A Country for Old Men?
Long-Term Home Care Utilisation in Europe

Silvia Balia and Rinaldo Brau

Abstract

This paper investigates long-term home care utilisation in Europe. Data from the first wave of SHARE on formal (nursing care and paid domestic help) and informal care (support provided by relatives) are used to study the probability and the quantity of both types of care. The overall process is framed in a fully simultaneous equation system which takes the form of a bivariate two-part model where the reciprocal interaction between formal and informal care is estimated. Endogeneity and unobservable heterogeneity are addressed using a common latent factors approach. The analysis of the relative impact of age and disability on home care utilisation is enriched by the use of a proximity to death (PtD) indicator built using the second wave of SHARE. All these indicators are important predictors of home care utilisation. In particular, a strong significant effect of PtD is found in the paid domestic help and informal care model. The relationship between formal and informal care moves from substitutability to complementarity depending on the type of care considered and the estimated effects are small in absolute size. This might call for a reconsideration of the effectiveness of incentives for informal care as instruments to reduce public expenditure for home care services.

Keywords: long-term care, ageing, discrete latent factors, proximity to death.
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1 Introduction

Over the last decades, European and other developed countries have been undergoing a process of population ageing, mainly due to lower fertility rates and increased life expectancy and partly driven by advances in medicine. For the European Union, the latest Ageing Report of the European Commission (2009) foresees an increase, in the period 2008-2060, of 5.4 years in life expectancy at the age of 65 for men and of 5.2 years for women, with a parallel increase in the old-age dependency ratio from 25.4% to 53.5%. The downside of a longer life expectancy is that public and private health care expenditure (HCE) are expected to increase, both with the number of elderly people and the average age of the population. This is particular cause for concern about the sustainability of national welfare and health care systems. The same report estimates a shift in the average EU share of public HCE over GDP from 6.8 to 7.8 by 2035 up to 8.3 in 2060. Under these scenarios, one of the fastest growing components of HCE is long-term care (LTC), with an expected increase of 50% between 2008 and 2035 (from 1.2 of GDP to 1.8) and of 100% by 2060.

The reliability of these forecasts crucially depends on the accurateness of the estimates of age effects. Since the seminal paper by Zweifel, Felder and Meiers (1999), several studies have tried to assess the role of individual age on HCE as well as that of competing predictors of expenditures. In particular, measures of proximity to death (PtD) appear to be better than individual age at capturing health deterioration and the fact that, when approaching death, the actual demand for health care services increases due to greater health needs rather than age *per se*. In this respect, the simple ageing of the population has been claimed to be a “red herring” in the study of the evolution of HCE over time (see Stearns and Norton, 2004; Seshamani and Gray, 2004a,b and, for a review of the literature, Payne *et al.*, 2007).

For LTC expenditure, however, the recent literature provides mixed evidence about the relative contributions of age and PtD, while it emphasizes a prominent role of disability indicators. In an analysis of the components of Swiss HCE, Werblow, Felder and Zweifel (2007) find that age matters only for LTC expenditures, regardless of individuals' remaining lifespan, whereas PtD is a significant predictor of other types of HCEs. Somewhat similarly, in a study based on Dutch data, De Meijer *et al*. (2011) show that PtD is not a good predictor of homecare expenditure when disability indicators are taken into account. In this sense, they argue that PtD itself appears to be a "red herring", and conclude that both age and PtD can become redundant in models that appropriately control for disability. Additional insights are offered by studies carried out with US data. Weaver *et al.* (2009) estimate the marginal effect of PtD on the probability of nursing home and formal home care use and assess its robustness to the inclusion of informal care indicators (defined as being married or living with an adult child). They find that, overall, PtD increases the likelihood of using formal home care and, to a greater extent, nursing homes. When considering the role of informal support, however, the impact of PtD reduces significantly. On the whole, these studies have generally focused on formal LTC and have not considered that also informal care could be seen as a "dependent variable" to be explained in light of the effects of age, PtD and disability indicators.

In analyses of LTC, the primary interest in informal support lies in its being relatively interchangeable with formal care. Unlike acute medical care, a large part of the care needed is provided at home, not only by specialised or licensed personnel (e.g., nurses, carers, therapists) but also, and more often, by unpaid caregivers who usually are adult children, other relatives or friends of older adults. Often, LTC services do not require high level skills or capital equipment.[1] This allows, at least in principle, for a certain degree of substitutability between professional (paid) and informal (unpaid) care. On one hand, support by family and friends would be less frequent as more formal care services are available to the elderly and the other way round, thus justifying welfare policies that ration formal care to contain expenditures. On the other hand, informal care may substitute formal care when the decision to provide care is conditional to the expectation of inheriting a larger portion of the elderly bequest and use of formal care will be considered only as

[1] Since these services require low-to-medium skilled personnel, wage variability among formal caregivers is low, thus implying that the amount of LTC expenditure is essentially determined by the number of hours of care provided.

the last resort. However, alternative economic explanations, discussed in detail in Van Houtven and Norton (2004) and Jiménez-Martín and Prieto (2011), support the hypothesis of complementarity in the relationship between formal and informal care, particularly for the severely disabled whose needs are likely to exceed informal care resources. Generally speaking, complementarity may also arise when support from family and friends consists of organising the provision of formal care, operating different and lower skill tasks relative to professional carers, or even replacing them in some occasions (e.g. to grant them a day off).

Most empirical studies find that informal care is a substitute for formal care. For example, Van Houtven and Norton (2004) find that care giving by one's children substitutes home care as well as hospital care and physician visits and also reduces nursing home admissions; however, it is a complement to outpatient surgery. Van Houtven and Norton (2008) show that care provided by adult children is a net substitute for Medicare LTC expenditure of the single elderly, significantly reducing the likelihood of incurring expenditure for home care. Such informal support is less effective among elderly couples. Using European data, Bolin, Lindgren, and Lundborg (2008) find evidence of substitutability between informal care and home care (nursing care and paid domestic help) whilst some complementary effect is found between informal care and doctor and hospital visits. In a research work on the same data, Bonsang (2009) confirms the substitution effect between informal and formal care, and finds that the effect disappears for the elderly suffering from severe disabilities.[2] Overall, these studies focus on the substitution/complementarity debate and pay little attention to the impact of informal care *vis-à-vis* the other important determinants of LTC use, such as age, PtD and disability. They also show little interest in modelling informal care provision *per se*.

In this paper we propose a unified framework for the study of LTC. On the one hand, the impact of informal care is assessed in comparison to other drivers of formal home care use. On the other hand, the analysis is extended to investigate the determinants of informal support. This requires

[2] Spillman and Pezzin (2000) even find complementarity for this population subgroup.

appropriate empirical modelling. Previous works have usually presented models for formal care only where informal care enters as an endogenous regressor and consistent estimates are achieved by means of instrumental variables techniques. This approach does not provide, in our opinion, a complete view of the relationship between formal and informal care, as it does not fully account for simultaneity in the processes that determine both types of LTC utilisation. We claim that structural equations for informal care should also be estimated, where formal care is included as an endogenous explanatory variable, jointly with the structural equations for formal care. We therefore propose a fully simultaneous system of four equations which models both the probability as well as the number of hours of both formal and informal care received. This takes the form of a bivariate two-part model with correlated errors.

Endogeneity in formal and informal care models arises from unobservable heterogeneity and simultaneity bias. This is a common problem to many analyses of health care demand and, in the case of LTC, is exacerbated by the use of survey data which often lack information on the whole set of LTC determinants. Heterogeneous preferences between care recipients and caregivers, the cost of formal home care and the availability and cost of nursing home services are usually unobserved. Our work contributes to the empirical literature by addressing these issues in a common latent factors framework. In particular, we adapt Mroz's (1999) semiparametric maximum likelihood approach, which uses a discrete factor approximation of the unknown distribution of heterogeneity, to our bivariate two-part model.

We use data on long-term home care utilisation and PtD in the European elderly population from the longitudinal Survey on Health, Ageing and Retirement (SHARE), and estimate three separate models of formal care (as measured by total formal care, paid domestic help and nursing care) and informal care. We calculate average partial effects to assess the nature of the relationship between formal and informal care and the relative impact of age, PtD and disability on both types of care in Europe. We further simulate their interaction effect for different hypothetical types of individuals. In particular, we compare survivors and decedents, the youngest and the oldest old individuals as well as individuals in different levels of LTC needs (where needs are proxied by disability indicators).

We find that age, PtD and disability have sizeable explanatory power on LTC use. Being severely disabled or an oldest old has the greatest impact on formal and informal care use, but no prominent role for any specific determinant emerges. Overall, our findings suggest that indicators of age, PtD and disability should be jointly included in models of LTC. Our results also suggest that the link between formal and informal care changes depending on whether nursing care or paid domestic help is considered. Complementarity is found in the first case whilst substitutability prevails in the latter. Average partial effects are however negligible in both cases. Focusing on the *size* of these effects may have important policy implications. Economic incentives aimed at encouraging informal support can hardly modify the use of LTC services at home.

2 Data and key variables

Our analysis uses data on individuals who participated in the first wave (2004) of SHARE, a European survey which has been designed after the US Health and Retirement Study (HRS) and the English Longitudinal Study of Aging (ELSA). The original sample consists of 28,517 non-institutionalised individuals aged 50 years or older.

SHARE provides a rich set of information about formal and informal care received at home. Formal caregivers have an employment contract and can either be paid out-of-pocket or by private or public coverage schemes. It is common to distinguish between nursing care (NC), typically provided at home by professionals within public or private insurance schemes, and paid domestic help (PDH) for those cleaning tasks that the respondent was unable to do because of health problems, services mainly provided by low or unskilled workers, often immigrants, or black market workers (see Lippi Bruni and Ugolini, 2006a, b). We use data on the number of weeks and hours of formal care received and define two continuous variables indicating the average number of hours received per month in the last year (hNC and hPDH). Information on these two types of formal care is aggregated to build a general indicator for total formal care (TFC): a continuous variable for the number of hours defined as the combination of NC and PDH that can be received by an individual in the same year (hTFC).

Informal caregivers are usually relatives or friends. An accurate quantification of informal care (IC) is problematic because this type of LTC is a non-market good. The SHARE questionnaire identifies informal care as support received exclusively from family members outside the household, and provides information about the nature of the relationship between caregivers and recipients, the frequency of support (daily, weekly, monthly or annual) and the average number of hours received (per day, week, month and year).[3] Like most existing literature, we consider informal support received from children, grandchildren and children-in-law in the last year, and build a continuous variable for the average number of hours received per month. Following Van Houtven and Norton (2004), we use observations for respondents aged 65 or older, who have at least one child and up to 4 children, and do not live with any of them. Unlike other studies, only individuals living alone are considered.[4] Due to poor accuracy in the responses, a few interviews report unreliable values which have been dropped. In particular, we have eliminated from the sample those individuals who reported having received more than 24 hours of care per day, more than 168 hours per week, or more than 720 hours per month and more than 8640 in a year. Additionally, we have eliminated those individuals who reported having received LTC but did not report any disability such as mobility limitations, activity limitations, chronic disease or long-term illness. This enables us to exclude from the sample individuals who might have received any type of LTC (particularly, paid domestic help) for reasons not strictly related with health care needs.

New information about the living status of respondents was collected two years after the interview (i.e., in the second wave of the survey). This makes it possible to construct a binary

[3] In the absence of data on actual informal care, indicators of coresidence have been often employed (see e.g., Van Houtven and Norton, 2004; De Meijer et al., 2011; Weaver et al., 2009).

