es/profesionales/saludPublica/prevPromocion/promocion/desigualdadSalud/docs/Analisis_reducir_desigualdes.pdf adulthood or childhood. Concerning more objective health measures, Karlsson *et al.* (2009) analyse the interdependences of survival probabilities, cohabitation and employment over time, concluding that health status has a strong impact on subsequent survival probabilities.

Moreover, Hernández-Quevedo *et al.* (2008) compare state dependence and unobserved heterogeneity for binary measures of health limitations for a selection of European countries, including Spain. They show that people hampered by any physical or mental problem suffer from a major degree of state dependence. However, a comparative perspective leads them to conclude that a lower degree of state dependence is associated with a greater importance of unobserved heterogeneity – as found in Spain.

To the best of our knowledge, no other evidence based on the Spanish case exists in the literature. That is, the main contribution of this paper is to measure state dependence for self-assessed health (SAH) in Spain. We seek to disentangle the causes of the persistence of health outcomes by focusing on its three main sources: socioeconomic heterogeneity, state dependence and unobserved heterogeneity. With this objective in mind, we base our results on a series of econometric strategies that take these sources into account and also control for the initial conditions problem and a possible correlation between random effects and time-varying explanatory variables. In addition to previous models already used in the literature, a new feature of our analysis is the inclusion of a new econometric strategy based on a Heckman model with an initial conditions equation run as an ordinal probit. Hence, all models follow an ordinal approach to therefore maximise the use of information available in the data set.

Our main results indicate that state dependence and unobserved heterogeneity are the most important explanatory factors for a given health status. As a matter of fact, most of the explanatory power of the observed variables vanishes when introducing individual-specific effects and lags of the dependent variable. However, while the direction of our results is clear in the sense that past health status determines *by itself* future levels of health, its degree of influence diminishes as the structure of the model error terms is improved.

The structure of the paper is as follows. Section 2 describes the data set and the final sample used in our analysis. In section 3, we focus on health dynamics in Spain and on the descriptive of SAH persistence. Section 4 presents the econometric techniques used in the empirical analysis and outlines the estimation procedures, while Section 5 shows the main results. Finally, Section 6 provides some concluding remarks.

2. Data set, sample and definitions

Our data set is the Spanish component of the European Community Household Panel (ECHP) which is a harmonised cross-national longitudinal survey collected across all members of the former European Union-15 between 1994 and 2001 – except for Austria and Finland who joined the project in 1995 and 1996, respectively.[4]

The greatest advantage of the ECHP is that an standardised questionnaire is answered each year by a representative sample of individuals and households which allows longitudinal analysis. Moreover, it collects information related to income, education, employment, health, household composition, housing, social relations and individual satisfaction. On the negative side, only the population living in private households is represented in the ECHP, so our study does not cover individuals living in community housing (old people's homes, hospitals, etc.).

Our working sample is composed of the adult population with individuals older than 18 being allowed to enter the panel at any time. After excluding missing values due to attrition and item non-response, we are left with a working sample of 14,657 individuals and 78,156 individual-wave observations in our final regressions.

Individual health is measured by a self-assessed health indicator which reflects individual perception of health in different dimensions: physical, psychological and socioeconomic. SAH is taken from the individual answer to the question: 'How is your health in general?'. Individuals can report five different answers ordered from 'very poor' (value 1) to 'very good' health (value 5). This subjective health measure has been found to be a good predictor of morbidity and mortality (Idler and Benyamini, 1997; Deaton, 2003) therefore, it is commonly used in the analysis of health.[5]

As for the main covariates used in the analysis, and following Contoyannis *et al.* (2004a), we include age as a fourth-order polynomial, marital status, educational qualifications, being an immigrant, deflated equivalent household income, household demographic composition and labour market status.[6] Note that household income has been equivalised using the modified OECD equivalent scale, deflated to 2000 prices and transformed to logarithms to allow concavity between health and income.[7] Table A.1 in the Appendix contains labels, definitions and descriptives of all variables.

[4] We are aware that eight waves introduce some limitations to our analysis as it is not a long period of time for the study of health. However, for Spain, there is no other longitudinal data set available that would contain all the variables needed.

[5] Literature has shown that self-assessed measures might suffer from a reporting heterogeneity bias – also called 'state dependent reporting bias' or 'scale of reference bias'. Some population groups may systematically rate their health status differently to another due to cultural or socioeconomic differences. Therefore, this phenomenon of differential reporting also exists within countries when samples are stratified by education, age, gender or income (Ziebarth, 2010; Bago d'Uva *et al.*, 2008; and Etilé and Milcent, 2006). In order to correct the reporting heterogeneity bias vignettes or other objective health measures might be used to mirror SAH. Unfortunately, the ECHP does not contain vignettes and it is difficult to find an objective health measure which might help us to correct the reporting bias.

[6] Note we cannot control for certain characteristics such as body mass index (BMI) or behaviour (e.g. smoking) even though it is known that being a non-smoker and having a lower BMI are both health enhancing. However, these variables are not available for the whole time span of our study, 1994-2001.

[7] Income is collected retrospectively in the ECHP. So, for instance, interviews that took place during the first wave of the panel in 1994 asked about the income obtained in 1993. We are aware of this time bias

3. Self-assessed health in Spain: a description

In this section, we analyse SAH evolution in Spain for the aforementioned sample. First, we look at those descriptives that may show some evidence of health persistence. And, second, we focus our attention on the relationship between health and the set of socioeconomic variables that are used in our model to control for observed heterogeneity.

As shown in figure 1, on average, around 11.88% of the adult population report a poor or a very poor health in Spain during the analysed period. Nearly half of the sample reports that they are in good health and around 17.42% say that they enjoy very good health. Moreover, the mean SAH in Spain has undergone a slight increase with 85.32% of individuals reporting a healthy status (fair, good or very good) in 1994 while 90.07% did so in 2001.[8]

[FIGURE 1 AROUND HERE]

Additionally, table 1 shows self-assessed health transitions between $t-1$ and t highlighting a certain degree of persistence in health outcomes as shown by the values in its diagonal. For example, 44.67% of individuals with poor health at $t-1$ reported the same outcome in the next wave, being around 63.87% in the case of good health. At the same time, transitions between extreme outcomes are rare: individuals tend to remain close to their initial state throughout the whole period. This suggests that health is affected by a certain degree of state dependence with a higher probability of having poor health if a poor health status has been reported in the previous year.

[TABLE 1 AROUND HERE]

Next, we turn our attention to the relationship between SAH and certain socioeconomic characteristics: education, labour market activity and income.[9] The first graph in figure 2 displays the relationship between the maximum level of education and self-assessed health. Clearly, there is a gradient between education and health, meaning that individuals with a higher level of education report higher health outcomes. Education might facilitate access to health enhancing goods or to better information which has a positive impact on health.

