I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13228

'More Than One Red Herring'? Heterogeneous Effects of Ageing on Healthcare Utilisation

Joan Costa-Font
Cristina Vilaplana-Prieto

MAY 2020

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13228

'More Than One Red Herring'? Heterogeneous Effects of Ageing on Healthcare Utilisation

Joan Costa-Font
LSE, CESIfo and IZA

Cristina Vilaplana-Prieto
University of Murcia

MAY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

'More Than One Red Herring'? Heterogeneous Effects of Ageing on Healthcare Utilisation*

We study the effect of ageing, defined an extra year of life, on health care utilisation, disentangling the effect from other alternative explanations such as the presence of comorbidities and endogenous time to death (TTD), the influence of which is argued to render the effect of ageing on health care a 'red herring'. We exploit individual level end of life data from several European countries that records the use of medicine, outpatient and inpatient care as well as long-term care. Consistently with a 'red herring hypothesis', we find that corrected TTD estimates are significantly different from uncorrected ones, and its effect size exceeds that of an extra year of life, which in turn is moderated by individual comorbidities. Corrected estimates suggest an overall moderate effect of ageing, which does not influence outpatient care utilisation. These results suggest the presence of 'more than one red herring' depending on the type of health care examined.

JEL Classification: I18

Keywords: time to death, ageing, health care utilization, hospital care, medicines use, home help use and comorbidity, endogeneous time to death (TTD), comorbidities

Corresponding author:
Joan Costa-Font
Department of Health Policy
London School of Economics
Houghton Street WC2A 2AE
London
United Kingdom
E-mail: j.costa-font@lse.ac.uk

* We are grateful to the participants of the Workshop on "Sustaining Innovation, Containing Costs and Providing Equity in Health Care" University of Genova, September 13-14, 2019. We are grateful to Rosella Levaggi, Rita Santos, Marcello Montefiori, Cinzia Dinovi, Francesca Barigozzi, Domenico Depalo, Paolo Berta, A. Cavaliere.

1. Introduction

Population ageing is commonly portrayed as a central determinant of health care spending (WHO, 2015; Marino et al, 2017). In 2012-2013, the percentage of health care expenditure concentrated in the cohort aged 65 and older ranges between 38.8% in the Czech Republic and 46.7% in Germany (European Union, 2016). Given that the percentage of old age population in the countries of the Organisation of Economic Cooperation and Development (OECD) is projected to rise to 25% by 2050 (Lafortune et al, 2007), it is important to understand how ageing affects health care use. Several studies have documented that the effect of ageing on health expenditure is overestimated. One of the main explanations is that a significant share of expenditures takes place around the time of death. Some studies even go as far as to argue that the effect of ageing on health care reflect a 'red herring' as when time to death (TTD) is accounted for, the effect of ageing disappears (Zweifel et al, 1999; Zweifel et al, 2004; Hall and Jones 2007; Shang and Goldman 2007)[1].

In addition to the consideration of TTD, another source of overestimation of ageing effects on health expenditure results from the correlation between *morbidity and individual's age*[2]. This explanation suggests that TTD is endogenous, and morbidity is subject to omitted variable bias. The effect of such omitted variable bias can be analysed using individual longitudinal data, that captures the influence of early lifestyles. This paper addresses some of these econometric concerns by drawing on individual data that can explain both individual and country level variation in morbidity and TTD.

[1] In fact, the effect of TTD decreases with age (Felder et al, 2010), and Seshamani and Gray (2004) have shown that hospital expenditures increase well over fifteen years before death, and decline once an individual's turns 80, hence casting doubts about the effects of age on health care expenditures.

[2] Consistently, Dormont et al (2006) establish using French data that the compression of morbidity offsets the potential effects of ageing in health spending. Similarly, Howdon and Rice (2018) find that the effect of chronic conditions weakens the effect of ageing on hospital expenditures.

Finally, another potential red herring results from the fact that aging can change the composition of health care towards a more intense use of end of life care, hospital care and long-term care[3]. Hence, the effect of ageing is likely to be heterogeneous across different types of health care, which especially differ in their intensity in the use of technology (Breyer et al, 2010). Ageing can incentivise the utilisation of new technologies that specifically cater to the health care needs of an ageing population[4]. Hence it is important to understand how ageing impacts on different types of health care that differ in their intensity of technology (e.g., medicines, hospital care, home care etc).

This paper to examine the effect of ageing on different types of health care use, to disentangle the effect of additional confounding effects on health expenditure, namely (i) proximity to death, (ii) co-morbidities and lifestyles and (iii) differences in the composition of health care. Previous research so far has been country specific, and mainly relies on cross sectional insurance data records, often limited to hospital care. We exploit longitudinal end of life data that covers a long list of European countries for the period 2004-2017 Survey for Health, Ageing and Retirement in Europe (SHARE). The use of a multi-country panel which allows the inclusion of both individual and country fixed effects that net out specific institutional reasons for differences in the effect of ageing on health care (HC) expenditures. The survey contains an end of life module that identifies the cause of death of the individual, and helps distinguishing between survivors and deceased, namely those that have died between two consecutive waves. We report both parametric and nonparametric specifications and address the problem of endogeneity of TTD by correcting the estimations with rich instruments for parental survival in the dataset.

[3] This puts the coordination of health and long-term care services at the centre stage (Costa-Font et al, 2018).
[4] Consistently, Goldman *et al.* (2005) using United States data, and Wong et al. (2012) using Dutch data found that medical innovations give rise to a differential shift of health expenditures to older age groups.