[4] We think that simply controlling for the presence of cohabiting spouse and children cannot be considered a satisfactory way to fill the lack of quantitative information on support provided within the household. The downside is that, since spouses and children living within the household are known to be the most common informal caregivers, IC indicators based on the SHARE data might underestimate the actual role of informal caregivers.

indicator of PtD, which takes value 1 if the respondent died within two years of the interview, and 0 otherwise. Data on PtD cover about 70 per cent of our target sample. This leaves us with a sample of 1,337 observations representing respondents living in Denmark, Sweden, Austria, France, Germany, Belgium, the Netherland, Spain and Italy.[5]

We provide a complete picture of LTC use within our sample in Table 1. LTC recipients (defined as individuals receiving either formal or informal care) represent 47% of respondents. For this group of people (LTC=1 column), informal support appears to be the main source of LTC, given that about 83% of them received IC, compared to 44% of TFC receivers.[6] The average number of hours of care received per month in the last year is around 50: 38 of IC plus 12 of TFC. Focusing on respondents who received TFC (TFC=1 column), it can be noted that most of them received PDH (about 80%, against 44% NC), with an average amount of TFC received of about 27 hours per month. Looking at the specific types of formal care considered (PDH=1 and NC=1 columns, respectively), we find higher values for PDH, with 26.5 hours per month, while NC counts for about 14 hours.

-Table 1 about here-

In Table 2 we report the descriptive statistics for standard demographics, socioeconomic status and other individual characteristics that will be used in the econometric analysis.[7] Our sample consists of 77.6% women and the average age is about 76. The oldest old (over 85) account for about 12% of the sample. Around 5.2% died between the first and the second wave of SHARE.

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[5] Greece and Switzerland have been excluded because they would have added to the sample only 3 additional observations.

[6] Clearly, subsamples in Table 1 are overlapping (meaning, for example, that individuals who receive formal care can also have received informal care) and the sum of percentages by row is not equal to 100% since respondents can receive both types of care.

[7] As for socioeconomic indicators, we use a standard indicator of years of education based on the international standard classification of Education 1997 (ISCED-97), which is known to allow for cross-country comparisons in the presence of high heterogeneity. Income is defined as equivalent total gross household income, adjusted for 2004 purchasing power parity, and it does not report missing values because we have used the imputed indicator available in SHARE.

The survey provides detailed information about morbidity and disability. We use indicators of mobility limitations (mobility), limitations in usual activities because of health problems (GALI), limitations in activities of daily living (ADL), chronic diseases (chronic) and long-term illnesses (ltillness).[8] Long-term illnesses are represented by dichotomous variables taking value 1 for individuals with illnesses, and 0 otherwise. The other indicators are expressed in categories that depend on the severity level of the disease or limitation. Roughly 54% of the sample reports having GALI limitations, 16.6% reports ADL limitations, 68% reports limitations in mobility, and 57% reports having long-term illnesses.

Caregivers' characteristics may determine the availability and the quantity of informal support received. We use available information about geographical distance between children and their parents.[9] Respondents are asked whether their child lives in the same household, in the same building, less than 1 km away, between 1 and 5 km, 5 and 25 km, 25 and 100 km, 100 and 500 km, more than 500 km away or more than 500 km away in another country. We calculate an indicator of distance between the respondent and the nearest child, assigning each observation the number of kilometres corresponding to half the bandwidth of each possible category. The average distance from the nearest child is about 40 kilometres. This kind of measure, used also in Greene (1983) and Bonsang (2009), is usually assumed to be an important driver of informal care since children who live farther away would be less keen to provide support as compared to those living closer.

Finally, a few studies look at the role of LTC insurance and find that modest effects in the demand of formal care (Van Houvten and Norton, 2004; Charles and Sevak, 2005; Li and Jensen, 2011). In our sample, 11% of respondents have some general voluntary, supplementary or private health insurance in order to complement the coverage offered by their National Health System for LTC services. Those who only have an insurance for nursing care at home in case of chronic

[8] A dummy indicator for the presence of limitations in instrumental activities of daily living (IADL) was finally excluded because of collinearity with the GALI indicators.

[9] Due to the nature of the data in use, however, we are not able to distinguish among adult children caregivers and non-caregivers, and this may lead to neglecting differences in the quality of care.

disease or disability are about 8%, whilst those who have an insurance for domestic help for activities of daily living are about 4%.

TABLE 2 about HERE.

3 Empirical strategy

When modelling the overall process of formal and informal care use, simultaneous equation models allowing for reverse causation have seldom been used. To our knowledge, only Greene (1983) proposes a two-equation model for levels of formal and informal support and estimate a non recursive model using three-stage least squares to allow for the interrelation between the two endogenous dependent variables. More often, reciprocal interaction between types of LTC has not been considered. Most existing studies estimate two-stage regression models or bivariate probit models that focus on the formal care process only and relies on the availability of valid instruments to identify the effect of informal support on formal care (e.g.; Lo Sasso and Johnson, 2002;Van Houtven and Norton 2004, 2008; Charles and Sevak, 2005; Bolin *et al*., 2008; Bonsang, 2009). In this literature, a specific focus on the determinants of informal care is missing and the genuine relationship between interrelated types of LTC is not explored. In light of this, in this work we propose a fully simultaneous (non recursive) model where both equations for formal and informal care are structural.

Similarly to previous studies, we use a standard two-part model (Cragg, 1971; Duan, 1983; Jones, 2000), which specifies the probability of receiving care and the quantity of care received as two different processes, for both formal and informal care.[10] Our contribution is to propose a unifying empirical framework to estimate jointly both processes. This takes the form of a bivariate two-part model that, in practice, is a system of four simultaneous equations with correlated error terms.

[10] A prominent characteristic of measures of formal and informal care is that they can exhibit a substantial number of zeros: in our SHARE sample, zeros count for about 79% for TFC, 83% for PDH, 91 % for NC and 61% for IC. Two-part models are appropriate to account for this feature of the data.

In order to make our results comparable to the existing literature, we also estimate a recursive specification of our model where formal care is assumed to have no effect on informal care. Recursive models are obtained by setting an exclusion restriction in one equation of the system for one of the endogenous variables, yielding a triangular system specification. The estimation of recursive models lessens the need for informational requirements in terms of instrumental variables (i.e., informal care is completely determined by exogenous variables). However, only if this restriction is totally supported by a strong economic rationale (i.e., feedback effects can be ruled out), the equation without the endogenous variable can also be interpreted as a structural form, otherwise it is better intended as a reduced form. In the specific case of LTC, it seems reasonable that the quantity of formal care affects both the probability and the amount of informal care.

3.1 A joint model for formal and informal care

The first component of the two-part model represents a hurdle to utilization and describes the probability of observing a positive number of hours of care, $y_{F(I)}$ (where F and I stand for the alternatives of formal and informal care respectively), conditional on a vector of exogenous regressors, $\boldsymbol{x}_{F(I)}$, and the endogenous indicator of the amount of informal or formal care received, $y_{I(F)}$. This is modelled using a probit functional form for the conditional probability:

$$\Pr(y_{F(I)} > 0 \mid x_{F(I)}, y_{I(F)}) = \Phi(\beta_{F(I)}' x_{F(I)} + \gamma_{F(I)}' y_{I(F)}) \tag{1}$$

The second component is the conditional density for $y_{F(I)}$ given that the respondent receives some care. To ensure positive values of the quantity of care, and following several examples in the recent literature (e.g., Manning and Mullay, 2005; Deb Trivedi and Zimmer, 2009), this density is specified as a gamma function with two parameters:

$$f(y_{F(I)} \mid y_{F(I)} > 0, x_{F(I)}, y_{I(F)}) = \frac{\left[y_{F(I)}^{(\alpha-1)} \exp(-\frac{y_{F(I)}}{\sigma}) \right]}{\sigma^{\alpha} \Gamma(\alpha)}; \sigma > 0, \alpha > 0 \tag{2}$$

where $\sigma = \exp(b_{F(I)}' x_{F(I)} + g_{F(I)}' y_{I(F)})$ is the scale of the gamma distribution and α is the shape parameter. In the absence of precise indications from the underlying economic theory, we specify both components of each two-part model as identical in terms of exogenous explanatory variables. Vectors $\boldsymbol{x}_F$ and $\boldsymbol{x}_I$ therefore include covariates such as gender, age classes, PtD, household income (in logs), the number of years of education, disability and morbidity indicators, distance from the nearest child, health insurance indicators and country dummy variables. The first part is estimated on the whole sample; the second part is estimated only on the sub-sample of individuals who receive some care.

We are interested in the (unconditional) expected number of hours of care received yielded by the two components of the model:

$$E(y_{F(I)} \mid x_{F(I)}) = \Phi(\beta_{F(I)}' x_{F(I)} + \gamma_{F(I)}' y_{I(F)}) \cdot \exp(b_{F(I)}' x_{F(I)} + g_{F(I)}' y_{I(F)})\alpha \qquad (3)$$

where the second term of the product is the conditional expected number of hours, $E(y_{F(I)} \mid y_{F(I)} > 0) = \sigma\alpha$, derived from the gamma distribution.

The expected number of hours of formal and informal care described in equations (3) could be estimated using separate two-part regression models. Here we consider that formal and informal care are interrelated components of the overall demand for LTC and, in view of that, estimate them jointly as a bivariate two-part model. The econometric issue in the estimation of a fully simultaneous system of four equations is the endogeneity arising from the omission, in each equation, of unobservable factors correlated to the observed component of the model. [11]

In the presence of unobservable heterogeneity, the likelihood function of the joint model is analytically intractable within a standard ML optimization problem, thus requiring an appropriate estimation approach. A way to integrate the unobservable heterogeneity out of the joint density is offered by discrete latent factor models (DLFM) that specify the errors structure using discrete distributions, thus giving an additive form to the likelihood function and allowing for standard full-

[11] Previous works on HCE have highlighted the importance of accounting for potential endogeneity of PtD, since remaining life expectancy might be influenced by current total HCE (e.g., Zweifel, Felder and Werblow, 2004; Felder, Werblow and Zweifel, 2010). Note that is a minor issue in the analysis of LTC at home, given that formal and informal care can only have a secondary effect on remaining lifespan compared to medical care provided in hospitals or in nursing homes (e.g., De Meijer *et al.* 2011). A similar argument applies to potential endogeneity of disability indicators.

information maximum likelihood estimation. Such approach is based on a technique introduced in the literature by Heckman and Singer (1984) and Mroz (1999). Since the DLFM are finite mixture models, they are semiparametric and the discrete distributions can, in principle, approximate any continuous distributions (Jones, 2009). This provides the advantage of avoiding any parametric assumption on the distribution of the unobservable heterogeneity, differently from alternative parametric approaches commonly used to estimate multiple equation models - such as maximum simulated likelihood or Gauss-Hermite quadrature - where normal heterogeneity is assumed (e.g., Deb and Trivedi, 2006). DLFM have been shown to reduce the bias in identification of the distribution of the latent factors when they are non-normal and to perform well in the presence of weak instruments (Mroz, 1999). Recent applications of the discrete factor model to labour and health care data can be found also in Bray (2005), Fabbri and Monfardini (2009), Lien *et al* (2010), Picone *et al*. (2003), van Ours and Williams (2011).