[FIGURE 2 AROUND HERE]

in relation to the remaining variables but we preferred to be able to model health dynamics with the eight waves available in the panel. Furthermore, by accepting the time bias in the household income variable we do not need to deal with the number of missing values that arise when one of the household members attrit or does not inform about his/her income.

[8] Despite the use of weights, these results may be partly explained by the fact that individuals with the poorest health tend to be more likely to leave the panel because of their difficulties with answering the questionnaire or death.

[9] See Cantarero and Pascual (2005), Pascual and Cantarero (2007) or Hildebrand and Van Kerm (2009) for detailed analyses of the socio-economic determinants of self-assessed health in Spain using the same data set.

Similarly, labour market status has been considered a determinant of health. In figure 2, we observe that employed individuals present higher rates of good or very good health status. This observation has been traditionally supported by the idea that labour generates positive psychological effects – for instance, through self-esteem – which might favour better health. In addition, being part of the workforce might allow individuals to enjoy better economic conditions (Gravelle and Sutton, 2006). Therefore, we expect a positive effect of being employed on health.

The last graph in figure 2 describes the percentage of individuals reporting a given health outcome by household equivalent income quartile. Individuals with poor or very poor health are mainly placed in the first income quartile while those in better health conditions have higher incomes. Overall, data descriptives indicate a certain gradient between socioeconomic variables and health – its degree of importance is assessed in the following sections.

4. Models and estimation methods

In this section, the different econometric strategies are presented. We build our models step-by-step, from the simplest possible to more complex structures. First, we introduce a pooled ordered probit (Model 1) and a dynamic pooled ordered probit (Model 2), followed by a random-effects ordered probit which adopts Wooldridge's solution in the treatment of initial conditions and unobserved heterogeneity (Model 3) (see below). In order to control for a possible correlation between the random effects and the time-variant explanatory variables, Model 4 adds to Model 3, the average of all these variables (see Mundlak, 1978). Finally, Model 5 follows Heckman's solution in the treatment of initial conditions.

4.1. Static and dynamic pooled ordered probit

In the first place, and as a baseline against which to compare the results, we estimate a pooled ordered probit (Model 1) and a dynamic pooled ordered probit (Model 2). Formally, the dynamic specification can be written as follows,

$$h_{it}^{*} = \beta' X_{it} + \gamma' h_{it-1} + v_{it} \qquad (1)$$

where $i = 1, 2, ..., N$ refers to adult individuals and $t = 1, 2, ..., T$ are the number of periods under study. X_{it} are the observed explanatory variables; h_{it-1} is an indicator of the individual health status in the previous wave and γ is the state dependence parameter to be estimated. v_{it} is the serially independent error term assumed to follow a standard normal distribution with zero mean and unit variance.

Furthermore, the latent outcome, h_{it}^{*}, is not observed, although, we do know of an indicator of the category in which the latent variable falls, h_{it}. As similarly expressed in Contoyannis *et al.* (2004a):

$$h_{it} = j \quad \text{if} \quad \mu_{j-1} < h_{it}^{*} \le \mu_{j+1}, \qquad j = 1,...,m \tag{2}$$

where $\mu_0 = -\infty$, $\mu_j \le \mu_{j+1}$, $\mu_m = \infty$.[10] In our case, self-assessed health status has five categories (j), as explained in the descriptive section of this paper.

While, neither the static nor the dynamic strategy take into account unobserved heterogeneity or the initial conditions problem, it has been shown that the Maximum Likelihood estimator for β is consistent whether the error structure is correctly specified or not (see Contoyannis *et al.*, 2004a; Biewen, 2009).

4.2. A dynamic random-effects model: Wooldridge's solution

In order to take into account unobserved heterogeneity, we next propose the estimation of a dynamic random-effects ordered probit model following Wooldridge in the treatment of initial conditions (Model 3). That is, we define the equation to have the following structure:

$$h_{it}^{*} = \beta' X_{it} + \gamma' h_{it-1} + c_i + u_{it} \tag{3}$$

where c_i is the individual-specific effect and u_{it} the idiosyncratic error term assumed to follow a standard normal distribution with zero mean and unit variance and to be serially independent. As a result, the probability of observing a particular category of self-assessed health for an individual i in a period t is given by:

$$P_{itj} = P(h_{it} = j) = \Phi(\mu_j - \beta' X_{it} - \gamma' h_{it-1} - c_i) - \Phi(\mu_{j-1} - \beta' X_{it} - \gamma' h_{it-1} - c_i) \tag{4}$$

where $\Phi(\cdot)$ is the standard normal distribution function.

As shown in the literature (see, for instance, Biewen, 2009; Weber, 2002), it is important to take into account unobserved heterogeneity because ignoring it does overestimate the degree of state dependence. On the other hand, the presence of the individual-specific effects results in an initial conditions (IC) problem which arises because the start of the observation window may not be the same as the start of the outcome experience. Therefore, it is reasonable to believe that initial conditions are

[10] As explained by Contoyannis *et al.* (2004a), it would be impossible to separately identify an intercept (β_0) and the cut points (μ) thus, note that all models have adopted the normalisation $\beta_0 = 0$.

correlated with the individual specific effect (c_i). Ignoring the IC problem yields inconsistent estimates.[11] [12]

Following Wooldridge (2005) in the treatment of initial conditions, we find the density of the dependent variables from $t = 2,...,T$ conditional on the initial conditions and the explanatory variables – instead of finding the density for the whole period $t = 1, 2,...,T$ given the explanatory variables. This implies the need to specify the density of the unobserved specific effects conditional on the dependent variables at $t = 1$.

Finally, while following the same structure as Model 3, in Model 4 we assume a certain correlation between X_{it} and c_i and therefore time-averages of all time-varying explanatory variables are included in the specification, $\overline{X_i}$ (see Stewart, 2007; Chamberlain, 1984; Alessie *et al.*, 2004 or Mundlak, 1978).[13]

Thus, c_i can be specified as follows:

$$c_i = \alpha + \delta h_{i1} + \eta' \overline{X_i} + \kappa_i \tag{5}$$

by which, unobserved heterogeneity is estimated conditional to the initial conditions and the average of the time-varying explanatory variables. In order to get consistent estimates, κ_i is integrated out using Gauss-Hermite quadrature with 12 points while assuming it follows a normal distribution with zero mean and $\partial^2_{\kappa_i}$ variance. Estimates of the model parameters are obtained by Conditional Maximum Likelihood (CML).