Our findings suggest that corrected TTD estimates are significantly different from uncorrected ones and affect both the extensive and intensive margin of hospital admissions and length of stay, as well as home and nursing home care use, consistently with a 'red herring hypothesis'. Second, the effect size of TTD exceeds that of ageing, which in turn is tempered by comorbidities. Corrected estimates indicate that the effect size of ageing is far more moderate when it is statically significant. Finally, aging does not explain (both the internal and external margins of) outpatient visits with doctors after TTD and comorbidities are controlled for. However, when significant, we find that the effect of ageing is lower than uncorrected estimates.

The structure of the paper is as follows. Section two reviews the most relevant literature. Next, we describe the data and empirical exercise. Section five and six contains the results and a final section concludes.

2. Related Literature

Red herring hypothesis. The effect of ageing on health spending has been brought to question based on the fact that age is correlated with mortality. A seminal study used a sample of deceased patients from a Swiss sickness fund and found that the effect of age on healthcare expenditure disappears once it is controlled by the effect of time to death (TTD) (Zweifel et al., 1999). This opened a long list of contributions to the question of ageing and health spending, and this paper aims to add value to the same endeavour.

Econometric specifications. Almost all estimates of the effect of ageing on health expenditure have received a significant deal of criticism due to a series of econometric issues, mainly omitted variable bias, and the potential reverse causality of the TTD (Salas and Raftery, 2001; Seshamani and Gray, 2004). The logic is that if health care investments (e.g., such as new drugs) improve patient's health status, they could extend life. Therefore,

estimates that fail to account the dynamic influence of current and previous health expenditures on life expectancy would overestimate the effect of ageing. In a later work, Zweifel et al. (2004) also used Swiss sickness fund data but with three novelties: (i) restricted the sample to a single year to ensure that HC expenditures only affect the probability of survival in cases in which death was very close, (ii) introduced the TTD as a single explanatory variable and (iii) considered both survival and deceased individuals in the sample. The results confirm that age is not a significant variable in explaining the HC expenditures of the deceased and, in the case of survivors, the effect of age is much lower when the TTD variable is introduced. For their part, Seshami and Gray (2004) concluded that the number of trimesters before death is a significant explanatory variable, and its impact on cost is higher at the end of life. Therefore, the omission of TTD from the analysis would overestimate the effect of ageing. Some estimates suggest that TTD accounts for 16.7% and 24.5% of lifetime HC and LTC expenditures (French et al. 2017). Similarly, Breyer et al. (2017), estimates that HC expenditures in the last 4 years of life account for 30% of total expenditures over a lifetime, even though part of such effects result from the effects of life expectancy (Breyer et al, 2012).

Endogeneity. TTD is likely to be affected by both reverse causality and omitted variable bias. Stearns and Norton (2004) use data from the Medicare Current Beneficiary Survey (1992–1998) to document evidence of omitted variables, which is accounted for by adding individual specific fixed effects, which correct the effect of unobserved time-invariant characteristics. However, such strategy does not deal with reverse causality. An alternative strategy lies in employing instrumental variables, namely a variable influencing health expenditure only via TTD, but not the age at which the individual is interviewed (Steinmann et al., 2007). OLS estimates would be biased if health care expenditures (HCE)

and medical innovations prolong life (Lichtenberg et al, 2012)[5]. Felder et al. (2010) address the problem of endogeneity using an instrumental variable strategy that employs lags as instruments. They document that TTD and its square retain their explanatory power in explaining HCE in its intensive and extensive margin. However, as they recognize that are not able to fully purge TTD of its endogeneity. When errors are AR(1) distributed, the parameter is not estimated consistently from a lagged instrument[6].

Heterogeneity. The effect of ageing might be heterogeneous to different types of health care use that differ in the intensity of use of technology. Werblow et al. (2007) eluded the problem of endogeneity and focused on relating the individual HCE in a given year with the remaining TTD. They find evidence of heterogeneous effects as the majority of the HC expenditure components (drugs, hospital outpatient and hospital inpatient) are found not be influenced by age, but by TTD. The most significant exception is the acute care provided to patients who also receive long-term care (LTC) regardless of their survival. They explain these results by the fact that patients with limited survival prospects attract a large share of medical technology. Finally, Kelley et al. (2013) estimate that the increase in out-of-pocket expenditure in the last years of life shows a wide variability, which is explained by the increasing share of out-of-pocket expenditure that results from dementia or Alzheimer's diseases which is more than double that of gastrointestinal diseases or cancer.

Technology and Ageing. One interpretation of the effects of ageing is that technological progress is geared more intensively towards older age cohorts, and hence, changes in clinical practice would increase accordingly with age (Breyer et al, 2010). Consistently,

[5] There is a literature examining the effect size, namely whether it is small (months rather than years). Lichtenberg et al (2012) estimates that between 1991 and 2004, increased life expectancy by 0.62-0.71 years resulting from imaging technology, 0.96-1.26 years from use of newer outpatient prescription drugs, and 0.48-0.54 years from the use of newer provider-administered drugs.

[6] The two instruments (predicted TTD obtained from an auxiliary regression and accident insurance) pass the test for the overidentifying restrictions, but the Hausman test rejects the null hypothesis for exogeneity for TTC.

Goldman et al. (2005) in the United States and Wong et al. (2012) in the Netherlands also concluded that most medical innovations have shifted health expenditures to older age groups. In the same line, but using French data, Dormont and Huber (2006) applied microsimulation techniques to retrospectively evaluate the components of drift in the age profile of HC expenditures during 1992–2000. They observed that the impact of a change in practices (12.9%) was 3.8 times higher than the increase in HC expenditures given changes in the structure of the population (3.4%). Therefore, technological progress was possibly geared more towards older age cohorts – in this case, the impacts of changes in practices would increase with age. In contrast, Breyer et al. (2012) found that the cost in the last year of life tends to decrease and interpret it as a preference of physicians to treat younger patients with similar diagnoses more aggressively.