3.2 Estimation method

One way to estimate a joint model of formal and informal care choice and utilisation that accounts for the interdependence between the two types of LTC care is to assume that the error structure depends on common latent factors affecting each component of the two-part models.

The econometric problem of correlated unobservable heterogeneity in the outcome and choice equations is addressed by choosing a latent factor specification. As proposed in Balia and Jones (2011), we define the overall error terms in each equation (ε_j) as composite errors:

$$\varepsilon_j = l_j + \omega_j = \rho_j u + \delta_j v + \omega_j . \qquad j = 1,...,4 \tag{6}$$

Latent factors l_j reflect unobservable heterogeneity and are unknown. By assuming a discrete density function for the distribution of l_j, we integrate it out of the joint density. In the above equation, the l_j consist of two additive random variables u and v, and the ω_j are idiosyncratic error components assumed to be mutually independent and independent of outcomes, covariates and latent factors. The variables u and v have a Bernoulli distribution; they take value 1 with probability p_u and p_v and value 0 with probability $(1-p_u)$ and $(1-p_v)$, respectively. The effect of u and v on the outcomes is allowed to vary thanks to equation-specific factor loadings ρ_j and δ_j. Probabilities p_u and p_v, are estimated by means of a logistic distribution: $p_h = \frac{e^{\theta_h}}{1+e^{\theta_h}}$, where $h = u, v$. The θ_h are additional parameters to be estimated together with the factor-loadings (ρ_j, δ_j) and other parameters (intercepts and slopes) of the model.

The DLFM is based on a finite density estimator that approximates the unknown distribution of l_j by using a step function with K location mass points, η_k :

$$\Pr(l_j = \eta_k) = \pi_k, \qquad \pi_k \geq 0 \qquad \sum_{k=1}^{K} \pi_k = 1 \tag{7}$$

where π_k is the probability that the latent factor realises in a specific mass point. It follows that the individual contribution to the sample likelihood for bivariate two-part model using the DLFM is given by:

$$L_i = \sum_{k=1}^{K} \pi_k f_k(\cdot) \tag{8}$$

The DLFM describes a special case of the finite mixture model where maximum likelihood estimation is carried out over a weighted sum of K densities (components of the mixture) where only the intercepts vary, as shown in equation (9), and π_k are the mixing probabilities.

For identification, only some additional normalisation restrictions is needed. In our factor-loading specification, K is equal to 4 since this is the number of all possible combinations of u and v. This yields: $l_j = 0$ with probability $\pi_1 = \Pr(u=0, v=0) = (1-p_u)(1-p_v)$; $l_j = \rho_j$ with probability $\pi_2 = \Pr(u=1, v=0) = p_u(1-p_v)$; $l_j = \delta_j$ with probability $\pi_3 = \Pr(u=0, v=1) = (1-p_u)p_v$; and $l_j = \rho_j + \delta_j$ with probability $\pi_4 = \Pr(u=1, v=1) = p_u p_v$. The definition of the number of mass points and the mixing probabilities depends on the assumption that u and v are Bernoulli random variables. This allows us to achieve identification of the parameters of the distribution of l_j through restriction of the range of mass points as well as easily recovering mixing probabilities from the moments of u and v.[12]

Using the DLFM, equation (8) can be expressed in terms of summations over u and v:

$$
\begin{aligned}
L_i = \sum_{u=0}^{1}\sum_{v=0}^{1} p_u{}^u(1-p_u)^u p_v{}^v(1-p_v)^v \Big\{ & \big[(1-\Pr(y_F>0\,|\,x_F,y_I,\rho_1 u+\delta_1 v))(1-\Pr(y_I>0\,|\,x_I,y_F,\rho_3 u+\delta_3 v))\big]_{y_F^0,y_I^0} \\
\times & \big[\Pr(y_F>0\,|\,x_F,y_I,\rho_1 u+\delta_1 v)\, f(y_F\,|\,y_F>0,x_F,y_I,\rho_2 u+\delta_2 v)(1-\Pr(y_I>0\,|\,x_I,y_F,\rho_3 u+\delta_3 v))\big]_{y_F^+,y_I^0} \\
\times & \big[(1-\Pr(y_F>0\,|\,x_F,y_I,\rho_1 u+\delta_1 v))\Pr(y_I>0\,|\,x_I,y_F,\rho_3 u+\delta_3 v)\, f(y_I\,|\,y_I>0,x_I,y_F,\rho_4 u+\delta_4 v)\big]_{y_F^0,y_I^+} \\
\times & \big[\Pr(y_F>0\,|\,x_F,y_I,\rho_1 u+\delta_1 v)\, f(y_F\,|\,y_F>0,x_F,y_I,\rho_2 u+\delta_2 v)\cdot \\
\cdot & \Pr(y_I>0\,|\,x_I,y_F,\rho_3 u+\delta_3 v)\, f(y_I\,|\,y_I>0,x_I,y_F,\rho_4 u+\delta_4 v)\big]_{y_F^+,y_I^+}\Big\}
\end{aligned}
\qquad (9)
$$

A specific advantage of the assumption of Bernoulli random variables is that it nicely matches with the economic framework of our model, since u and v can be interpreted as omitted dummies detecting a differential unobservable preference respectively for formal and informal care. It follows that classes (or types) in our population can be defined on the basis of possible combinations of u and v: a baseline type with no differential preferences for neither formal nor informal care (u=0, v=0); two types characterized by a differential preference for one type of care only (u=1, v=0 for formal care, for example, and u=0, v=1 for informal care); a type where both differential preferences are in place (u=1 and v=1).

3.3 Identification issues

Identification of the mixture model defined in equation (9) relies on the latent factor specification in the error process described in equation (6) and on the discrete factor approximation method. This allows for correlations between equations and captures the effect of unobservable heterogeneity given that factor loadings estimates can be interpreted as coefficients of the omitted variables. As outlined by Bray (2005), the DLFM controls for endogeneity since the distribution of the

[12] The distribution of the latent factors is not identified without further assumptions (Mroz, 1999). The location of l_j is arbitrary when each equation has an intercept, and the scale of l_j is also indeterminate. Therefore, identification requires a normalization that implies restricting the support of l_j.

unobserved heterogeneity, which is at the heart of the endogeneity bias, is approximated with a multivariate discrete distribution.

Some recent research shows that identification in simultaneous equation models in which error correlations are due to unobserved common factors, such as the DLFM, is actually reinforced by conditional heteroscedasticity in the errors. Lewbel (2012) shows that identification of triangular and fully simultaneous linear equation systems is ensured by exploiting the heteroscedasticity of the error terms and imposing, as a moment condition, the restriction that regressors are uncorrelated with the product of equation-specific error terms. This restriction is implicit in factor models. The step-function approximation of the distribution of the l_j - the unobserved common factors in the overall error terms ε_j described in equation (6) - allows the variances of l_j, and consequently the variances of ε_j, to be non constant. Piecewise heteroscedasticity between components of the mixture in equation (9) is based on the presence of K location mass points, thus making the DLFM consistent with the "identification with heteroscedasticity" approaches. [13]

In principle, identification of each component of the mixture arises from non linearity in the functional form of each equation. Functional form assumptions, however, are usually considered untestable (see e.g., Van Ours and Williams, 2011). In view of that, exclusions restrictions are generally used to achieve more robust identification. In our model for long-term home care utilisation, traditional exclusion restrictions can be used to get instrumental variables, i.e. exogenous covariates which directly affect informal care but not formal care, and *vice versa.*

Following the existing literature, indicators of geographical distance between the elderly and their children could be excluded from the formal care equation, as they are assumed to directly

[13] A rigorous extension of these results to our DLFM is beyond the scope of the present paper. In particular, such results apply to models where endogenous variables enter linearly. In our model, however, though non linear, the system consists of single linear index models, for which the same full rank assumptions of linear regression models may be sufficient (e.g., Greene, 2008, ch. 14).

affect only informal support.[14] However, their validity requires that: i) children's location decisions are independent of their parents' health status; ii) children's location decisions are independent of the availability of formal care services in the area where their parents live;[15] iii) location decisions of needy parents are independent of their own health status as well as availability of formal care services. We believe that these requirements are rather strong.

Indicators of geographical distance alone can be used in a recursive specification of the model, where instruments are only needed for one endogenous variable. This suggests a unidirectional causal relationship among dependent variables, thus ruling out the presence of direct effects of formal care on informal care (i.e., $\gamma_F = 0$ and $g_F = 0$ in equation (3)). The non recursive model relaxes this assumption, meaning that there is not an *a priori* ordering in causation, and allows for a better understanding of the whole process of home care provision. In this case, also instruments for formal care can be added. In the SHARE, possible candidates for instruments are binary indicators of LTC insurance, which in principle should directly influence formal care use only. The drawback of such indicators is that they do not show enough variability in the sample.[16]

Given that the economic *a-priori* on instruments are weak, our preferred strategy is to include them as regressors in both models of formal and informal care.[17] For the sake of completeness and comparison purposes, in the next section we will present results from the non recursive and the recursive specification of our model with and without exclusion restrictions.

[14] For studies with the SHARE database, see Bonsang (2009) and Bolin *et al.* (2008). By considering different subsamples, possible instruments for IC could be also the number of children and the age of the oldest child. These variables were however disregarded in the preliminary stages of this work due to their lack of statistical significance.

[15] See Rainer and Siedler (2009) for a theoretical model of the location and employment decisions of adult children conditional their long-term family caregiving responsibilities and an empirical application with the German Socio-Economic Panel survey.

[16] Moreover, also the assumption of the absence of a direct relationship between informal care and LTC insurance might be questionable, since (consistently with the intra-family moral hazard theories) LTC insurance could encourage children to reduce or substitute their help (Courbage and Roudaut, 2008).

[17] This is also in line with the identification through heteroscedasticity approach by Lewbel (2012).

4 Results

We start this section by presenting the main results from the estimation of the DLFM for different specifications of the bivariate two-part model for TFC and IC. Table 3 and Table A.1 report full results from the non recursive (fully simultaneous) and the recursive (triangular) model, respectively.[18]

In Model I of Table 3, exclusion restrictions are imposed. As anticipated, we use as instrument for IC an indicator of geographical distance between the dependent elderly and the nearest child.[19] As instrument for TFC, a possible candidate is a binary indicator of LTC insurance. While distance is shown to be a significant determinant of IC, LTC insurance is not statistically significant in the TFC equations. Model II of Table 3 relaxes exclusions restrictions by including distance in the TFC equations and LTC insurance in the IC equations, so that identification of each component of the mixture model simply relies on non linearity of the functional forms. Comparison of the two models shows that the estimates for the endogenous regressors (hIC and hTFC) are stable across specifications. Hence, the specification approach based on standard exclusion restrictions does not outperform the specification which admits the same set of exogenous covariates in all equations. Therefore, within the discrete factor approximation framework, we do not find any additional gain in using the conventional exclusion restrictions approach usually implemented in the previous empirical literature. The estimated coefficients of hIC and hTFC are negative and significant in both components of the two-part models for TFC and IC, and very close to zero.

[18] The bottom panel of each table reports point estimates of the additional parameters that define the distribution of the unobservable heterogeneity. We have computed a test of equality of factor loadings in the components of each two-part model $(\rho_1 = \rho_2; \delta_1 = \delta_2; \rho_3 = \rho_4; \delta_3 = \delta_4)$ for the non recursive as well as the recursive specification. The hypothesis that the latent factors equally affect both components is always rejected.