4.3. A dynamic random-effects model: Heckman's solution

An alternative to Wooldridge's treatment of initial conditions is the one proposed by Heckman (1981). According to the author, the initial conditions problem can be dealt with by specifying a linearised approximation to the reduced form equation for the initial value of the latent variable which is jointly estimated with the main equation (Model 5). That is,

$$h^*_{it} = \beta' X_{it} + \gamma' h_{it-1} + c_i + u_{it} \tag{6}$$

is estimated together with,

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[11] See Hsiao (1986), Wooldridge (2005) and Chay and Hyslop (2000) for a review of the different strategies that have dealt with the initial conditions problem.

[12] Carro and Traferri (2011) avoid the IC problem by assessing the degree of state dependence in SAH for the British case with a dynamic fixed-effects ordered probit with one fixed-effect in the linear index equation (that is meant to account, for example, for genetic traits) and another one in the cut points which enables the control for unobserved heterogeneity and reporting behaviour.

[13] In our analysis, it includes the fourth age polynomials, marital status, household size, number of children, number of adults, labour market status and income.

$$h_{i1}^* = \Pi' Z_{i1} + a_i \quad (7)$$

for $i = 1, 2, ..., N$ and $t = 2, ..., T$ and where Z_{i1} is a vector of explanatory variables including X_{i1} – those of the main equation. It is important to note that, in our case, the equation for the initial conditions is estimated by means of an ordered probit.[14] That is, the latent outcome, h_{i1}^*, is not observed but we do know of an indicator of the category in which the latent variable falls, h_{i1}. So,

$$h_{i1} = j \quad \text{if} \quad \mu_{j-1} < h_{i1}^* \leq \mu_{j+1}, \qquad j = 1, ..., m \quad (8)$$

where $\mu_0 = -\infty$, $\mu_j \leq \mu_{j+1}$, $\mu_m = \infty$.

Furthermore, a_i is assumed to be correlated with c_i – otherwise, we would need to accept that individual health status in the first period is unrelated with the individual specific effect c_i which is unrealistic in the given context. However, a_i is uncorrelated with u_{it} for $t \geq 2$. Finally, a_i can be written as follows:

$$a_i = \theta c_i + u_{i1} \quad (9)$$

where $\theta > 0$ and c_i and u_{i1} are independent of each other. And, the initial conditions equation is specified as:

$$h_{i1} = \Pi' Z_{i1} + \theta c_i + u_{i1} \quad (10)$$

The integral is approximated numerically by Gauss-Hermite quadrature with 12 integration points.[15]

5. Empirical results

In this section, we present our empirical findings by comparing first the results of the different model specifications and choosing the model with the best fit. We also explicitly describe observed heterogeneity and present Average Partial Effects (APE) which show, in absolute terms, the impact of a change in an explanatory variable on the likelihood of a very good health status.[16] For example,

[14] We are not aware of a similar application in the literature of a Heckman model with an initial conditions equation run as an ordered probit.
[15] We verified that the results were very similar when using a smaller or greater number of integration points.
[16] Note that we have only computed APE for underlying coefficients that are statistically significant at least at 95% confidence level.

$$\widehat{APE}(P(h_{it}=5)) = \left[1-\Phi(\hat{\mu}_4 - \hat{\beta}' X_{it} - \hat{\gamma}' h_{it-1} \cdot 1 - c_i)\right] - \\ - \left[1-\Phi(\hat{\mu}_4 - \hat{\beta}' X_{it} - \hat{\gamma}' h_{it-1} \cdot 0 - c_i)\right] \qquad (11)$$

where all the parameters estimated have been multiplied by $(1+\hat{\sigma}^2_{\kappa_i})^{-1/2}$.[17]

5.1. Model specification and state dependence

Let's first turn our attention to the results for state dependence. As shown in table 2, all the coefficients that account for the lagged value of SAH in Spain are clearly significant at 1%.[18] That is, health shocks are not immediately adjusted and *current* health clearly depends on *past* health experiences, as shown in Models 2 to 5. However, Model 4 not only controls for unobserved heterogeneity and initial conditions but also allows for a correlation between the time-varying covariates and the random effect, which is the specification where state dependence proves to be less important.

[TABLE 2 AROUND HERE]

Furthermore, the results clearly show the need to control for unobserved heterogeneity when analysing self-assessed health. Note how in models 3 to 5, the standard deviation of the random effect is significant at 1%, ranging from 0.56 in the case of Model 3 to 0.70 in Model 5. This means that between 24% and 32% of the variance is due to the panel-level variance component.

The coefficients associated with the initial conditions are significant at 1% indicating the need to control for self-assessed health at the beginning of the observation window. Moreover, note how in the Heckman specification, the load factor *theta* is clearly positive which rejects the hypothesis of exogenous initial conditions.

Following Hernández-Quevedo *et al.* (2008), we assess the statistical fit of the different models using Akaike and Bayesian Information Criteria (AIC and BIC, respectively) for model selection. Formally,

$$AIC = -2lnL + 2q \qquad (12)$$

$$BIC = -2lnL + \left(lnM\right)q \qquad (13)$$

where q represents the number of parameters in each specification and M the number of individual-wave observations. In order to compare Models 4 and 5, we have combined the Wooldridge estimator based on $t \geq 2$ with a simple probit model for $t = 1$ (see Stewart, 2007).

[17] Multiplying by this constant does make the results comparable with other econometric strategies such as pooled probit (see Arulampalam, 1999).
[18] All model parameters and standard errors can be found in table A.2 of the Appendix.

As table 3 shows, Model 4 is the specification with the best fit as it reports the lowest AIC and BIC values indicating that self-assessed health needs to be studied by controlling for state dependence, unobserved heterogeneity and initial conditions while allowing for a correlation between time-varying explanatory variables and random effects. Wooldridge and Heckman's solutions yield similar results but the former performs slightly better.[19]

[TABLE 3 AROUND HERE]

Therefore, and following the specification of Model 4, APE indicate that the probability of enjoying very good health reduces by 9.3% when reporting a very poor health status in the previous year, 8.2% if suffering poor health and 4.6% if health was fair. In turn, the chances of a very good health status increase by 1.3% for those adults that declared that they were in very good health in the previous wave. Results are clear as for the direction of the state dependence impact, but the size of the effects is limited.

5.2. Observed heterogeneity

In this section, we focus on the results concerning the set of covariates that were included in the five models to control for observed heterogeneity. As shown in table A.2, nearly all covariates are significant at 99% confidence level in our base model, Model 1, and have the expected sign. Thus, as is traditionally indicated in the literature, highly educated young men that are married, have children and receive higher income would be more likely to report a better health status. Only two variables, unemployment status and household size, are not precisely estimated in this first specification. However, when adding a control for past health status, thus moving from Model 1 to 2, some of the variables lose explanatory power and others are no longer statistically significant.