*Morbidity and health spending***.** The effect of morbidity on health expenditure and utilization is well established**.** Geue et al. (2015) examined hospital spending data from individuals in the last 3 years of life using data from Scotland for a period of 35 years and documents that costs of younger cohorts (less than 65 years and 65-69 years) exceed those of their last 11 quarters of life, and compared to the last 11 quarters of life of the older cohorts. Atella and Conti (2014) using primary care data from Italy report higher costs among those groups aged 70-79 reports than the eldest cohort. TTD coefficients suggest that 14 quarters remaining before death affect positively primary care costs although they do not vary significantly by age cohort between the 14th and the 10th quarter. In contrast, primary care costs at 8 quarters before death steadily increase by 50% between the age of 45 until age 75. Similarly, Dormont et al. (2006) estimates suggest that changes in spending for a given morbidity was almost four times higher than equivalent changes in the structure of the population (+3.4%). Payne et al. (2013) analysed hospital admissions among people aged 20 and over in Scotland and found that the presence of physical multimorbidity was

strongly associated with a higher probability of hospitalization, especially related to diagnosed mental health conditions. Palladino et al. (2016) found a positive and significant relationship between the number of chronic diseases and the use of primary, specialized and hospital care, and Schneider et al. (2009) found a positive relationship between the use of Medicare fee-for-service without institutional claims and the number of chronic diseases. Ishizaki et al. (2016) find that age was negatively associated with the probability of hospitalization and that no significant effect of age on length of stay at hospital exists in the three months before death. Carreras et al. (2018) using Spanish data document that the inclusion of morbidity controls reduced the effect of TTD up to 92%. Consistently, Howdon and Rice (2018) found that when morbidity is controlled for, it absolves two-thirds of the effect of TTD on HCE, which confirms the underestimation of the TTD effect when the potential endogeneity of this variable is not taken into account.

*Ageing and long-term care substitution. Finally, a set of s*tudies examines the relationship between long-term care and TTD. De Meijer et al. (2011) analysed the use of institutional LTC and home care from a Dutch dataset of individuals 55 years and older. They observed that once the effect of age was controlled by disability and morbidity, it remained significant, but TTD was no longer significant. Similarly, Larsson (2008) documents that whilst age is a significant variable in predicting the probability of receiving formal home care, TTD explained the probability of hospitalization, and both predict the use of nursing home care[7]. In addition, Karlsson and Klohn (2011) addressed the problem of the endogeneity of TTD using instrumental variables, and Karlsson and Klohn (2014) showed that TTD was diving the use of institutional care whilst age was more important for home care.

[7] More specific drawing on two instruments: (i) the absolute value of the difference between the mortality of men and women being 80 years and older divided by the total population of this age group, and (ii) the aggregate of this year's and next year's mortality rate of the middle-age population (25–55 years). The estimations show that age still has a strong impact on costs even after controlling for mortality rates, and that the impact of TTD is driven by the youngest cohort (70–74 years).

3. The Data and Descriptive Analysis

Longitudinal dataset. We use evidence of the SHARE (Survey of Health, Ageing, and Retirement in Europe) data corresponding to waves 1, 2, 4, 5, 6 and 7[8]. Our variation comes from representative samples of individuals aged 50 years or above followed through during 13 years (2004-2017). We exploit a cross-country variation of 17 countries, a sample of 288,555 observations. The following steps were taken to retrieve our sample (see Table 1). First, only individuals who we observe in at least two consecutive waves were selected given that only for those we can verify whether they were still alive in the next wave. This leaves a sample of 186,336 observations. To build the panel dataset we select individuals who are interviewed at least twice. This requirement allows us to determine accurately if the individual living status in the subsequent wave is survivor or deceased[9]. Individuals who are only interviewed once are discarded because we cannot be sure of their living status in the subsequent wave. Nevertheless, in the robustness checks we study the effect of attrition on our estimates and we show no effect on the results. The final sample contains 156,979 observations corresponding to 54,549 individuals (51,789 survivors and 2,760 deceased).

Descriptive statistic and sample design. Table 2 reports the descriptive statistics for the dependent variables both in the extensive and intensive margins. In some cases, a high percentage of zeros is observed (hospitalisation, stays in other health care facilities, nursing homes and formal personal care). However, the duration or intensity of providing these services may be very high (overdispersion). Similarly, when we examine outpatient visits

[8] Unfortunately, Wave 3 cannot be included as the questionnaire is not comparable to the other waves.

[9] In case a respondent deceased, interviewers conduct an end-of-life interview with a proxy respondent. Proxy-respondents can be a family or household member, a neighbour or any other person of the closer social network of the deceased respondent. The end-of-life interview mainly contains information on respondent's last year of life and the circumstance of death like time and cause of death. (SHARE Release Guide 7.0.0; http://www.share-project.org/fileadmin/pdf_documentation/SHARE_release_guide_7-0-0.pdf)

with a doctor or nurse and the consumption of prescription drugs, we document that the probability of an outpatient visit in the last year or the probability of consuming at least one medication is on average high (89% and 75%, respectively), but exhibits overdispersion.

The table A1 breaks down the descriptive statistics, differentiating between survivors and deceased. The percentage of deceased individuals in the 85+ age cohort is six times higher than that of survivors (25.17% vs. 3.65%). There is a higher percentage of men and individuals who have only completed primary education in the deceased sub-sample than in the survivor sub-sample. The deceased sample exhibits lower income and wealth (even adjusted for household size. However, to the extent that the differences between survivors and deceased are largely time invariant, they will be absorbed by our fixed-effects model.