[19] In preliminary versions of this study, we have used a more general set of children-related variables, such as children's gender, marital status, employment status and age, to build indicators for the proportion of daughters, the proportion of unemployed children, the age of the youngest child and for whether the child lives with a spouse or not. They have been disregarded due to their low statistical significance. Results presented here are unaffected by their inclusion/exclusion in the analysis.

The estimates for the exogenous regressors are also very stable across specification: coefficients and associated standard errors change only at the third digit after decimal point. Looking at the main determinants of LTC use, we see that PtD has a positive and significant effect on the number of hours of both TFC and IC. Age indicators are highly significant and display a much stronger positive effect on TFC than on IC. As expected, the coefficients of disability indicators (ADL, mobility and GALI) and long-term illnesses generally show high statistical significance and both the probability and the amount of care rise as severity in disabilities increases.

-Table 3 about here-

For comparison with the existing literature and as a robustness check, Table A.1 in the Appendix reports point estimates from a recursive simultaneous equations system where IC appears in the right-hand side of the TFC equations and feedback effects of TFC are ruled out from the informal care equations. In the first specification (Model I), we use distance as an instrumental variable for IC. Again, in the second specification (Model II) exclusion restrictions are not imposed. This determines only minor changes in the size and significance of estimated coefficients. The coefficient of IC has negative sign in both TFC equations only in Model I, and its value is essentially zero; in Model II, it remains very close to zero and loses significance.

We further compare the previous four specifications by looking at variations in the expected unconditional number of hours of formal and informal care yielded by changes in the main drivers of home LTC (i.e., age classes, PtD and indicators of severe disability). In view of that, we estimate average partial effects (APEs). For each individual, partial effects are computed as the change in the expected outcome resulting from a single unit change in the explanatory variable, as yielded by the two-part model specified in equation (3), then averaged across the whole sample, so that they are referred to the entire population. Partial effects are calculated by hand using the finite difference method. Note that in the DLFM, the estimation of the APEs has some technical complications:

calculation of the expected outcome is obtained as a weighted average of the outcome calculated at each mass point of the unobservable heterogeneity distribution.[20]

Table 4 largely indicates stability of the DLFM estimates to alternative specifications, with the exception of the recursive specification without exclusion restrictions. Overall, the other three specifications show quite large APEs for PtD and age. Being close to death determines an increase of 7.4 - 8.8 hours per month in expected TFC and of 13.2 and 14.5 hours in expected IC. Also the APEs of age classes are higher on expected IC. Being 75-85 years old has a smaller effect than PtD on care use. It augments TFC and IC of about 4.6 - 4.9 hours and 6.2 - 6.4 hours, respectively. Being in the group of the oldest old determines an even higher increase in LTC use (about 13.3 - 17.3 hours for TFC and 19.8 - 21.9 hours for IC). The effect of having severe disabilities can be even larger: an increment of more than 32 hours of TFC is associated with severe ADL, whilst severe limitations in mobility determine an increase of more than 18 hours of IC. Finally, the APEs show evidence of negligible substitutability between formal and informal care. One additional hour of informal care leads, however, to a monthly reduction of about 3 minutes in expected TFC use. Similarly, one additional hour of TFC reduces IC use of about 6 minutes.

-Table 4 about here-

4.1 Nursing Care and Paid Domestic Help models

On the basis of the results discussed above, hereafter we only consider the most general specification yielded by the fully simultaneous system without exclusion restrictions for the estimation of two separate bivariate two-part models for NC and PDH. Regression estimates are reported in Table 5, whilst the whole set of APEs is contained in Table A.2 in the Appendix.

Once we distinguish between types of formal care, the estimated relationship between formal and informal care is very different. A significant substitution effect is found when estimating the model for PDH and IC, though only in the second component of the two-part models. In the model

[20] This implies taking into account *K* outcomes arising from equations with *K* different intercepts. Weights are the estimated mixing probabilities. Significance level depends on estimated regression coefficients.

for NC, the positive sign of coefficients indicate the prevalence of complementarity effects: in this case, coefficients are statistically significant only in the first component of the two-part model. NC is known to be the most costly type of long-term home care and the absence of substitutability effects clearly frustrates some simplistic views according to which informal care would significantly contribute to reducing the future burden of LTC expenditures.[21] Overall, our results show evidence of moving from substitution to complementarity between formal and informal care as more professional and skilled services are needed. The associated APEs, however, are again extremely small (at maximum, they predict a positive change of about 21 minutes in IC for one additional hour of NC and a negative change of 7 minutes for one additional hour of PDH), thus suggesting that the "traditional" focus on substitutability vs. complementarity is of small empirical relevance.

For both PDH and NC, the coefficients of the oldest old age class is significant and positive. Table A.2 in the appendix shows that being older than 85 implies an increase of 5 hours of NC and 21 hours of IC, and an increase of 6 hours of PDH and 18 hours of IC. Also the coefficients of PtD are positive and statistically significant in both parts of the models for PDH and IC. In fact, additional low-skilled home care assistance can be easily purchased in the market when approaching the end of life. By contrast, a less clear role of PtD emerges in the NC model, where significant positive effects are found only on the number of hours of NC and the likelihood to receive IC. This might be due either to the fact that NC services are subject to in-kind rationing by insurance coverage, or to the scarcity of professional caregivers in the market. Looking at APEs in Table A.2, we find that being close to death has a larger positive impact on the expected use of IC (11 hours in the NC model and 17.5 in the PDH model) than on the two types of formal care (1.4 hours on NC and 4.7 hours on PDH).

[21] In line with Sloan and Norton (1997), Mellor (2001) and Courbage and Roudaut (2008), this result also undermines a necessary condition of the so-called intra-family moral hazard hypothesis, which is often invoked to explain the lack of systematic purchasing of LTC insurance. Brau and Lippi Bruni (2008) reach a similar conclusion in an application of stated preference approaches to the demand for LTC insurance.

Disability indicators have a very high explanatory power in both PDH and NC models. ADL, GALI and mobility indicators are significant in the equations describing the probability of receiving PDH and the quantity of NC used, and a higher severity is associated with higher likelihood of receiving formal care and heavier use. Their role in the equations for IC is less univocal. While severe mobility limitations still capture the highest use of IC in both the PDH and NC model, moderate ADL captures the highest variation in the probability of receiving IC.

The remaining control variables either do not show clear significant effects or are difficult to interpret. Lack of significant effects mainly applies to income. A priori, one could expect no effects from this variable since LTC is in most cases a necessary good driven by limitations in daily living. However, one could have expected also some positive supplemental effect on formal (e.g., by allowing an easier access to private market services) as well as on informal care (e.g. by making bequest promises to informal caregivers more appealing). Not immediately interpretable results are found for education and chronic disease in the case of the IC equation, where negative effects are found.

4.2 Using APEs to assess the relative importance of the main drivers of LTC

We now evaluate the extent to which LTC use at home is affected by the interaction between ageing, PtD and disability. For each bivariate model (TFC, NC and PDH), we have calculated APEs of explanatory variables through simulations for different types of individuals for both the formal care and informal care equations.

In Table 6, this enables us to show how APEs of age and IC on the expected number of hours of formal and informal care vary according to whether individuals are in proximity to death or not, and in response to different LTC needs as proxied by the severity of disability. This results in calculating the partial effects assuming that individuals are all in “low need” (with mild ADL, mobility and GALI), “high need” (with moderate ADL and mobility and severe GALI) or “very high need" (with severe ADL, mobility and GALI).[22] For each need category we further compute the partial effects by setting that all individuals will either die (decedents) or survive (survivors). The reported ratio (*R*) between decedents and survivors measures the multiplicative power of PtD on the APEs.

-Table 6 about here-

The APE of IC on formal care slightly increases with needs and is doubled by PtD. This multiplicative effect, however, tend to decrease with higher needs. Interestingly, the ratio *R* around 2 confirms previous results covering a large set of HCE categories and other geographical areas found by Payne *et al.*, 2007. As shown in the bottom panel of Table 6, PtD has a similar multiplicative power on the APEs of TFC and PDH on IC calculated for the same needs types, with the exception of the APE of NC (*R* is between 1.1. and 1.3). This suggests that complementarity between NC and IC is poorly responsive to deterioration of health conditions as proxied by PtD.

The APEs of age can reach very large values due to the combined effect of PtD and disability. As an example, moving from the group of "low need" survivors to the "very high needs" decedents in the TFC model, we observe a variation of more than 100 hours of formal care per month in the first age category, of which about 49 hours (55.12 minus 6.10) attributed to variations in the disability level, and the remaining 52 hours (107.38 minus 55.12) attributed to PtD. The variation can reach 264 hours when considering the oldest old category.

We further investigate the interactions between the main determinants of LTC, that is PtD, age and disability on formal care (Table 7) and informal care (Table 8), where APEs are simulated distinguishing between survivors and decedents, youngest and oldest old, individuals in different levels of need. Therefore, the ratios *R* are intended to measure the multiplicative power of PtD, age and disability separately. This analysis enables us to highlight a few interesting elements: i) individual ageing has a prominent role (the ratios *R* are in the range 5 – 9.4) in amplifying formal care, whilst its multiplicative effect is much smaller (1.6 – 3.2) on informal care use; ii) the multiplicative power of disabilities is always important, particularly when we consider the most severe situations (the ratios *R*

[22] The latter category only represents 1.3% of our sample, but it is of interest because HCEs are typically concentrated in the most severe cases.

often reach values above 7); iii) a strong interaction is found between “very high need” and PtD (about 71 hours of additional TFC per month) and age (e.g., 152 hours of additional TFC per month); iv) combinations of age and PtD determine much smaller effects; v) the APEs of the disability indicators are usually more responsive to age than PtD (the largest variation in formal care is associated with ADL dummies, while the largest variations in informal care is associated with severe GALI and mobility).

Overall, our results on the impact of ageing, PtD and disability draw a fairly complex picture where no dominant role for a single determinant emerges.

-Table 7 and 8 about here-

5 Conclusions

The current debate on LTC has been developed along two main lines. One focuses on the residual impact of population ageing on expenditures’ growth when more precise indicators of health deterioration and needs, such as PtD and disability, are taken into account. The other focuses on the nature of the relationship between formal and informal care (complementarity *vs.* substitutability). These research issues are interconnected: where a significant substitution effect of informal support on formal care is found, then a valid policy instrument to control the evolution of LTC expenditure would be available.

Within this research framework, this paper develops a unified empirical approach for the study of long-term home care utilisation. We explicitly model the overall process of formal and informal care by means of a bivariate two-part model with correlated errors, which specifies both the probability and amount of the two types of care. By adopting a fully simultaneous specification we estimate the reciprocal interaction between formal and informal care and evaluate the relative impact of age, PtD and disability. For the estimation of our bivariate two-part model we adopt a latent factor approach, thus making a step forward with respect to previous works based on recursive models for formal care where endogeneity of informal care was treated by means of instrumental variables approaches.

Using data from SHARE and exploiting the longitudinal dimension of the survey to recover information on respondents' living status, we find that age, PtD and disability should be jointly considered in models for utilisation of long-term home care. Estimation of separate models for TFC, PDH and NC provide evidence that disability and age play a more important role than PtD on both formal and informal care utilisation. The relevance of PtD varies according to the type of formal care considered: it is a strong significant explanatory variable in the model for PDH and IC, while it has a less clear role in the model for NC and IC.