More importantly, when controlling for state dependence and unobserved heterogeneity and correcting for the initial conditions problem (Models 3 to 5), the significance of most of the observed explanatory variables vanishes. These results suggest that the effect of observed heterogeneity on self-assessed health is generally overestimated given that it captures the impact that should be attributed to previous health status or other variables not present in the most commonly used data sets. Our results contrast to the widespread belief that *current* income and other socioeconomic variables are the major determinants of health status (Wilkinson, 2000; Van Ourti *et al.*, 2009).[20]

In particular, regarding the estimation of our preferred model (Model 4), we observe that only gender, education and being inactive or unemployed are statistically significant. At the same time, education has the largest effect on health with respect to

[19] Additionally, the solution proposed by Wooldridge can be more easily estimated using standard software (e.g. Stata) while the Heckman model requires the use of aML, a multi-level multi-process programme.

[20] Note that we have not taken into account the inverse relationship between income and health in our analysis. We leave for a future study the analysis of the feedback effects of *past* income on *current* health and reversely.

the gender and employment status of the individual. In this case, having a University degree increases the chances of reporting very good health by 6.0% as opposed to individuals that never completed primary education. Women are less likely to report a very good health status yet the APE of the underlying coefficient is only -0.5%. Unemployment exerts a positive effect on health (of about 0,8%), a result that contrasts with the idea that unemployment generates negative psychological effects that reduce the level of health (Wilkinson, 1996). However, other authors suggest that being unemployed for a short period of time gives the opportunity to enjoy free time and therefore a better quality of life (Knabe *et al.*, 2010). Finally, note that due to the inclusion of the time-average variables in Model 4, some of the *current* values are not precisely estimated while the means are. For example, the logarithm for household equivalent income is not statistically significant although its average value is at 1%. In this case, the fact that the time-average variable is significant suggests that a proxy for permanent income is more relevant for individual health than current income – even after controlling for state dependence. We observe the same effect in the case of the age variables indicating that belonging to a certain age group is more relevant than current age.

6. Discussion

This paper studies, for the first time, the importance of state dependence, socioeconomic heterogeneity and unobserved heterogeneity when explaining self-assessed health in Spain. With this objective in mind, we propose different econometric solutions in order to compare and assess the influence of each source when studying health dynamics.

Using the Spanish component of the ECHP for 1994-2001, we find evidence of state dependence considering a five category SAH measure, namely, past health status influences *by itself* the probability of current health. That is, individuals who enter in a spiral of bad health have greater difficulties to leave it behind (or recover from health shocks). In this sense, improving our knowledge on the persistence of self-assessed health (as measured by state dependence) can be used for a better understanding of mortality and medical care use (see, for example, Van Doorslaer and Gerdtham, 2003 and Erdogan-Ciftci *et al.*, 2010). For instance, given socio-economic inequalities in survival risk, state dependence in SAH will predict inequalities to persist. This is an argument in favour of short-run policy interventions to improve health which will have longer term implications. Nevertheless, our results suggest that the impact of state dependence on health is relatively small as we improve the structure of the models' error terms.[21]

In the analysis of health, observed heterogeneity measured by socioeconomic variables has so far played an important role in explaining individual health status and its

[21] Hernández-Quevedo *et al.* (2008) find also a small impact of state dependence in health limitations for Spain.

dynamics. However, this paper suggests that state dependence and unobserved heterogeneity account for much of the probability of reporting a specific health status. As similarly found by Contoyannis *et al.* (2004a) and (2004b), most of the explanatory power of observed heterogeneity vanishes when correcting for state dependence and unobserved heterogeneity, and only gender, education and labour status seem to be relevant in explaining health status. Alternatively, the main determinants of health might be captured by unobserved heterogeneity which in our preferred model accounts for 24% of the panel-level variance.

Our results for state dependence have also been shown to be robust with the new econometric strategy that we have proposed in this paper based on a Heckman model with an initial conditions equation run as an ordered probit. Nevertheless, we recommend the use of Wooldridge's solution for this type of analysis given that is slightly more efficient and, at the same time, is more user-friendly in terms of standard software programming and requires less computation time.

Given our results, we propose that future research should focus on new variables that are not generally taken into account in the analysis of health dynamics, such as individual childhood characteristics or childhood environment as health determinants which may account for part of the unobserved heterogeneity.[22] Finally, despite the fact that the effect of socioeconomic variables on health almost vanishes when accounting for state dependence and unobserved heterogeneity, these results might be contrasted with an analysis of the effect of *past* socioeconomic characteristics, given that only *current* socioeconomic values have been included in our models. For example, present income is not significant in our *best fit* model but past income or even permanent income might be relevant for health. These results are important in order to design health enhancing policies by improving those socioeconomic factors that truly determine health – as intended by the Spanish public health agenda.

7. References

Ahlburg, D. (1998). "Intergenerational Transmission of Health", American *Economic Review*, 88(2): 265-270.

Alessie, R., Hochguertel, S. and Van Soest, A. (2004). "Ownership of stocks and mutual funds: A panel data analysis", *The Review of Economics and Statistics*, 86(3): 783-796.

Arulampalam, W. (1999). "Practitioners' corner. A note on estimated coefficients in random effects probit models", *Oxford Bulletin of Economics and Statistics*, 61(4): 597-602.

Arulampalam, W., Booth, A. and Taylor, M. (2000). "Unemployment persistence", *Oxford Economic Papers*, 52(1): 24-50.

[22] Ahlburg (1998) for a discussion on self-assessed health being partly explained by genetics. Case *et al.* (2005) and Case *et al.* (2002) show how childhood health and socioeconomic circumstances have lasting effects on adult health, employment and socioeconomic status – especially as the individual ages. See also Trannoy *et al.* (2010) for an analysis of the influence of parents'longevity and occupation on the health status of descendants in adulthood.

Bago d'Uva, T., O'Donnel, O. and Van Doorslaer, E. (2008). “Differential health reporting by education level and its impact on the measurement of health inequalities among older Europeans”, *International Journal of Epidemiology*, 37: 1375-1383.

Biewen, M. (2009). “Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition”, *Journal of Applied Econometrics*, 24(7): 1095-1116.

Blanco Pérez, C. and Ramos, X. (2010). “Polarization and health”, *Review of Income and Wealth*, 56(1): 171-185.

Cantarero, D. and Pascual, M. (2005). “Socio-economic status and health: Evidence from the ECHP”, *Economics Bulletin*, 9(9): 1-17.

Carro, J. M. and Traferri, A. (2011). “State dependence and heterogeneity in health using a bias corrected fixed effects estimator”, Economics Working Papers we1118, Universidad Carlos III, Departamento de Economía.