Our estimations controls for co-morbidity by using the Charlston Comorbidity Index (CCI) calculated as the sum of the scores that are obtained for seven items (Charslton et al. (1987) adapted for SHARE by Kusumastuti et al. (2017). The share of individuals without any comorbidity is 20 percentage points higher among the deceased[10]. Compared to survivors, the percentage of deceased respondents that report any of these comorbidities is significantly higher for all items except for arthritis and stomach/duodenal ulcers[11].

4. Empirical Strategy

Empirical Specification. The analysis of the descriptive statistics suggests that there is a significant group of people who never use these services, which is known as the *zero-mass problem*. Second, the variance of health care use is higher than the mean variance (overdispersion), resulting in highly skewed (to the right) distributions of the variables

[10] One explanation lies in that deceased individuals with no initial comorbidities, the "End-of-Life" module reports that 33% had been sick for less than 1 month and 21% had been sick between 1 and 6 months. Hence, the majority deathly illnesses came about in a very short interval of time (less than 6 months).

[11] Tables A2 to A6 report the descriptive statistics of the dependent variables. Comments are reported on Appendix A.

because there are a few individuals with high consumption levels. Modelling a variable with excessive zeros and overdispersion and then introducing fixed effects is highly complex, and typically boils down to either running a negative Poisson or binomial model[12] (Hausman et al., 1984; Allison and Waterman, 2002). Recently, Winkelman (2008) developed a double-hurdle model and Majo and Soest (2011) presented a zero-inflated Poisson model of a panel with only two periods. Gilles and Kim (2017) refined this approach within a framework where the true generation process is unknown and unobserved individual heterogeneity exists. Our empirical specification can initially be expressed as follows:

$$Y_{it} = X_{it}\beta + \eta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the outcome variable, X_{it} is a vector of explanatory variables, η_i represents an individual fixed effect, δ_t is a time-fixed effect, and ε_{it} contains other unobservable shocks that are common to all individuals. We could take into account intra-region unobservable heterogeneity (at the NUTS (Nomenclature of Territorial Units for Statistics) level), and especially, an instrumental variable approach that considers the potential endogeneity of time to death (TTD). The main drawback is that a linear model does not fit well a count data-generating process, and negative and non-integer predicted values could be obtained (Wooldridge, 2002). Hence, an appropriate model for modelling count data is the Poisson model (2). However, if Y_{it} is modelled as a Poisson random variable with parameter μ_t, it is implicitly assumed that the conditional mean and variance of the outcome variable are equal to μ_t. The model is specified as follows:

$$E[Y_{it}|X_{it}, \eta_i, \delta_t] = exp(X_{it}\beta + \eta_i + \delta_t) \quad (2)$$

[12] The Poisson model is preferred to the negative binomial because the latter does not eliminate the influence of unmeasured characteristics (Allison and Waterman, 2002). The consistency of the fixed effects estimator is conditional on the assumption that the potential sample selection operates only through the individual specific terms (Vella, 1998).

$$E[Y_{it}|\mu_t] = Var[Y_{it}|\mu_t] = \mu_t$$

Individual fixed effects (η_i) pose another problem as they cannot be net out as in linear models (i.e., first differences or mean deviations). Hence, if we proceed to estimate the Poisson model with fixed effects, the number of observations that are available to estimate each individual *i* remains fixed, which will produce inconsistent estimates of η_i (Neyman and Scott, 1948). However, when panel data are available, it is possible to separate the β and δ_t estimates from the fixed effects estimates, which allows retrieving consistent β and δ_t estimates (Blundell et al., 2002). Yet, we face the additional challenge of the potential endogeneity of the TTD problem. To address this concern, we follow Imbens and Wooldridge (2007) and their proposed control function (CF) approach, which can be extended to panel data. To do this, a linear regression for the TTD is first estimated using all the exogenous regressors and the proposed instruments to obtain the residuals. Next, a Poisson model is estimated using all explanatory variables and the residuals[13].

However, the Poisson model that is applied to panel data cannot account for the overdispersion that exists in many of the outcome variables. Therefore, the predictions that are made using these outcomes would only have a small percentage of zeros. For this reason, our panel data specification should allow us to separate two data-generating processes: an extensive margin process (probability of the outcome being positive) and an intensive margin process (change in the outcome frequency of use). Both are independent processes such that once the outcome is positive, it can be modelled using a truncated distribution (Cameron and Trivedi, 2013)[14].

[13] Guo and Small (2016) show that the control function (CF) estimator applied to non-linear models is more efficient that two-stage least squares (2SLS) provided that instrumental variables are valid. To test the convenience of the CF approach we have estimated both models (CF and 2SLS) and performed a Hausman test. For all variables, the null hypothesis cannot be rejected, which confirms the suitability of the CF estimator (results are available upon request.

[14] We model the zero value (i.e., absence of consultations or hospitalizations, no consumption of any prescribed drug…) as a conscious decision rather than a missing observation as it is considered in the Heckman approach. In fact, the separation between patients and not patients overcome the requirement of an exclusion restriction which is needed in the Heckman approach in order to identify the correlation coefficient between the two margins. An additional advantage of the two-part

We estimate the extensive margin following a logit model with fixed effects as below:

$$Pr[Y_{it} > 0|X_{it}, \eta_i] = \frac{e^{(X_{it}\beta+\eta_i)}}{1+e^{(X_{it}\beta+\eta_i)}} \quad (3)$$

where Y_{it} is the outcome variable, X_{it} is the explanatory variables, and η_i is the unobservable heterogeneity of the individual i (i.e., the propensity of a person to use a health care service or long-term care service at least once in the period). The estimation of this model using conditional maximum likelihood is based on a restricted dataset that excludes all individuals whose outcomes (0 or 1) do not vary throughout the period (Chamberlain, 1980)[15].