To better assess the contribution of age, PtD and disability, we present post-estimation predictions of changes in the expected number of hours of formal and informal care due to changes in explanatory variables for hypothetical individuals. The APEs of age and PtD are especially relevant if combined with disability. For example, when considering "very high need" individuals, the APEs of the oldest age category and PtD predict an increase of 152 and 71 hours per month in TFC, respectively. Overall, though non-negligible differences among the main drivers of LTC use emerge, we believe that age, PtD and disability should be used jointly as predictors of LTC use.

Our analysis shows evidence of significant, though negligible, substitutability between formal care and IC when a general indicator of TFC is used. Estimated APEs suggest that a more intense use of one type of care generates a reduction of a few minutes only in the use of the other one. Focusing on PDH and NC separately, we find clear evidence of substitutability in the former case and of complementarity in the latter, perhaps because here more professional and skilled services are needed. Estimated APEs, however, are again extremely small, thus suggesting that the "traditional" focus on substitutability *vs.* complementarity is of small empirical relevance. In light of these findings we believe that emphasis should be placed not only on the *sign* of estimation results, but also on their *size*. Irrespective of whether a substitution or complementarity effect is found, the policy implication is that incentives for informal support are not likely to strongly modify the demand of paid LTC home services in Europe. The role of informal care as an effective cost-saving instrument to reduce the financial burden on public budgets for paid LTC probably needs reconsideration.

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Tables

Table 1 – *Formal and Informal LTC utilisation*

	Overall sample		***LTC =1***		***TFC =1***		***NC =1***		***PDH =1***		***IC =1***	
	N=1337		N=628		N=277		N=123		N=222		N=521	
Variables	Mean	*s.d.*	Mean	*s.d.*	Mean	*s.d.*	Mean	*s.d.*	Mean	*s.d.*	Mean	*s.d.*
LTC	0.470	*(0.499)*										
hLTC	23.511	*(63.700)*	50.054	*(85.530)*	64.278	*(112.320)*	86.049	*(134.148)*	68.320	*(120.759)*	55.179	*(81.633)*
TFC	0.207	*(0.405)*	0.441	*(0.497)*							0.326	*(0.469)*
hTFC	5.670	*(41.728)*	12.072	*(60.272)*	27.369	*(88.501)*	36.949	*(109.162)*	32.658	*(97.742)*	9.396	*(48.332)*
NC	0.092	*(0.289)*	0.196	*(0.397)*	0.444	*(0.498)*			0.306	*(0.462)*	0.159	*(0.366)*
hNC	1.262	*(12.226)*	2.687	*(17.738)*	6.091	*(26.343)*	13.718	*(38.269)*	6.110	*(27.931)*	2.903	*(19.341)*
PDH	0.166	*(0.372)*	0.354	*(0.478)*	0.801	*(0.400)*	0.553	*(0.499)*			0.263	*(0.441)*
hPDH	4.408	*(37.912)*	9.385	*(54.917)*	21.277	*(81.224)*	23.231	*(96.342)*	26.549	*(89.993)*	6.494	*(39.800)*
IC	0.390	*(0.488)*	0.830	*(0.376)*	0.614	*(0.488)*	0.675	*(0.470)*	0.617	*(0.487)*		
hIC	17.841	*(43.227)*	37.982	*(56.703)*	36.909	*(60.520)*	49.100	*(70.703)*	35.661	*(60.267)*	45.783	*(59.321)*

Table 2 – *Sample characteristics*

Variables	Mean	*s.d.*
PtD	0.052	*(0.223)*
age	75.925	*(7.043)*
age 6575	0.448	*(0.497)*
age 7585	0.436	*(0.496)*
age over85	0.116	*(0.320)*
female	0.776	*(0.417)*
chronic no	0.117	*(0.321)*
chronic mild	0.281	*(0.450)*
chronic moderate	0.418	*(0.493)*
chronic severe	0.184	*(0.388)*
gali no	0.462	*(0.499)*
gali mild	0.351	*(0.477)*
gali severe	0.187	*(0.390)*
adl no	0.835	*(0.372)*
adl mild	0.091	*(0.287)*
adl moderate	0.060	*(0.237)*
adl severe	0.015	*(0.121)*
mobility no	0.320	*(0.467)*
mobility mild	0.307	*(0.461)*
mobility moderate	0.189	*(0.392)*
mobility severe	0.184	*(0.388)*
ltillness	0.572	*(0.495)*
income	66607	*(165000)*
education (years)	8.561	*(4.301)*
LTC insurance	0.114	*(0.318)*
NC insurance	0.079	*(0.270)*
PDH insurance	0.038	*(0.192)*
distance nearest child	40.009	*99.827*

Table 3 - *Results from the Discrete Latent Factor estimation for Total Formal Care*

Bivariate two-part model for Total Formal Care and Informal Care								
	Non Recursive Model I				**Non Recursive Model II**			
Variables	**P(hTFC>0)**	**E(hTFC|hTFC>0)**	**P(hIC>0)**	**E(hIC|hIC>0)**	**P(hTFC>0)**	**E(hTFC|hTFC>0)**	**P(hIC>0)**	**E(hIC|hIC>0)**
hIC	-0.002 (0.002)	-0.007 (0.002) ***			-0.002 (0.002)	-0.007 (0.002) ***		
hTFC			-0.003 (0.002) **	-0.005 (0.001) ***			-0.003 (0.002) **	-0.005 (0.001) ***
PtD	0.374 (0.214) *	0.664 (0.280) **	0.400 (0.236) *	0.483 (0.205) **	0.370 (0.214) *	0.641 (0.279) **	0.403 (0.238) *	0.463 (0.203) **
age 7585	0.738 (0.124) ***	0.834 (0.217) ***	0.360 (0.117) ***	0.302 (0.119) **	0.737 (0.124) ***	0.830 (0.218) ***	0.359 (0.118) ***	0.297 (0.119) **
age over85	1.240 (0.181) ***	1.457 (0.303) ***	0.517 (0.186) ***	0.900 (0.174) ***	1.237 (0.181) ***	1.480 (0.289) ***	0.520 (0.187) ***	0.892 (0.173) ***
female	0.006 (0.129)	-0.525 (0.194) ***	0.406 (0.132) ***	-0.270 (0.157) *	0.002 (0.129)	-0.512 (0.194) ***	0.405 (0.133) ***	-0.273 (0.157) *
gali mild	0.416 (0.142) ***	0.414 (0.234) *	0.307 (0.136) **	0.235 (0.142) *	0.415 (0.141) ***	0.425 (0.237) *	0.307 (0.137) **	0.238 (0.142) *
gali severe	0.720 (0.177) ***	0.363 (0.282)	0.475 (0.182) ***	0.690 (0.177) ***	0.704 (0.178) ***	0.348 (0.293)	0.475 (0.185) **	0.684 (0.176) ***
adl mild	0.486 (0.165) ***	0.673 (0.244) ***	0.155 (0.180)	0.192 (0.171)	0.487 (0.164) ***	0.671 (0.238) ***	0.159 (0.180)	0.187 (0.168)
adl moderate	0.686 (0.212) ***	1.258 (0.261) ***	0.852 (0.250) ***	0.360 (0.201) *	0.677 (0.213) ***	1.242 (0.262) ***	0.851 (0.254) ***	0.352 (0.202) *
adl severe	1.477 (0.485) ***	1.860 (0.396) ***	0.105 (0.439)	0.630 (0.349) *	1.490 (0.486) ***	1.871 (0.393) ***	0.093 (0.442)	0.598 (0.355) *
mobility mild	0.679 (0.159) ***	0.670 (0.297) **	0.599 (0.141) ***	0.163 (0.170)	0.690 (0.160) ***	0.692 (0.298) **	0.603 (0.142) ***	0.172 (0.170)
mobility moderate	0.570 (0.188) ***	0.778 (0.331) **	0.771 (0.187) ***	0.625 (0.194) ***	0.595 (0.189) ***	0.826 (0.327) **	0.782 (0.190) ***	0.635 (0.193) ***
mobility severe	1.080 (0.216) ***	1.234 (0.352) ***	0.885 (0.234) ***	0.911 (0.217) ***	1.100 (0.217) ***	1.263 (0.352) ***	0.887 (0.238) ***	0.919 (0.219) ***
chronic mild	-0.045 (0.223)	0.059 (0.396)	0.604 (0.204) ***	-0.374 (0.282)	-0.050 (0.224)	0.054 (0.400)	0.597 (0.205) ***	-0.392 (0.287)
chronic moderate	0.017 (0.215)	-0.127 (0.389)	0.408 (0.196) **	-0.446 (0.276)	0.020 (0.215)	-0.114 (0.393)	0.404 (0.197) **	-0.458 (0.279) *
chronic severe	0.407 (0.233) *	0.416 (0.411)	0.437 (0.225) *	-0.346 (0.296)	0.406 (0.234) *	0.434 (0.412)	0.433 (0.226) *	-0.350 (0.298)
ltillness	0.176 (0.131)	0.379 (0.207) *	0.290 (0.126) **	-0.005 (0.136)	0.176 (0.132)	0.392 (0.210) *	0.292 (0.127) **	-0.006 (0.136)
lnincome	0.030 (0.061)	0.069 (0.111)	-0.006 (0.039)	-0.001 (0.040)	0.027 (0.061)	0.071 (0.109)	-0.006 (0.040)	-0.002 (0.041)
education (years)	0.015 (0.015)	0.016 (0.023)	-0.011 (0.014)	-0.061 (0.015) ***	0.014 (0.015)	0.013 (0.023)	-0.012 (0.014)	-0.062 (0.015) ***
LTC insurance	-0.030 (0.229)	0.198 (0.318)			-0.041 (0.230)	0.212 (0.322)	-0.147 (0.250)	0.115 (0.233)
distance nearest child			-0.002 (0.001) ***	-0.002 (0.001) ***	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001) ***	-0.002 (0.001) ***
intercept	-4.418 (0.833) ***	0.307 (1.607)	-1.180 (0.798)	3.881 (0.678) ***	-4.435 (0.832) ***	0.273 (1.573)	-1.217 (0.810)	3.890 (0.682) ***
α		0.932 (0.100) ***		1.254 (0.124) ***		0.928 (0.100) ***		1.247 (0.125) ***
Latent factor parameters								
	ρ_1	-0.653 (0.354) *	δ_1	0.949 (0.262) ***	ρ_1	-0.643 (0.354) *	δ_1	0.934 (0.265) ***
	ρ_2	-2.464 (0.342) ***	δ_2	1.361 (0.396) ***	ρ_2	-2.482 (0.335) ***	δ_2	1.342 (0.384) ***
	ρ_3	-1.823 (0.543) ***	δ_3	1.606 (0.373) ***	ρ_3	-1.797 (0.536) ***	δ_3	1.629 (0.395) ***
	ρ_4	-2.142 (0.200) ***	δ_4	1.810 (0.247) ***	ρ_4	-2.126 (0.200) ***	δ_4	1.817 (0.254) ***
	θ_1	2.703 (0.256) ***	θ_2	0.274 (0.285)	θ_1	2.708 (0.260) ***	θ_2	0.285 (0.292)
logL	-4549.706				-4548.385			
N	1337				1337			

Notes. Standard errors in parenthesis. Level of significance: *** 1%; ** 5%; * 10%.
In Model I "distance from the nearest child" is included only in the informal care equations to identify its effect on formal care and "LTC insurance" is included only in the formal care equations to identify its effect on informal care; in Model II formal and informal care are regressed against the same covariates. All models also include country dummy variables.