Case, A., Fertig, A. and Paxson, C. (2005). “The lasting impact of childhood health and circumstance”, *Journal of Health Economics*, 24(2): 365-389.

Case, A., Lubotsky, D. and Paxson, C. (2002). “Economic status and health in childhood: The origins of the gradient”, *American Economic Review*, 92(5): 1308-1334.

Chamberlain, G. (1984). “Panel Data”, in Z. Giliches, and M. Intriligator (eds.). *Handbook of Econometrics*, vol. 2, 1247-1318. Amsterdam, North Holland.

Chay, K. Y. and Hyslop, D. (2000). “Identification and estimation of dynamic binary response panel data models: Empirical evidence using alternative approaches”, unpublished Working Paper.

Contoyannis, P., Jones, A. M. and Rice, N. (2004a). “The dynamics of health in the British Household Panel Survey”, *Journal of Applied Econometrics*, 19(4): 473-503.

Contoyannis, P., Jones, A. M. and Rice, N. (2004b). “Simulation-based inference in dynamic panel probit models: An application to health”, *Empirical Economics*, 29(1): 49-77.

Deaton, A. (2003). “Health, inequality and economic development”, *Journal of Economic Literature*, XLI: 113-158.

Erdogan-Ciftci, E., Van Doorslaer, E., Bago d'Uva, T. and Van Lenthe, F. (2010). “Do self-perceived health changes predict longevity?”, *Social Science and Medicine*, 71(11): 1981-1988.

Etilé, F. and Milcent, C. (2006). “Income-related reporting heterogeneity in self-assessed health: Evidence from France”, *Health Economics*, 15: 965-981.

Gravelle, H. and Sutton, M. (2006). “Income, relative income, and self-reported health in Britain 1979-2000”, Discussion Paper 10, Center for Health Economics Research Paper.

Halliday, T. J. (2008). “Heterogeneity, state dependence and health”, *Econometrics Journal*, 11(3): 499-516.

Heckman, J. J. (1981). “The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process”, in C. F. Manski and D.

McFadden (eds.). *Structural analysis of discrete data with econometric applications*, MIT Press, 179-195.

Hernández-Quevedo, C., Jones, A. M. and Rice, N. (2008). “Persistence in health limitations: A European comparative analysis”, *Journal of Health Economics*, 27: 1472-1488.

Hildebrand, V. and Van Kerm, P. (2009). “Income inequality and self-rated health status: Evidence from the European Community Household Panel”, *Demography*, 46(4): 805-825.

Hsiao, C. (1986). *Analysis of panel data*. Cambridge University Press.

Idler, E. and Benyamini, Y. (1997). “Self-rated health and mortality: A review of twenty-seven community studies”, *Journal of Health and Social Behaviour*, 38: 21-37.

Karlsson, M., Mayhew, L. and Rickayzen, B. (2009). “Individualised life tables: investigating dynamics of health, work and cohabitation in the UK”, *The Journal of Population Ageing*, 1: 153-191.

Knabe, A., Rätzel, S., Schöb, R. and Weimann, J. (2010). “Dissatisfied with life, but having a good day: Time-use and well-being of the unemployed”, *Economic Journal*, 120(547): 867-889.

Mundlak, D. R. (1978). “On the pooling of time series and cross section Data”, *Econometrica*, 46: 69-85.

Pascual, M. and Cantarero, D. (2007). “Socio-demographic determinants of disabled people: An empirical approach based on the European Community Household Panel”, *The Journal of Socio-Economics*, 36: 275-287.

Stewart, M. B. (2007). “The interrelated dynamics of unemployment and low-wage employment”, *Journal of Applied Econometrics*, 22(3): 511-531.

Trannoy, A., Tubeuf, S., Jusot, F. and Devaux, M. (2010). “Inequality of opportunities in health in France: A first pass”, *Health Economics*, 19: 921-938.

Van Doorslaer, E. and Gerdtham, U.-G. (2003). “Does inequality in self-assessed health predict inequality in survival by income? Evidence from Swedish data”, *Social Science and Medicine*, 57(9): 1621-1629.

Van Ourti, T., Van Doorslaer, E. and Koolman, X. (2009). “The effect of income growth and inequality on health inequality: Theory and empirical evidence from the European Panel”, *Journal of Health Economics*, 28(3): 525-539.

Weber, A. (2002). “State dependence and wage dynamics. A heterogeneous Markov chain odel for wage mobility in Austria”, Economic Series 114, Institute for Advanced Studies, Vienna.

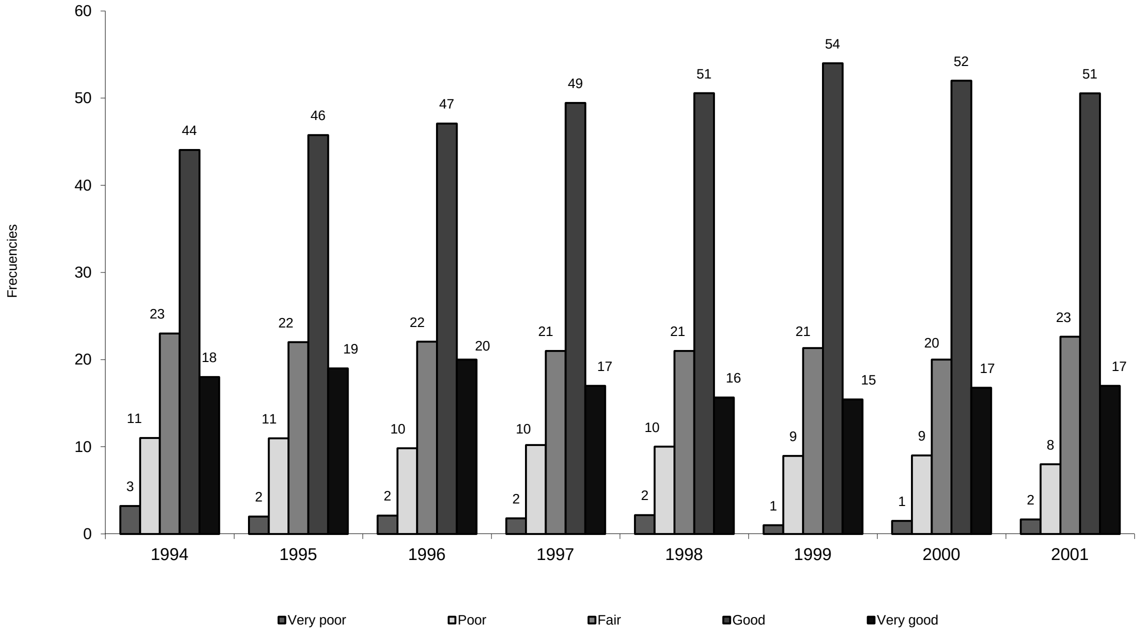
Wilkinson, R. (1996). *Unhealthy Societies: The Afflictions of Inequality*. Routledge, London.