Next, the intensive margin is estimated using a truncated Poisson model with fixed effects in which only the positive portion of Y_{it} is considered as follows:

$$Pr[Y_{it} = j|X_{it}, \eta_i] = \frac{e^{(X_{it}\gamma+\eta_i)^j}}{j!\left(e^{e^{(X_{it}\gamma+\eta_i)}}-1\right)} \; if \; Y_{it} > 0 \; , j = 1,2, ... \quad (4)$$

We include the same explanatory variables (X_{it}) in both steps of the model, but there is no reason to assume that the estimated coefficients (β and γ) will be equal. Furthermore, the unobservable individual heterogeneity (η_i) comes from those variables (resilience, desire for independence or level of concern about diseases) that influence the quantity of social and health care services that is consumed. This model is much more flexible than the Poisson model since it can model overdispersion and underdispersion:

model is that it is robust to endogenous selection for any lower bound (zero-bound) of an outcome variable (Drukker, 2017). To validate the suitability of modelling independent processes, we consider a test of the double-hurdle model against the Heckman selection model and perform a Voung test, which is suitable for the case of non-nested models. For all dependent variables, the test rejects the Heckman selection model. These results support the idea that consumption of healthcare and long-term care services follows two independent decision paths: the decision to consume a positive amount and the decision on the extent of consumption.

[15] The percentage of respondents who do not change behaviour is 59.02% for hospitalization, 64.97% for outpatient visits with doctor/nurse, 76.19% for the probability of nursing home stays, 68.27% for the probability of receiving personal care at home and 59.72% for the probability of consuming prescribed drugs

$$Var[Y_{it}|X_{it},\eta_i] = E[Y_{it}|X_{it},\eta_i] * \left(e^{(X_{it}\gamma+\eta_i)} - E[Y_{it}|X_{it},\eta_i]\right) + E[Y_{it}|X_{it},\eta_i] \quad (5)$$

If there is an excess of zeros, then $Pr[Y_{it} > 0|X_{it},\eta_i]$ will be small and so will $E[Y_{it}|X_{it},\eta_i]$. Thus, the variance will be greater than the mean (overdispersion). This is the case for hospitalisation, nursing homes and formal care at home. However, if there are few zeros, then $Pr[Y_{it} > 0|X_{it},\eta_i]$ and $E[Y_{it}|X_{it},\eta_i]$ will be larger, and the variance will be less than the mean (underdispersion). This is the case for outpatient visits with a doctor or nurse and consumption of prescribed drugs.

Estimating (4) using the maximum likelihood method does not provide consistent estimates because the individual fixed effects cannot be separated from the model parameters. Majo and van Soest (2011) used a two-period panel, and later Gillingham and Tsvetanov (2019) used an N-period panel to show that the estimates using the conditional maximum likelihood can eliminate the problem of fixed effects. If the number of periods for which $Y_{it} > 0$ is greater than or equal to two, and the explanatory variables are not constant in those periods, then, by conditioning the likelihood function to $\sum_{i=1}^{T} Y_{it}$, the truncated Poisson distribution does not depend on individual fixed effects, but it merely depends on explanatory variables (and time-fixed effects). In addition, Gillingham and Tsvetanov (2019) demonstrated that when the explanatory variables are strictly exogenous, the resulting estimator is consistent.

Endogeneity of TTD. The treatment of the endogeneity of the TTD in a truncated Poisson model remains to be addressed. Gillingham and Tsvetanov (2019) proposed an estimation procedure using the generalised method of moments (GMM), which provides consistent estimates of the parameters. This paper also uses this procedure and the STATA routine that they developed.

Instruments. We use parents' age at death as an instrument for the TTD. More specifically, a wealth of literature indicates that a long lifespan for a mother decreases the likelihood that her children will suffer from specific diseases, such as hypertension or lung disease (Goldberg et al. 1996; Gjonca and Zaninotto 2008). However, other studies, such as Ikeda et al. (2006), have found that the age at death of both the father and the mother are important, and a longer lifespan for the parents decreases the probability that their children will die between the ages of 40 and 79.

The SHARE data only reports the age at death of a mother or father for the deceased sample. Therefore, parental age at death is imputed for those respondents whose parents were alive when the survey was conducted. Since age is a continuous variable, we use a multiple imputation (MI) procedure proposed by Rubin (1987) to predict the age at death of living parents[16].

Instrument validity. To verify the validity of the instruments, we present in the appendix the results of a linear regression for the TTD using these instruments, the other explanatory variables and year fixed effects (Table B2). The four proposed instruments are significant with the effect of a mother's age at death being more intense for both men and women. Each additional year of life of father implies an increase in the TTD of 0.22 days for men and 0.09 days for women (0.29 and 0.17, respectively for an additional year of life of mother). Taking into account the average life expectancy[17] in the EU for 2017, offspring's' TTD would be between 17.43 and 22.86 days higher for men and between 7.92 and 14.02

[16] We use both the information from the Main Questionnaire (MQ) and from the End-of-Life Questionnaire (EoLQ) for each one of the SHARE waves. The necessary requirements to apply MI are the following ones. First, missing data must be random. This requirement is satisfied in our dataset because age at death is missing for all parents who are still alive by the time the respondent (adult children) answer the survey. Second, the variables with missing values we are trying to impute must be explained by other variables that do not have missing values. In our dataset, parents' age of decease can be predicted from other variables for which we have complete information (see Appendix B for a detailed explanation of these variables and the result of the MI).

[17] According to Eurostat statistics, life expectancy at birth in the European Union (EU) was estimated to be 80.9 years in 2017, reaching 83.5 years for women and 78.3 years for men.

days higher for women. We also appreciate that TTD decreases for men and lower educational levels, but on the other hand, increases with wealth and in smaller municipalities[18].