Table 4 - *Comparison of Average Partial Effects*

	Non Recursive Model I		Non Recursive Model II		Recursive Model I		Recursive Model II	
APE	E(hTFC)	E(hIC)	E(hTFC)	E(hIC)	E(hTFC)	E(hIC)	E(hTFC)	E(hIC)
hIC	-0.055		-0.054		-0.050		-0.010	
hTFC		-0.108		-0.102				
PtD	7.572	14.505	7.386	13.819	8.803	13.221	4.753	12.870
age 7585	4.680	6.315	4.687	6.181	4.625	6.356	3.788	6.406
age over85	13.246	21.916	13.703	21.552	17.258	19.844	12.470	19.966
gali severe	4.039	15.565	3.936	15.231	5.266	17.418	2.694	17.360
adl severe	32.102	13.544	33.167	12.439	34.666	5.812	32.811	6.117
mobility severe	8.415	19.524	8.601	19.358	8.918	18.008	6.372	17.993

Notes. Model I is estimated with exclusion restrictions; Model II is estimated without exclusion restrictions.

Table 5 – *Results from the Discrete Latent Factor estimation of the Bivariate two-part model for types of formal care*

	Bivariate two-part model for Nursing Care and Informal Care				Bivariate two-part model for Paid Domestic Help and Informal Care			
	Non Recursive Model II				**Non Recursive Model II**			
Variables	**P(hNC>0)**	**E(hNC|hNC>0)**	**P(hIC>0)**	**E(hIC|IhC>0)**	**P(hPDH>0)**	**E(hPDH|hPDH>0)**	**P(hIC>0)**	**E(hIC|hIC>0)**
hIC	0.004 (0.001) ***	0.002 (0.001)			-0.002 (0.002)	-0.006 (0.002) ***		
hPDH							-0 0.002 *	-0.01 0.001 ***
hNC			0.019 (0.010) *	0.003 (0.004)				
PtD	-0.176 (0.255)	0.862 (0.387) **	0.383 (0.212) *	0.173 (0.229)	0.535 (0.223) **	0.622 (0.246) **	0.430 (0.226) *	0.561 (0.205) ***
age 7585	0.291 (0.139) **	-0.259 (0.202)	0.367 (0.111) ***	-0.095 (0.138)	0.900 (0.149) ***	0.437 (0.229) *	0.337 (0.109) ***	0.258 (0.126) **
age over85	0.545 (0.198) ***	1.341 (0.269) ***	0.413 (0.168) **	0.483 (0.199) **	1.365 (0.207) ***	0.868 (0.267) ***	0.445 (0.173) ***	0.745 (0.179) ***
female	0.319 (0.167) *	-0.400 (0.255)	0.410 (0.134) ***	-0.578 (0.175) ***	-0.098 (0.138)	-0.416 (0.177) **	0.387 (0.127) ***	-0.269 (0.172)
gali mild	0.067 (0.172)	-0.491 (0.276) *	0.227 (0.126) *	-0.064 (0.162)	0.468 (0.157) ***	0.382 (0.222) *	0.268 (0.126) **	0.174 (0.147)
gali severe	0.387 (0.194) **	-1.073 (0.277) ***	0.388 (0.165) **	0.361 (0.208) *	0.766 (0.201) ***	0.477 (0.306)	0.459 (0.176) ***	0.691 (0.185) ***
adl mild	0.365 (0.184) **	1.591 (0.237) ***	0.220 (0.168)	-0.068 (0.223)	0.550 (0.171) ***	0.116 (0.198)	0.129 (0.166)	0.104 (0.169)
adl moderate	0.816 (0.213) ***	1.226 (0.250) ***	0.742 (0.211) ***	-0.051 (0.208)	0.523 (0.220) **	0.708 (0.292) **	0.756 (0.241) ***	0.243 (0.208)
adl severe	1.395 (0.385) ***	2.068 (0.367) ***	-0.171 (0.386)	0.572 (0.452)	1.037 (0.399) ***	1.650 (0.361) ***	0.162 (0.434)	0.700 (0.400) *
mobility mild	0.300 (0.189)	1.090 (0.294) ***	0.601 (0.147) ***	-0.176 (0.199)	0.809 (0.190) ***	0.595 (0.323) *	0.569 (0.131) ***	0.126 (0.180)
mobility moderate	0.221 (0.219)	1.148 (0.321) ***	0.683 (0.171) ***	-0.219 (0.223)	0.744 (0.220) ***	0.361 (0.332)	0.690 (0.167) ***	0.533 (0.207) **
mobility severe	0.471 (0.233) **	1.323 (0.335) ***	0.728 (0.193) ***	-0.001 (0.230)	1.107 (0.240) ***	0.686 (0.332) **	0.746 (0.195) ***	0.829 (0.226) ***
chronic mild	0.113 (0.287)	-0.874 (0.442) **	0.545 (0.204) ***	-0.782 (0.305) ***	-0.153 (0.251)	0.025 (0.371)	0.526 (0.192) ***	-0.489 (0.295) *
chronic moderate	0.121 (0.279)	-0.724 (0.421) *	0.286 (0.200)	-0.412 (0.304)	0.002 (0.240)	-0.227 (0.349)	0.347 (0.184) *	-0.499 (0.285) *
chronic severe	0.265 (0.297)	-0.755 (0.436) *	0.333 (0.220)	-0.447 (0.320) *	0.505 (0.258) *	-0.077 (0.362)	0.339 (0.213)	-0.523 (0.303) *
ltillness	0.281 (0.159) *	0.562 (0.236) **	0.276 (0.120) **	0.017 (0.151)	0.069 (0.144)	0.241 (0.189)	0.277 (0.118) **	-0.034 (0.140)
lnincome	-0.025 (0.053)	0.297 (0.111) ***	-0.001 (0.045)	-0.034 (0.052)	0.081 (0.082)	0.014 (0.145)	-0.005 (0.037)	-0.001 (0.044)
education (years)	0.008 (0.016)	0.010 (0.022)	-0.019 (0.014)	-0.050 (0.016) ***	0.014 (0.017)	-0.001 (0.027)	-0.013 (0.013)	-0.063 (0.016) ***
PDH insurance					-0.298 (0.328)	-0.756 (0.458) *	0.062 (0.268)	-0.169 (0.274)
NC insurance	0.168 (0.221)	-0.295 (0.285)	-0.010 (0.248)	0.652 (0.327) **				
distance nearest child	0.001 (0.001)	0.003 (0.001) ***	-0.002 (0.001) ***	-0.002 (0.001) ***	0.001 (0.001) **	-0.001 (0.001)	-0.001 (0.001) ***	-0.002 (0.001) ***
intercept	-2.917 (0.748) ***	-2.275 (1.276) *	-0.646 (0.772)	4.062 (0.789) ***	-5.259 (1.116) ***	2.812 (2.164)	-1.053 (0.801)	3.787 (1.169) **
α		1.890 (0.245) ***		1.149 (0.110) ***		1.380 (0.209) ***		1.165 (0.141) ***
Latent factor parameters								
	ρ_1	-0.235 (0.387)	δ_1	-0.252 (0.222)	ρ_1	-1.004 (0.422) **	δ_1	0.971 (0.402) **
	ρ_2	-3.039 (0.196) ***	δ_2	0.232 (0.316)	ρ_2	-1.885 (0.284) ***	δ_2	0.844 (0.740)
	ρ_3	0.470 (0.452)	δ_3	-1.791 (0.460) ***	ρ_3	-1.812 (0.594) ***	δ_3	1.430 (0.424) ***
	ρ_4	0.177 (0.447)	δ_4	1.723 (0.206) ***	ρ_4	-1.982 (0.232) ***	δ_4	1.999 (0.782) **
	θ_1	1.433 (0.506) ***	θ_2	1.335 (0.328) ***	θ_1	2.761 (0.278) ***	θ_2	0.777 (0.550)
logL	-3683.142				-4305.562			
N	1337				1337			

Notes. Standard errors in parenthesis. Level of significance: *** 1%; ** 5%; * 10%.
"PDH insurance" is included only in the model for Paid Domestic Help and Informal Care; "NC insurance" is included only in the model for Nursing Care and Informal Care. Both models include country dummy variables.

Table 6 – *Average Partial Effects of formal and informal care and age on expected outcomes in hypothetical scenarios*

APEs on formal care in each separate bivariate two-part model										
		low need			***high need***			***very high need***		
		survivors	*decedents*	*R*	*survivors*	*decedents*	*R*	*survivors*	*decedents*	*R*
hIC	E(hTFC)	-0.05	-0.12	*2.3*	-0.12	-0.26	*2.2*	-0.49	-0.98	*2.0*
	E(hNC)	0.03	0.05	*1.9*	0.02	0.04	*2.1*	0.09	0.20	*2.2*
	E(hPDH)	-0.03	-0.07	*2.5*	-0.05	-0.13	*2.4*	-0.28	-0.60	*2.2*
age 7585	E(hTFC)	6.10	13.94	*2.3*	13.83	30.07	*2.2*	55.12	107.38	*1.9*
	E(hNC)	0.49	0.97	*2.0*	0.25	0.61	*2.5*	-0.55	-0.27	*0.5*
	E(hPDH)	3.34	8.09	*2.4*	5.89	13.67	*2.3*	28.56	57.68	*2.0*
age over85	E(hTFC)	18.58	40.63	*2.2*	40.24	84.44	*2.1*	146.48	282.47	*1.9*
	E(hNC)	15.32	28.15	*1.8*	14.09	27.97	*2.0*	70.60	151.89	*2.2*
	E(hPDH)	8.40	19.47	*2.3*	14.53	32.54	*2.2*	66.97	133.65	*2.0*
APEs on informal care in each separate bivariate two-part model										
hTFC	$E(hIC)_{TFC}$	-0.07	-0.12	*1.9*	-0.27	-0.46	*1.7*	-0.38	-0.68	*1.8*
hNC	$E(hIC)_{NC}$	0.30	0.39	*1.3*	0.48	0.52	*1.1*	1.02	1.32	*1.3*
hPDH	$E(hIC)_{PDH}$	-0.08	-0.16	*2.1*	-0.31	-0.59	*1.9*	-0.57	-1.13	*2.0*
age 7585	$E(hIC)_{TFC}$	4.55	8.24	*1.8*	17.26	28.62	*1.7*	25.65	44.71	*1.7*
	$E(hIC)_{NC}$	2.68	2.89	*1.1*	2.59	1.23	*0.5*	9.27	10.43	*1.1*
	$E(hIC)_{PDH}$	4.21	8.48	*2.0*	15.30	27.66	*1.8*	29.53	56.24	*1.9*
age over85	$E(hIC)_{TFC}$	15.49	28.73	*1.9*	62.62	106.47	*1.7*	89.37	159.74	*1.8*
	$E(hIC)_{NC}$	18.53	25.95	*1.4*	36.31	46.10	*1.3*	60.75	86.27	*1.4*
	$E(hIC)_{PDH}$	12.22	25.52	*2.1*	48.27	90.82	*1.9*	88.58	175.61	*2.0*

Table 7 – *Selected Average Partial Effects on formal care in hypothetical scenarios*