Wilkinson, R. (2000). *Mind the Gap; Hierarchies, Health and Human Evolution*. London, Weidenfeld and Nicolson.

Wooldridge, J. M. (2005). "Simple solutions to the initial conditions problem in dynamic, non linear panel data models with unobserved heterogeneity", *Journal of Applied Econometrics*, 20: 39-54.

Ziebarth, N. (2010). "Measurement of health, health inequality, and reporting heterogeneity", *Social Science and Medicine*, 71(1): 116-124.

Figure 1
PERCENTAGE OF INDIVIDUALS PER SELF-ASSESSED HEALTH CATEGORY BY YEAR IN SPAIN, 1994-2001



Source: Own calculation on the ECHP, 1994-2001. Weighted results

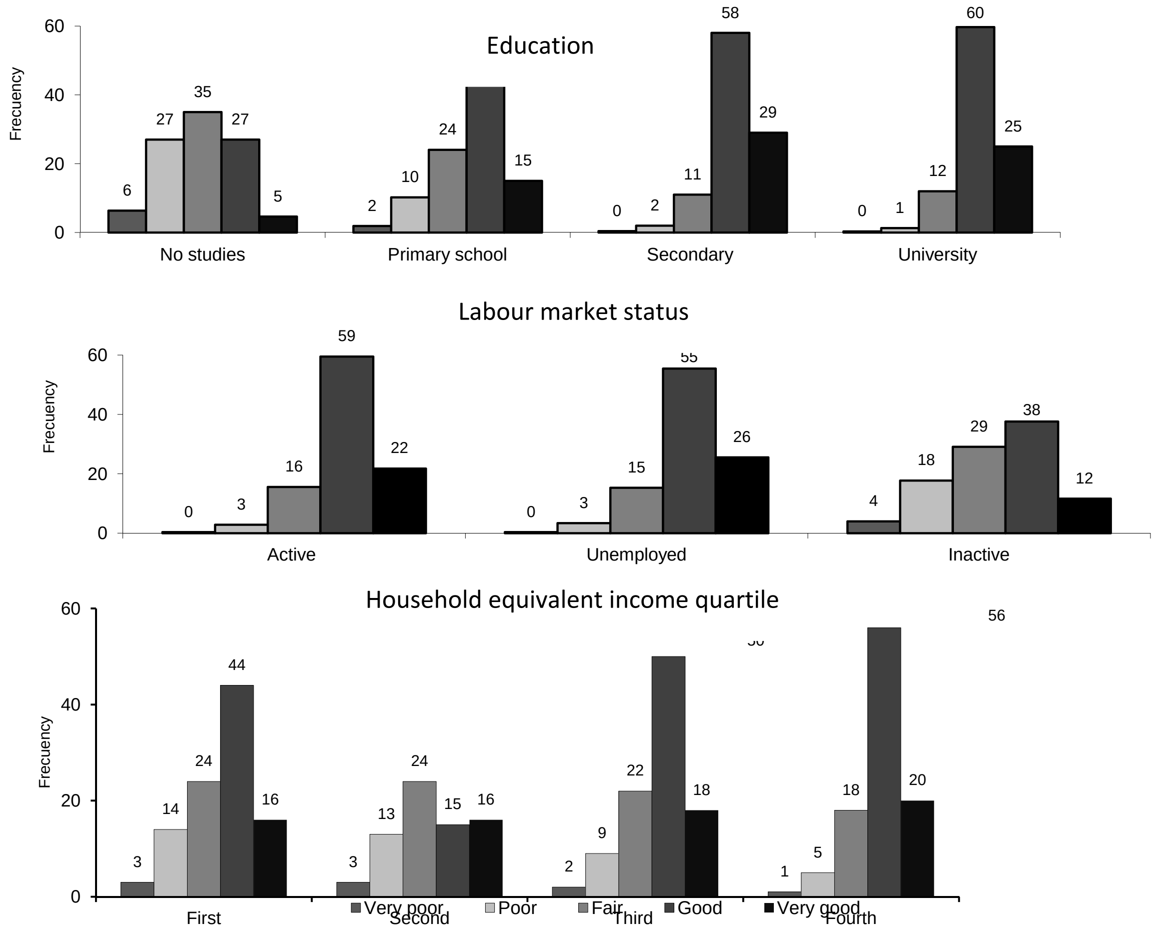
Table 1
SELF-ASSESSED HEALTH TRANSITIONS BETWEEN *t-1* AND *t* IN SPAIN, 1994-2001 (percentages)

		SAH at *t*					
		Very poor	Poor	Fair	Good	Very Good	Total
SAH at *t-1*	Very Poor	23.36	48.15	20.95	6.10	1.45 [a]	100.00
	Poor	8.69	44.67	34.21	10.60	1.83	100.00
	Fair	1.97	14.75	44.59	33.82	4.87	100.00
	Good	0.21	2.35	15.00	63.87	18.57	100.00
	Very Good	0.11[a]	0.72	6.77	54.01	37.39	100.00
	Total	1.81	9.62	21.86	49.64	17.07	100.00

Source: Own calculation on the ECHP, 1994-2001. Weighted results. [a] Imply less than 50 observations in the cell.

Figure 2

SELF-ASSESSED HEALTH BY LEVEL OF EDUCATION, LABOUR MARKET STATUS AND HOUSEHOLD EQUIVALENT INCOME QUARTILE IN SPAIN, 1994-2001



Source: Own calculation on the ECHP, 1994-2001. Weighted results.