One potential thread to the identification is the argument of intergeneration transmission of lifestyles, namely that in case that certain behaviours that shorten parent's life expectancy were adopted by their children, they would also experience a reduction of TTD. To address this specific concern, we have estimated the effect of parents' age of decease, as well as other explanatory variables, over the probability of having sedentary lifestyle, having overweight, being obese, having ever smoked daily, being smoker at present time and having consumed at least one alcoholic beverage during the last 7 days (Table B4). Overall, our results suggest that the effect of parent's age of decease over TTD is not channelled through potential inherited habits from parents. Finally, although genetic is important, it does not change overall in later life, and using a FE estimator we are implicitly addressing this potential drawback[19].

5. Results

[18] Table B3 displays the direct effect of the instruments on the outcome variables and confirms that the instruments are not correlated with unobserved variables affecting the dependent variables at a 5% significance. The exception being the probability of hospitalisation or one instrument. We are concerned with respect to idiosyncratic heterogeneity, which arises when which arises when some of the explanatory variables are correlated with time-varying unobserved shocks. following Card (1999), the correlation between the instrument and the dependent variable through the unobservables can give rise to bias in IV estimates. To address this issue Lin and Wooldridge (2019) propose a test for idiosyncratic exogeneity based on the robustness properties of the Poisson fixed-effects estimator combined with the control function approach, that is robust to robust to distributional misspecification and serial dependence. First, we estimate a fixed effects model and retrieve the fixed effects residuals. Second, use a Poisson fixed effects model over the mean function and test the significance of the residuals through a Wald test. Applying this procedure to all the dependent variables, we conclude that the null of no idiosyncratic endogeneity cannot be rejected (results available upon request)

[19] We have re-estimated the logit and truncated models for the subsample of respondents whose parents had already deceased by the time of the survey to account for the possibility that deceased parents transmit the worst characteristics to their children. However, estimated coefficients for age, TTD and CCI do not show significant differences with re (results are available upon request)".

Baseline results. Table 3 reports the results of the logit model with fixed effects for the probability of using the service (extensive margin) and the truncated Poisson model for the duration (intensive margin). Both margins were estimated using five different specifications. The first set of estimates M1-M3 models were not estimated using instrumental variables (IV) and consider a different set of controls. In model M1 we include age, age squared, marital status, income and wealth adjusted by the number of household members, municipality size, healthcare resources by NUTS, and year fixed effects[20]. Next, we add TTD in the M2 and the CCI is included in the M3 model. The M4 and M5 specifications report the effect of the same explanatory variables as before but instrument (provide IV estimates) TTD (CF for logit with fixed effects and a GMM truncated Poisson). To ease the interpretation, marginal effects are reported in the logit specification, and the incidence risk ratio is reported in the truncated Poisson specification. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models.

Extensive margin. Results from the M5 model specification, TTD and CCI have opposite effects (negative for the former and positive for the later one) for the probability of hospitalization, the probability of nursing home stays, receiving home care and consuming any prescribed drug. Comparing the M2 and M4 estimates for the probability of hospitalisation, one can observe an increase in the effect of age (from 0.005 to 0.117) and TTD (from -0.016 to -0.376). Hence, IV estimates correct for the underestimation of the two-reference variable. Yet, even more importantly, the magnitude of the TTD coefficient

[20] Descriptive statistics are shown on Table A7. Specifically, the number of hospital beds per 100,000 inhabitants is included in the probability of hospitalization and length of stay at the hospital. The number of beds in nursing and residential care facilities per 100,000 inhabitants in the regressions for the probability of staying in a nursing home and length of stay. Finally, the number of doctors and nurses per 100,00 inhabitants is included in the probability of outpatient visits and number of outpatient visits with doctor/nurse. For those individuals whose region of residence is unknown we have applied the country average.

is reduced to one-seventh (-0.054) of its previous value when we control for co-morbidities (using the CCI as in M5). Both TTD and CCI are statistically significant and exhibit opposite signs. A closer time to death reduces the likelihood of hospitalisation, but an increase in the CCI increases the likelihood of hospitalisation, and the effect increases with TTD. It is important to note that, as expected, controlling for comorbidities using CCI (in M5) significantly reduces the effect of ageing. Without the CCI, an additional year of life increased the probability of hospitalisation by 11.7 percentage points, whilst after controlling for CCI, an additional year of life only increases this probability by 1.4 percentage points.

When examining the extensive margin of doctor or nurse consultations, we find that IV estimates results in a series of relevant changes. First, age is no longer a significant variable, indicating that ageing per se does not create the need to see a doctor. Second, the positive effect of the TTD increases (from 0.001 to 0.042). Therefore, visiting a doctor or nurse is primarily included by TTD and the presence of comorbidities, especially the latter.

When we turn to nursing home use, we can observe that both age and the TTD reduce the probability of nursing home care use. That said, when our estimates are corrected using an IV strategy, the effect of the TTD is four times larger (increases from -0.002 to M2 to -0.008 in M4). However, when CCI is controlled for in M5, the effect of TTD decreases by 25% (until -0.006). The positive effect of CCI exceeds in absolute value the negative effect of age.

Next, home care is examined using the same strategy, the IV estimation produces a TTD effect that is almost 10 times larger (from -0.010 in M2 to -0.095 in M3), which reinforces the idea that TTD is underestimated when omitted variables bias and reverse causality are adjusted for. However, this effect decreases by half when the CCI is included (-0.049),

which supports the idea that the need for home care is spurred by TTD and the existence of comorbidities.