APEs		*survivors*	*decedents*	*R*	*youngest old*	*oldest old*	*R*	*low need*	*high need*	*R*	*very high need*	*R*
	E(hTFC)	-0.05	-0.10	*2.2*	-0.02	-0.12	*7.6*	-0.06	-0.13	*2.2*	-0.53	*9.3*
hIC	E(hNC)	0.01	0.02	*2.0*	0.01	0.03	*6.6*	0.03	0.02	*0.8*	0.09	*3.4*
	E(hPDH)	-0.02	-0.06	*2.4*	-0.01	-0.05	*5.7*	-0.03	-0.06	*1.8*	-0.30	*9.3*
	E(hTFC)				2.34	16.50	*7.1*	8.88	19.20	*2.2*	71.50	*8.1*
PtD	E(hNC)				0.62	5.00	*8.1*	2.87	3.40	*1.2*	23.05	*8.0*
	E(hPDH)				1.83	9.22	*5.0*	6.11	10.54	*1.7*	49.38	*8.1*
	E(hTFC)	4.23	9.28	*2.2*				6.42	14.51	*2.3*	57.40	*8.9*
age 7585	E(hNC)	0.09	0.19	*2.2*				0.50	0.25	*0.5*	-0.56	*-1.1*
	E(hPDH)	2.10	5.16	*2.5*				3.56	6.25	*1.8*	30.09	*8.5*
	E(hTFC)	12.47	26.63	*2.1*				19.50	42.10	*2.2*	152.43	*7.8*
age over85	E(hNC)	4.68	9.07	*1.9*				15.72	14.48	*0.9*	72.71	*4.6*
	E(hPDH)	5.35	12.74	*2.4*				8.92	15.39	*1.7*	70.51	*7.9*
	E(hTFC)	4.00	8.88	*2.2*	1.33	11.42	*8.6*					
adl mild	E(hNC)	3.12	5.72	*1.8*	1.66	14.18	*8.5*					
	E(hPDH)	1.17	2.67	*2.3*	0.53	2.69	*5.1*					
	E(hTFC)	10.12	22.41	*2.2*	3.42	28.80	*8.4*					
adl moderate	E(hNC)	4.00	7.69	*1.9*	2.38	17.44	*7.3*					
	E(hPDH)	3.26	8.21	*2.5*	1.29	8.20	*6.3*					
	E(hTFC)	30.37	63.11	*2.1*	12.19	79.76	*6.5*					
adl severe	E(hNC)	18.25	36.77	*2.0*	12.00	75.33	*6.3*					
	E(hPDH)	15.69	37.72	*2.4*	6.91	37.74	*5.5*					
	E(hTFC)	3.15	6.75	*2.1*	1.03	7.89	*7.7*					
gali mild	E(hNC)	-0.88	-1.71	*1.9*	-0.41	-3.22	*7.9*					
	E(hPDH)	1.58	3.88	*2.5*	0.60	3.72	*6.2*					
	E(hTFC)	3.49	7.17	*2.1*	1.29	8.45	*6.6*					
gali severe	E(hNC)	-1.28	-2.45	*1.9*	-0.53	-4.57	*8.6*					
	E(hPDH)	2.61	6.17	*2.4*	1.09	5.97	*5.5*					
	E(hTFC)	2.77	6.15	*2.2*	0.86	7.64	*8.9*					
mobility mild	E(hNC)	0.99	1.89	*1.9*	0.52	4.15	*8.0*					
	E(hPDH)	2.16	5.45	*2.5*	0.81	5.34	*6.6*					
	E(hTFC)	3.11	7.02	*2.3*	0.92	8.68	*9.4*					
mobility moderate	E(hNC)	0.94	1.79	*1.9*	0.48	3.93	*8.2*					
	E(hPDH)	1.43	3.56	*2.5*	0.54	3.50	*6.5*					
	E(hTFC)	7.58	16.49	*2.2*	2.53	20.47	*8.1*					
mobility severe	E(hNC)	1.69	3.26	*1.9*	0.93	7.16	*7.7*					
	E(hPDH)	3.20	7.78	*2.4*	1.30	7.68	*5.9*					

Table 8 – *Selected Average Partial Effects on formal care in hypothetical scenarios*

APEs		*survivors*	*decedents*	*R*	*youngest old*	*oldest old*	*R*	*low need*	*high need*	*R*	*very high*	*R*
hTFC	$E(hIC)_{TFC}$	-0.09	-0.17	*1.8*	-0.06	-0.19	*2.9*	-0.07	-0.28	*4.0*	-0.41	*5.7*
hNC	$E(hIC)_{NC}$	0.34	0.45	*1.3*	0.31	0.58	*1.9*	0.31	0.48	*1.6*	1.04	*3.4*
hPDH	$E(hIC)_{PDH}$	-0.11	-0.23	*2.0*	-0.08	-0.21	*2.5*	-0.08	-0.33	*3.9*	-0.61	*7.2*
	$E(hIC)_{TFC}$				8.87	25.28	*2.8*	10.10	37.40	*3.7*	56.20	*5.6*
PtD	$E(hIC)_{NC}$				9.75	18.48	*1.9*	9.81	16.34	*1.7*	32.80	*3.3*
	$E(hIC)_{PDH}$				11.97	29.28	*2.4*	12.39	44.90	*3.6*	86.15	*7.0*
	$E(hIC)_{TFC}$	5.79	10.28	*1.8*				4.77	17.94	*3.8*	26.78	*5.6*
age 7585	$E(hIC)_{NC}$	3.01	3.47	*1.2*				2.71	2.50	*0.9*	9.39	*3.5*
	$E(hIC)_{PDH}$	5.56	11.03	*2.0*				4.47	16.05	*3.6*	31.13	*7.0*
	$E(hIC)_{TFC}$	20.11	36.51	*1.8*				16.27	65.24	*4.0*	93.53	*5.7*
age over85	$E(hIC)_{NC}$	20.51	29.24	*1.4*				19.07	37.04	*1.9*	62.59	*3.3*
	$E(hIC)_{PDH}$	16.51	33.82	*2.0*				13.00	50.81	*3.9*	93.76	*7.2*
	$E(hIC)_{TFC}$	3.86	6.97	*1.8*	2.64	7.80	*3.0*					
adl mild	$E(hIC)_{NC}$	1.68	1.78	*1.1*	1.68	2.62	*1.6*					
	$E(hIC)_{PDH}$	2.49	4.94	*2.0*	1.86	4.59	*2.5*					
	$E(hIC)_{TFC}$	13.21	21.87	*1.7*	9.61	25.33	*2.6*					
adl moderate	$E(hIC)_{NC}$	9.93	11.67	*1.2*	9.56	16.00	*1.7*					
	$E(hIC)_{PDH}$	10.76	19.34	*1.8*	8.49	18.84	*2.2*					
	$E(hIC)_{TFC}$	11.33	21.50	*1.9*	7.46	23.60	*3.2*					
adl severe	$E(hIC)_{NC}$	11.86	18.92	*1.6*	9.55	21.83	*2.3*					
	$E(hIC)_{PDH}$	15.25	32.49	*2.1*	10.97	29.14	*2.7*					
	$E(hIC)_{TFC}$	4.57	8.17	*1.8*	3.10	9.10	*2.9*					
gali mild	$E(hIC)_{NC}$	1.81	2.11	*1.2*	1.74	2.96	*1.7*					
	$E(hIC)_{PDH}$	3.75	7.46	*2.0*	2.76	6.89	*2.5*					
	$E(hIC)_{TFC}$	14.04	25.57	*1.8*	9.40	28.21	*3.0*					
gali severe	$E(hIC)_{NC}$	15.51	21.99	*1.4*	13.47	27.16	*2.0*					
	$E(hIC)_{PDH}$	14.81	30.50	*2.1*	10.75	27.62	*2.6*					
	$E(hIC)_{TFC}$	4.12	7.24	*1.8*	2.89	8.33	*2.9*					
mobility mild	$E(hIC)_{NC}$	5.16	6.21	*1.2*	4.88	8.53	*1.7*					
	$E(hIC)_{PDH}$	4.18	8.10	*1.9*	3.17	7.73	*2.4*					
	$E(hIC)_{TFC}$	11.28	20.57	*1.8*	7.72	23.24	*3.0*					
mobility moderat	$E(hIC)_{NC}$	5.39	6.28	*1.2*	5.18	8.80	*1.7*					
	$E(hIC)_{PDH}$	10.35	21.21	*2.0*	7.65	19.60	*2.6*					
	$E(hIC)_{TFC}$	17.94	32.84	*1.8*	12.27	37.03	*3.0*					
mobility severe	$E(hIC)_{NC}$	11.56	15.29	*1.3*	10.46	19.75	*1.9*					
	$E(hIC)_{PDH}$	16.65	34.60	*2.1*	12.22	31.72	*2.6*					

Appendix

Table A.1 - *Results from the Discrete Latent Factor estimation for Total Formal Care*