Table 2
MODEL SPECIFICATIONS FOR SELF-ASSSESSED HEALTH IN SPAIN, 1994-2001 (selected parameters)

	Model 1[a]		Model 2[b]		Model 3[c]		Model 4[d]		Model 5[e]			
									IC			
$h_{t-1}(1)$			-2.0769	***	-0.7414	***	-0.7348	***	-0.8605	***		
$h_{t-1}(2)$			-1.5766	***	-0.6118	***	-0.6070	***	-0.7089	***		
$h_{t-1}(3)$			-0.7858	***	-0.2938	***	-0.2910	***	-0.3237	***		
$h_{t-1}(5)$			0.4009	***	0.0747	***	0.0745	***	0.0364	***		
$h_0(1)$					-1.7155	***	-1.6955	***				
$h_0(2)$					-1.2731	***	-1.2566	***				
$h_0(3)$					-0.6180	***	-0.6097	***				
$h_0(5)$					0.3318	***	0.3316	***				
cut 1	-3.6550	***	-4.2742	***	-5.1966	***	-4.9414	***	-5.0023	***	-4.7578	***
cut 2	-2.5901	***	-2.9837	***	-3.6922	***	-3.4354	***	-3.5170	***	-3.4208	***
cut 3	-1.6023	***	-1.7814	***	-2.2781	***	-2.0197	***	-2.1184	***	-2.0908	***
cut 4	0.0659		0.0512		-0.1856		0.0739		-0.0225		-0.1822	
σ_{κ_i}					0.5664	***	0.5662	***	0.6999	***		
θ									1.1932	***		
ln-L	-88513.25		-80104.07		-77338.14		-77281.94		-95004.95			

Source: Own calculations on the ECHP, 1994-2001. Significance: *** 99% confidence level, ** 95% and * 90%.
Note:
[a] Ordered probit
[b] Dynamic ordered probit
[c] Random effects dynamic ordered probit
[d] Random effects dynamic ordered probit with time-varying variables mean
[e] Dynamic ordered Heckman probit with time-varying variables mean

Table 3
AIC AND BIC FOR THE DIFFERENT MODEL SPECIFICATIONS

	Model 1[a]	Model 2[b]	Model 3[c]	Model 4[d]	Model 5[e]
AIC	177086.5	157200.3	158772.5	154671.8	-
BIC	177364.4	157552.5	159096.8	155172.2	-
AIC	-	-	-	189641.3	190159.9
BIC	-	-	-	190377.5	190854.8

Source: Own calculations on the ECHP, 1994-2001.
Note:
[a] Ordered probit
[b] Dynamic ordered probit
[c] Random effects dynamic ordered probit
[d] Random effects dynamic ordered probit with time-varying variables mean
[e] Dynamic ordered Heckman probit with time-varying variables mean

Appendix

Table A.1
VARIABLE LABELS, DEFINTIONS AND DESCRIPTIVES

Variables	Definition	Mean	Std. Dev.
SAH	Self-Assessed Health	3.698	0.937
female	1 if female, 0 otherwise	0.518	0.450
age	Age in years of the individual	46.219	18.456
age2	Age^2/100	24.769	18.631
age3	Age^3/1000	14.833	15.747
age4	Age^4/10000	9.606	12.868
educmax2	1 if max. level of education is primary studies, 0 otherwise	0.463	0.499
educmax3	1 if max. level of education is secondary studies, 0 otherwise	0.211	0.408
educmax4	1 if max. level of education is tertiary studies, 0 otherwise	0.163	0.370
	(reference group of education is no studies)		
ln(income)	Log of equivalised total net household income	14.022	0.745
divorced	1 if divorced, 0 otherwise	0.021	0.143
widowed	1 if widow, 0 otherwise	0.082	0.275
single	1 if single, 0 otherwise	0.294	0.456
	(reference group of civil status is married)		
inactive	1 if inactive, 0 otherwise	0.468	0.499
unemployed	1 if unemployed, 0 otherwise	0.101	0.301
	(reference group of labour status is employed)		
immi	1 if immigrant, 0 otherwise	0.016	0.126
hhsize	Number of members of the household	3.873	1.738
numchild0-4	Number of children in household aged 0-4	0.125	0.380
numchild5-11	Number of children in household aged 5-11	0.245	0.551
numchild12-17	Number of children in household aged 12-18	0.290	0.587
numadults65	Number of adults in household aged 65 or more	0.531	0.766

Source: Own calculation on the ECHP, 1994-2001.

Table A.2
MODEL SPECIFICATIONS FOR SELF-ASSESSED HEALTH IN SPAIN, 1994-2001.

	Model 1[a]		Model 2[b]		Model 3[c]		Model 4[d]		Model 5[e]			
											IC	
$h_{t-1}(1)$			-2.0769	***	-0.7414	***	-0.7348	***	-0.8605	***		
			(-0.0239)		(-0.0336)		(-0.0337)		(-0.0326)			
$h_{t-1}(2)$			-1.5766	***	-0.6118	***	-0.607	***	-0.7089	***		
			(-0.0119)		(-0.0188)		(-0.0189)		(-0.0183)			
$h_{t-1}(3)$			-0.7858	***	-0.2938	***	-0.291	***	-0.3237	***		
			(-0.0093)		(-0.0129)		(-0.013)		(-0.0127)			
$h_{t-1}(5)$			0.4009	***	0.0747	***	0.0745	***	0.0364	***		
			(-0.011)		(-0.0141)		(-0.0141)		(-0.0141)			
$h_0(1)$					-1.7155	***	-1.6955	***				
					(-0.0435)		(-0.0438)					
$h_0(2)$					-1.2731	***	-1.2566	***				
					(-0.0245)		(-0.0246)					
$h_0(3)$					-0.618	***	-0.6097	***				
					(-0.0175)		(-0.0176)					
$h_0(5)$					0.3318	***	0.3316	***				
					(-0.0192)		(-0.0192)					
age	-0.1272	***	-0.0868	***	-0.0982	***	-0.0449		-0.06		-0.1648	***
	(-0.0152)		(-0.0213)		(-0.03)		(-0.0502)		(-0.0507)		(-0.0639)	
age2	0.276	***	0.1735	***	0.1937	**	-0.1016		-0.0872		0.3775	*
	(-0.0467)		(-0.0663)		(-0.0942)		(-0.1619)		(-0.1637)		(-0.2092)	
age3	-0.3348	***	-0.19	**	-0.2064	*	0.2408		0.2195		-0.4865	*
	(-0.0602)		(-0.0866)		(-0.1238)		(-0.2168)		(-0.2195)		(-0.2854)	

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Table A.2 - Continued from previous page