Lastly, when comparing the M2 and M4 estimates on medication consumption, it can be seen that the IV estimation amplifies the positive effect of age (from 0.049 to 0.236), and it also amplifies the negative effect of the TTD (from -0.005 to -0.607). Both effects decrease when the CCI is introduced in M5, and the effect of age on the probability of consuming a medication decreases by five percentage points reduce.

The probability of consuming five or more medications (polypharmacy) is then estimated using a sample that is limited to individuals who consume at least one medication. When comparing M2 and M4, we find that the effect of TTD effect increases considerably. In M2, each additional year closer to death produces a barely perceptible decrease in the probability of consuming five or more medications. In M4, each year closer to death decreases this probability by 14.7 percentage points. The inclusion of the CCI in M5 shows that an additional comorbidity increases the probability of polypharmacy by 12.6 percentage points, but the TTD variable is no longer significant and the effect of age reduces by two percentage points.

Intensive margin. According to the M5 model specification, it is observed that the TTD and CCI have opposite effects on hospital length of stay, on the number of doctor or nurse outpatient visits, and on the number of prescription drugs that are consumed. An additional comorbidity increases the probability that a hospital stay will be extended by an additional day by 15.3%. Likewise, it increases the probability that an additional outpatientvisits will occur by 31% and increases the probability of consuming an additional medication by 39.4%. Contrarily, a one-year increase in the TTD decreases the probability that a hospital stay will be extended for another day by 4.9%. Similarly, it also decreases the probability

that there will be an additional outpatient visit by 4.7% and decreases the probability of consuming an additional medication by 1%. Regarding age, including the CCI in M5 reduces its effect since each additional year of life only increases the probability of an additional day of hospitalisation by 2.3% instead of the 5.3% in M4 (without the CCI).

When home care is examined, we find that TTD produces the greatest differences. A one-year increase in the TTD decreases the probability of receiving an additional hour of personal care by 30.4%. Moreover, increasing the CCI increases the probability of personal care by 8%.

In some cases, the inclusion of the comorbidity variable (CCI) significantly decreases the effect of TTD. For example, TTD effect decreases from -16% to -4.9% for the hospital length of stay and from -34.2% to -4.7% for the number of doctor/nurse consultations. Regarding the length of stay in a nursing home and hours of home care, this decrease is much smaller.

Estimates for the number of prescribed drugs suggest that TTD ceases to be significant when the CCI is introduced (in estimates with and without IV). It can also be observed that by including the CCI in the IV estimate for M5, each year of additional life only increases the probability of higher medication consumption by 3.9% instead of 12.5% in M4 (without CCI).

Ageing effects. We find that each additional year has a positive (but minor) effect on the hospital length of stay (+2.3%) and on the number of medications consumed (+3.9%). This effect is six and 10 times lower, respectively, than the effect of an additional comorbidity. The significance of the CCI emerges when examining the number of doctor/nurse consultations, since age ceases to be significant once the CCI is introduced. Moreover, each additional life year decreases the lengths of stay in nursing homes by 13%. The greatest

impact of age corresponds to the frequency of home-based assistance for personal care since each additional year increases the probability of receiving one more hour by 13.6%.

Figure 1 shows the predicted probability and duration as a function of the age cohort, TTD, and the value of the Charlson Comorbidity Index. The probability of hospitalisation exhibits no differences with TTD horizon, but quadruples with a six-fold increase of the CCI as going from 0 to 6/7. In contrast, the length of stay at hospital, is shorter for a TTD and increases as the CCI rises, the probability of having a doctor/nurse consultation in the last year is higher for a TTD of more than three years. However, the number of consultations is lower for a TTD of more than three years compared to other TTD horizons. Figure 1 shows that the probability of a nursing home stay reaches 40-50% for the 75-84 and 85+ age cohorts with maximum levels of comorbidity and a TTD of 0-12 months. In contrast, it is almost zero for a TTD of more than three years and for all age cohorts and CCI values, and then length of stay has a U-shaped curve for all TTD horizons. The differences in the probability of receiving home care (for personal care) based on the TTD become more evident for the 75-84 and 85+ age cohorts. Increasing the CCI increases the distance between the predicted probabilities, and it reaches the maximum with a TTD of 0-12 months. Regarding the number of hours of received care, there is a substantial increase in the number of formal caregiving hours for CCI=5, and then it decreases for CCI=6. Finally, the probability of medication consumption is greater than 50% for all age cohorts (80% after the age of 75). As the CCI increases, the probability of consuming one medication or of consuming five or more medications (polypharmacy) is close to one for all age cohorts.

5.1. Robustness checks

Comparison between truncated Poisson and truncated negative binomial. Table C1 compares estimated odds ratios obtained for the truncated Poisson (the same shown on Table 3) and those obtained if the count data variables are modelled using a truncated negative binomial. Although the sign and significance of the estimated coefficients are the same in both estimations, the magnitude is always higher for the negative binomial. For example, a one unit increase in CCI, raises the probability that the number of outpatient visits increases between 40.9% (truncated negative binomial) and 31% (truncated Poisson). On the other hand, the comparison of the information criteria (AIC and BIC) and the log-likelihood indicates that the truncated Poisson outperforms the negative binomial for all the dependent variables (i.e., smaller information criteria and higher log-likelihood). As a final conclusion, it is worth to emphasize that the economic explanation of our results is satisfied regardless of the estimator.