Bivariate two-part model for Total Formal Care and Informal Care								
	Recursive Model I				**Recursive Model II**			
Variables	**P(hTFC>0)**	**E(hTFC|hTFC>0)**	**P(hIC>0)**	**E(hIC|hIC>0)**	**P(hTFC>0)**	**E(hTFC|hTFC>0)**	**P(hIC>0)**	**E(hIC|hIC>0)**
hIC	-0.0002 (0.002)	-0.006 (0.002) ***			0.002 (0.003)	-0.002 (0.002)		
PtD	0.369 (0.232)	0.731 (0.302) **	0.293 (0.190)	0.385 (0.196) **	0.477 (0.313)	0.490 (0.302)	0.283 (0.183)	0.369 (0.196) *
age 7585	0.813 (0.155) ***	0.944 (0.217) ***	0.291 (0.091) ***	0.215 (0.120) *	1.081 (0.269) ***	0.773 (0.229) ***	0.279 (0.087) ***	0.216 (0.118) *
age over85	1.340 (0.239) ***	1.860 (0.332) ***	0.418 (0.145) ***	0.681 (0.163) ***	1.928 (0.546) ***	1.454 (0.301) ***	0.409 (0.138) ***	0.677 (0.162) ***
female	-0.023 (0.140)	-0.637 (0.191) ***	0.322 (0.106) ***	-0.286 (0.161) *	0.000 (0.192)	-0.515 (0.193) ***	0.321 (0.103) ***	-0.290 (0.161) *
gali mild	0.457 (0.160) ***	0.575 (0.221) ***	0.220 (0.109) **	0.136 (0.156)	0.610 (0.239) **	0.378 (0.245)	0.206 (0.105) **	0.131 (0.153)
gali severe	0.771 (0.206) ***	0.567 (0.291) *	0.375 (0.146) **	0.631 (0.197) ***	1.046 (0.337) ***	0.165 (0.323)	0.360 (0.139) ***	0.623 (0.190) ***
adl mild	0.535 (0.186) ***	0.755 (0.261) ***	0.154 (0.148)	0.075 (0.172)	0.755 (0.287) ***	0.658 (0.249) ***	0.158 (0.141)	0.092 (0.167)
adl moderate	0.748 (0.233) ***	1.537 (0.280) ***	0.726 (0.195) ***	0.194 (0.184)	0.900 (0.314) ***	1.192 (0.274) ***	0.680 (0.187) ***	0.182 (0.181)
adl severe	1.566 (0.512) ***	2.121 (0.396) ***	-0.103 (0.331)	0.376 (0.341)	2.102 (0.712) ***	1.998 (0.460) ***	-0.069 (0.322)	0.366 (0.339)
mobility mild	0.758 (0.193) ***	0.843 (0.320) ***	0.514 (0.115) ***	-0.001 (0.187)	1.062 (0.326) ***	0.756 (0.307) **	0.494 (0.110) ***	-0.016 (0.190)
mobility moderate	0.567 (0.213) ***	0.758 (0.333) **	0.597 (0.140) ***	0.376 (0.200) *	0.777 (0.323) **	0.810 (0.323) **	0.581 (0.132) ***	0.384 (0.203) *
mobility severe	1.121 (0.253) ***	1.343 (0.391) ***	0.654 (0.167) ***	0.603 (0.221) ***	1.426 (0.366) ***	1.109 (0.351) ***	0.611 (0.157) ***	0.608 (0.223) ***
chronic mild	0.020 (0.250)	0.397 (0.395)	0.492 (0.169) ***	-0.600 (0.293) **	-0.063 (0.340)	0.068 (0.392)	0.442 (0.160) ***	-0.669 (0.304) **
chronic moderate	0.089 (0.241)	0.232 (0.363)	0.316 (0.165) *	-0.594 (0.291) **	0.038 (0.329)	-0.131 (0.381)	0.268 (0.157) *	-0.656 (0.302) **
chronic severe	0.516 (0.266) *	0.786 (0.368) **	0.319 (0.185) *	-0.622 (0.298) **	0.662 (0.396) *	0.481 (0.398)	0.277 (0.177)	-0.674 (0.312) **
ltillness	0.195 (0.147)	0.415 (0.205) **	0.267 (0.104) **	-0.013 (0.142)	0.318 (0.220)	0.526 (0.217) **	0.258 (0.099) ***	-0.013 (0.142)
lnincome	0.030 (0.067)	0.048 (0.104)	-0.011 (0.034)	0.002 (0.044)	0.060 (0.102)	0.033 (0.113)	-0.008 (0.033)	0.001 (0.044)
education (years)	0.025 (0.016)	0.032 (0.022)	-0.010 (0.012)	-0.066 (0.015) ***	0.027 (0.022)	0.026 (0.022)	-0.012 (0.011)	-0.067 (0.015) ***
distance nearest child			-0.001 (0.000) ***	-0.002 (0.001) ***	0.001 (0.001)	0.001 (0.001)	-0.001 (0.000) ***	-0.002 (0.001) ***
intercept	-4.832 (1.071) ***	-0.775 (1.598)	-0.497 (0.674)	6.206 (0.754) ***	-7.112 (2.111) ***	1.862 (2.175)	-0.118 (0.635)	6.396 (0.743) ***
α		1.190 (0.198) ***		0.972 (0.059) ***		0.818 (0.085) ***		0.967 (0.058) ***
Latent factor parameters								
	ρ_1	-0.679 (0.444)	δ_1	1.291 (0.420) ***	ρ_1	-0.710 (0.585)	δ_1	2.463 (0.773) ***
	ρ_2	-2.527 (0.365) ***	δ_2	1.911 (0.275) ***	ρ_2	-2.500 (0.398) ***	δ_2	0.554 (0.690)
	ρ_3	-1.339 (0.542) **	δ_3	0.800 (0.242) ***	ρ_3	-1.505 (0.523) ***	δ_3	0.477 (0.207) **
	ρ_4	-1.940 (0.221) ***	δ_4	0.045 (0.205)	ρ_4	-1.955 (0.226) ***	δ_4	-0.120 (0.218)
	θ_1	3.002 (0.311) ***	θ_2	-0.668 (0.371) *	θ_1	3.145 (0.306) ***	θ_2	-0.823 (0.443) *
logL	-4554.611				-4553.000			
N	1337				1337			

Notes. Standard errors in parenthesis. Level of significance: *** 1%; ** 5%; * 10%.
In Model I "distance from the nearest child" is included only in the informal care equations to identify its effect on formal care; in Model II formal and informal care are regressed against the same covariates. All models also include country dummy variables.

Table A.2 – *Average Partial Effects for three separate models for formal and informal care*

	Bivariate two part model for total formal care and informal care						**Bivariate two part model for paid domestic help and informal care**						**Bivariate two part model for nursing care and informal care**					
	TFC			**IC**			**PDH**			**IC**			**NC**			**IC**		
	P(y>0)	E(y|y>0)	**E(y)**	P(y>0)	E(y|y>0)	**E(y)**	P(y>0)	E(y|y>0)	**E(y)**	P(y>0)	E(y|y>0)	**E(y)**	P(y>0)	E(y|y>0)	**E(y)**	P(y>0)	E(y|y>0)	**E(y)**
hIC	-0.0003	-0.087	**-0.054**				-0.0004	-0.067	**-0.028**				0.0004	0.017	**0.009**			
hTFC/ hPDH/ hNC				-0.001	-0.148	**-0.102**				-0.001	-0.190	**-0.127**				0.005	0.167	**0.352**
PtD	0.067	10.692	**7.386**	0.097	17.717	**13.819**	0.088	8.810	**4.681**	0.114	23.111	**17.538**	-0.018	13.884	**1.413**	0.101	11.261	**11.181**
age 7585	0.120	7.549	**4.687**	0.085	7.808	**6.181**	0.121	4.059	**2.379**	0.088	7.274	**6.047**	0.031	-2.053	**0.093**	0.094	-5.222	**3.044**
age over85	0.231	19.820	**13.703**	0.125	32.498	**21.552**	0.213	10.230	**6.014**	0.117	27.347	**18.047**	0.066	25.407	**4.963**	0.106	35.709	**21.251**
female	0.000	-7.796	**-4.258**	0.094	-9.526	**-1.368**	-0.014	-5.196	**-1.986**	0.098	-9.723	**-1.011**	0.033	-4.939	**-0.080**	0.101	-40.897	**-8.122**
gali mild	0.069	5.118	**3.616**	0.074	6.206	**4.941**	0.065	3.786	**1.841**	0.071	4.700	**4.113**	0.007	-7.125	**-0.976**	0.058	-3.482	**1.834**
gali severe	0.127	4.022	**3.936**	0.116	22.636	**15.231**	0.117	4.970	**3.000**	0.124	24.548	**16.379**	0.048	-12.085	**-1.409**	0.102	24.546	**16.124**
adl mild	0.092	7.357	**4.437**	0.038	5.841	**4.195**	0.090	1.070	**1.285**	0.034	3.305	**2.740**	0.045	27.714	**3.351**	0.058	-3.945	**1.674**
adl moderate	0.133	18.945	**11.231**	0.210	11.972	**14.099**	0.085	8.927	**3.677**	0.204	8.302	**11.591**	0.125	17.078	**4.303**	0.202	-2.966	**10.049**
adl severe	0.329	42.307	**33.167**	0.022	23.222	**12.439**	0.190	36.487	**17.510**	0.043	30.566	**17.041**	0.267	49.008	**19.598**	-0.042	46.003	**12.585**
mobility mild	0.108	5.209	**3.171**	0.145	3.461	**4.411**	0.102	5.553	**2.546**	0.150	2.800	**4.529**	0.031	8.343	**1.082**	0.150	-10.581	**5.246**
mobility moderate	0.090	6.699	**3.585**	0.191	16.423	**12.161**	0.092	2.974	**1.672**	0.184	14.638	**11.346**	0.022	9.096	**1.030**	0.173	-12.891	**5.460**
mobility severe	0.194	13.246	**8.601**	0.219	27.865	**19.358**	0.156	6.734	**3.714**	0.200	26.879	**18.307**	0.053	11.645	**1.852**	0.186	-0.044	**11.907**
chronic mild	-0.008	0.654	**0.195**	0.138	-15.068	**-1.997**	-0.020	0.312	**-0.271**	0.134	-20.134	**-4.186**	0.012	-13.054	**-1.540**	0.136	-51.557	**-10.725**
chronic moderate	0.003	-1.276	**-0.602**	0.092	-17.100	**-4.564**	0.000	-2.512	**-0.770**	0.087	-20.427	**-5.853**	0.012	-11.549	**-1.304**	0.069	-32.101	**-6.010**
chronic severe	0.073	6.433	**4.893**	0.098	-13.727	**-2.521**	0.082	-0.918	**0.892**	0.084	-21.205	**-6.331**	0.029	-11.876	**-1.094**	0.080	-34.241	**-6.137**
ltillness	0.029	4.709	**2.951**	0.070	-0.183	**2.214**	0.010	2.543	**0.954**	0.073	-1.139	**1.930**	0.031	6.210	**1.324**	0.070	1.051	**4.546**
lnincome	0.003	0.291	**0.190**	-0.001	-0.026	**-0.030**	0.008	0.041	**0.065**	-0.001	-0.011	**-0.021**	-0.001	1.223	**0.188**	-0.0002	-0.995	**-0.329**
education (years)	0.002	0.175	**0.137**	-0.003	-1.939	**-1.127**	0.002	-0.011	**0.026**	-0.003	-2.012	**-1.155**	0.001	0.111	**0.030**	-0.005	-2.935	**-1.421**
LTC/ PDH/ NC insur.	-0.007	3.066	**1.544**	-0.034	3.851	**0.824**	-0.040	-6.024	**-2.298**	0.016	-5.189	**-2.231**	0.020	-2.850	**-0.188**	-0.003	52.324	**20.360**
distance nearest child	0.000	0.008	**0.006**	-0.0003	-0.074	**-0.051**	0.000	-0.006	**0.001**	0.000	-0.068	**-0.047**	0.0001	0.030	**0.005**	-0.0004	-0.105	**-0.064**
Sweden	0.170	-4.353	**-0.598**	-0.011	-23.873	**-13.033**	0.202	-12.177	**-2.686**	-0.011	-24.317	**-12.846**	-0.020	-0.181	**-0.344**	-0.007	-43.837	**-17.437**
Denmark	0.367	-5.880	**-0.580**	-0.031	-11.642	**-6.977**	0.399	-11.899	**-2.615**	-0.026	-9.482	**-5.616**	0.107	13.517	**5.546**	-0.049	-11.506	**-6.968**
Austria	0.135	18.290	**14.785**	-0.007	-8.743	**-4.894**	0.153	-8.675	**-1.790**	-0.010	-9.372	**-5.137**	0.024	115.635	**26.621**	-0.015	-19.442	**-8.296**
France	0.362	-2.660	**2.196**	-0.070	-14.339	**-9.472**	0.267	-7.100	**-0.242**	-0.099	-10.513	**-8.274**	0.183	1.512	**3.563**	-0.096	-21.227	**-13.065**
Belgium	0.419	20.235	**21.051**	0.021	-1.917	**-0.364**	0.420	-5.116	**2.446**	0.017	-2.010	**-0.495**	0.153	21.307	**9.289**	-0.003	-7.103	**-2.972**
Netherland	0.345	13.263	**14.830**	-0.003	-16.328	**-8.811**	0.410	-6.899	**0.130**	0.009	-14.673	**-7.407**	0.074	165.803	**46.709**	0.015	-26.828	**-9.948**
Spain	0.213	10.661	**10.577**	-0.173	4.950	**-4.334**	0.269	-6.762	**-0.556**	-0.173	11.279	**-2.297**	-0.030	-11.248	**-1.676**	-0.175	40.937	**-0.364**
Italy	-0.021	2.396	**0.892**	-0.119	-2.828	**-5.396**	0.063	-5.087	**-1.028**	-0.115	1.040	**-3.625**	-0.076	-11.152	**-1.699**	-0.121	-1.693	**-7.767**