	Model 1		Model 2		Model 3		Model 4		Model 5			
											IC	
age4	0.1568	***	0.0818	**	0.084		-0.1586		-0.1475		0.2385	*
	(-0.0277)		(-0.0402)		(-0.0577)		(-0.1022)		(-0.1035)		(-0.1378)	
divorced	-0.2254	***	-0.1387	***	-0.1416	***	-0.1238	*	-0.123	*	-0.0627	
	(-0.0151)		(-0.0229)		(-0.0353)		(-0.0678)		(-0.0682)		(-0.0695)	
widowed	-0.0536	***	-0.0237		-0.0084		0.0166		0.014		-0.0301	
	(-0.0089)		(-0.0146)		(-0.0232)		(-0.054)		(-0.0545)		(-0.0494)	
single	-0.0618	***	-0.0252	**	-0.0293		0.0153		0.0241		-0.0559	
	(-0.0084)		(-0.0126)		(-0.0197)		(-0.0428)		(-0.0427)		(-0.0395)	
hhsize	0.001		-0.0017		-0.0007		0.0075		0.0066		0.0137	
	(-0.0022)		(-0.0033)		(-0.0049)		(-0.0091)		(-0.0092)		(-0.0096)	
ln(income)	0.0861	***	0.0507	***	0.0413	***	0.012		0.0082		0.0837	***
	(-0.0045)		(-0.0058)		(-0.0073)		(-0.0091)		(-0.0091)		(-0.0138)	
immi	0.1472	***	0.0806	***	0.0557		0.0746		0.1559	***	0.2811	***
	(-0.0195)		(-0.0275)		(-0.0481)		(-0.0485)		(-0.055)		(-0.0875)	
educmax2	0.307	***	0.1589	***	0.1598	***	0.1474	***	0.3131	***	0.458	***
	(-0.0062)		(-0.0106)		(-0.0182)		(-0.0184)		(-0.0202)		(-0.032)	
educmax3	0.505	***	0.2849	***	0.2993	***	0.2615	***	0.5004	***	0.7602	***
	(-0.0092)		(-0.0141)		(-0.0245)		(-0.0253)		(-0.0277)		(-0.0437)	
educmax4	0.6272	***	0.3662	***	0.3901	***	0.3344	***	0.6199	***	0.9297	***
	(-0.0108)		(-0.0158)		(-0.0273)		(-0.029)		(-0.0317)		(-0.0544)	
numchild0-4	0.026	**	0.0161		0.0182		0.0014		0.0018		0.0125	
	(-0.0102)		(-0.0131)		(-0.0166)		(-0.0231)		(-0.0231)		(-0.0316)	

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Table A.2 - Continued from previous page												
	Model 1		Model 2		Model 3		Model 4		Model 5			
											IC	
numchild5-11	0.0405	***	0.031	***	0.0326	***	0.0186		0.0187		-0.0317	
	(-0.0066)		(-0.009)		(-0.0124)		(-0.0199)		(-0.02)		(-0.024)	
numchild12-17	0.029	***	0.0177	**	0.0167		0.0125		0.013		0.0396	*
	(-0.0062)		(-0.0086)		(-0.0111)		(-0.0157)		(-0.0159)		(-0.0216)	
numadults65	-0.018	***	-0.0152	**	-0.0043		0.028	*	0.0261		0.0439	**
	(-0.0047)		(-0.0071)		(-0.0103)		(-0.0157)		(-0.0159)		(-0.0214)	
female	-0.0711	***	-0.0445	***	-0.0465	***	-0.0282	**	-0.0588	***	-0.0841	***
	(-0.005)		(-0.0077)		(-0.0133)		(-0.0139)		(-0.0155)		(-0.0249)	
unemployed	-0.0204		-0.004		-0.0003		0.0481	**	0.0499	**	-0.0283	
	-0.0131		(-0.0154)		(-0.0183)		(-0.0211)		(-0.0212)		(-0.0373)	
inactive	-0.2517	***	-0.131	***	-0.1264	***	-0.048	**	-0.033	*	-0.3386	***
	(-0.0075)		(-0.0105)		(-0.0145)		(-0.0197)		(-0.0198)		(-0.0301)	
cut 1	-3.655	***	-4.2742	***	-5.1966	***	-4.9414	***	-5.0023	***	-4.7578	***
	(-0.1844)		(-0.254)		(-0.3553)		(-0.4771)		(-0.5352)		(-0.7145)	
cut 2	-2.5901	***	-2.9837	***	-3.6922	***	-3.4354	***	-3.517	***	-3.4208	***
	(-0.1841)		(-0.2536)		(-0.3547)		(-0.4768)		(-0.5348)		(-0.7135)	
cut 3	-1.6023	***	-1.7814	***	-2.2781	***	-2.0197	***	-2.1184	***	-2.0908	***
	(-0.1843)		(-0.2536)		(-0.3546)		(-0.4768)		(-0.5348)		(-0.7127)	
cut 4	0.0659		0.0512		-0.1856		0.0739		-0.0225		-0.1822	
	(-0.1842)		(-0.2536)		(-0.3546)		(-0.4767)		(-0.5347)		(-0.7122)	
σ_{κ_i}					0.5664	***	0.5662	***	0.6999	***		
					(-0.0078)		(-0.0078)		(-0.009)			

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Table A.2 - Continued from previous page								
	Model 1	Model 2	Model 3	Model 4		Model 5		
								IC
m(age)				-0.0883		-0.1239	*	
				(-0.0638)		(-0.0679)		
m(age2)				0.4003	*	0.5111	**	
				(-0.2048)		(-0.217)		
m(age3)				-0.5857	**	-0.732	**	
				(-0.2739)		(-0.2895)		
m(age4)				0.3122	**	0.3833	***	
				(-0.1292)		(-0.1363)		
m(divorced)				-0.021		-0.0674		
				(-0.0799)		(-0.0827)		
m(widowed)				-0.0558		-0.0684		
				(-0.0608)		(-0.0622)		
m(single)				-0.0514		-0.0959	*	
				(-0.0492)		(-0.0508)		
m(hhsize)				-0.0106		-0.0075		
				(-0.011)		(-0.0116)		
m(numchild0-4)				0.0187		0.0202		
				(-0.0375)		(-0.039)		
m(numchild5-11)				0.023		0.036		
				(-0.0268)		(-0.0285)		
m(numchild12-17)				0.0019		0.0207		
				(-0.0239)		(-0.0253)		

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Table A.2 - Continued from previous page							
	Model 1	Model 2	Model 3	Model 4		Model 5	
							IC
m(numadults)65				-0.0598	***	-0.0504	**
				(-0.0214)		(-0.0223)	
m(unemployed)				-0.0945	**	-0.0927	**
				(-0.0436)		(-0.0462)	
m(inactive)				-0.1547	***	-0.2892	***
				(-0.0298)		(-0.0313)	
m(ln(income)				0.0777	***	0.1172	***
				(-0.0161)		(-0.0168)	
θ						1.1932	***
						(-0.0276)	
ln-L	-88513.25	-80104.07	-77338.14	-77281.94		-95004.95	

Source: Own calculation on the ECHP, 1994-2001. Significance: *** 99% confidence level, ** 95% and * 90%. Each regression includes year dummies. m(variable) refers to time-varying variables mean. Standard errors in parenthesis.

Note:

[a] Ordered probit

[b] Dynamic ordered probit

[c] Random effects dynamic ordered probit

[d] Random effects dynamic ordered probit with time-varying variables mean

[e] Dynamic ordered Heckman probit with time-varying variables mean