Attrition. Given that our estimates could be biased by potential non-random selection of the final sample, Table C2 compares the outcome variables between the initial sample and the final sample. Test statistics for equality of means between samples accept the null hypothesis of equal means for all variables. We have also implemented the test for attrition suggested by Verbeek and Nijman (1992) which involves the estimation of all the cross-sections introducing as explanatory variable, a binary indicator that takes the value 1 in case that the individual is present in the final sample, and 0 otherwise. Results are shown on tables C3 (binary outcomes) and C4 (count data variables). The variable "present in all samples" is only significant for the probability of staying at nursing home and length of stay at nursing home. The effect over the probability of staying in a nursing home is very small (1.3pp.), but the effect over the length of stay is more substantial (e.g., being in the final sample increases the probability that the length of stay raises 1 week by 14.4%). In any case, we consider that attrition does not blurs the validity of our estimations.

Instrument validity: In order to dispel any cloud of invalidity surrounding our instruments (parent's age of decease) and to show that the causal inferences about TTD on healthcare outcomes are credible, we rely on two bound methods proposed by Conley et al. (2012) that allow to obtain inferences even when the instrumental variables do not satisfy the exogeneity restriction (see Appendix D for explanation of both approaches). Figure D1 shows the results of testing both approaches for the instrument "male & father's age of decease" (similar results have been obtained for the other instruments; results available upon request). The solid line represents the 2SLS father's age of decease effect estimate for the respective outcome variable. The two dash lines represent upper and lower limits of the respective test scores. Overall the results confirm that even with substantial deviation from the exclusion restriction, the instrument has still a considerable effect over the outcome variable[21].

Effect of CCI over estimations: To verify model fitting after introducing CCI, Figure E1 compares the residuals from the logit and truncated Poisson models (using IV for CCI) conditioned on including or not CCI, that is comparing M4 with M5. For all regressions, residuals are significantly lower in the models with CCI which confirms the overperformance of M5.

6. Heterogeneity

Finally, in this section we study whether results were driven by specific groups of people or countries all the models were re-estimated for men and women and for two groups of countries.

[21] In the right column figures for union of confidence intervals are presented. The x axis measures how strong does the violation of the exclusion restriction needs to be in order for the instrument to turn insignificant. In all figures, the confidence intervals do not include the value 0 (red line), so we can infer that the IV estimations are robust to possible violations of the exclusion restriction

Differences between men and women: Table A8 shows descriptive statistics for outcome variables and Table E1 contains the model estimation results. A one-year increase in the TTD decreases both, the probability of hospitalization and hospital length of stay, more intensively for men than for women (-3.9 pp. vs. -2.5 pp. for the probability and -5.2% vs. -3.1% for length of stay). By the contrary, the effect is more intense for women in the following cases: (i) a one-year increase in the TTD decreases the probability of one additional outpatient visit with a doctor/nurse by 4.8% for men and by 10.1% for women, and (ii) a one-year increase in the TTD decreases the probability of receiving one additional hour of home care by 21.2% for men and 32.2% for women.

With respect to the effect of CCI, each additional CCI increases the probability of receiving and additional hour of personal care by 3% for men and 10.6% for women, but decreases the probability of extending length of stay at a nursing home by one week 12.1% for men and 5.5% for women. The most intense effect of age is observed for the number of prescribed medicines consumed: each additional year increases the probability of consuming one additional prescribed drug by 2.6% for men, and 5.8% for women.

Figure E2 show the predicted probabilities and predicted values of count data variables distinguishing by gender, TTD and CCI. It is worth noting that hospital length of stay increases significantly from the age of 75 (for high CCI, but regardless of TTD). In contrast, the length of stay at nursing home describes a U shape, with a minimum length for the cohort age 75-84 years (regardless CCI and TTD). The number of home care hours exhibits a substantial jump for the oldest cohort. Finally, we appreciate that for men and women, as the individual gets older, the higher TTD is, the steeper is the probability of consuming any prescribed drug (for low CCI).

Northern and Southern European countries: We have selected four northern countries (Denmark, Estonia, Poland and Sweden) and three southern countries (Greece, Italy and Spain). Table A9 shows descriptive statistics for outcome variables and Table E3 shows the model estimation results.

The most striking result is the different impact of the CCI on the probability of hospital use (and length of stay), which turns out to be two (three) percentage points lower in southern countries than in the northern countries. The effect of ageing on hospitalisation is less intense in the southern countries. In northern countries, each additional year increases the likelihood that hospitalisation will be extended by one day by 13.5% compared to 11.2% in southern countries. Furthermore, in both groups of countries, the TTD variable is significant for the probability of hospitalisation, but not for length of stay. All estimates show that the absolute value of the coefficient of TTD decreases when including the CCI.

The probability and the number of an outpatient visit with a doctor or nurse decrease with the TTD. The most intense effect is on the count variable. A one-year step towards death increases the number of outpatient visits in a unit to 12.8% for southern countries and to 8.2% for northern countries. Another significant difference between both country groups is the effect of CCI, which is more intense in southern countries. An increase in comorbidity increases the probability of an outpatient visit by 6.9 percentage points in southern countries, and by 5.1 percentage points in northern countries. An increase in comorbidity increases the number of outpatient visits by 34.3% in southern countries and by 29.1% in northern countries. The results for home care are also interesting. The probability of receiving formal care at home increases slightly with the TTD for both country groups. However, the TTD's effect on the number of formal, in-home care hours is different for each country group. A one-year step towards death increases the provision of personal care by one hour (+ 26.1% in southern countries and +16.9% in northern countries).

There are significant differences in the effects of age, TTD and CCI on medication. (i) Each year of life increases the probability of consuming a medication by five percentage points in northern countries versus an increase of 3.8 percentage points in southern countries. (ii) Each one-year increase in the TTD decreases the number of medications consumed by 2.8% (and the probability of polypharmacy with a sample limited to individuals who consume at least one medication by 7.1 percentage points) in northern countries versus 12.2% (10.8 percentage points) in southern countries. (iii) Each increase in comorbidity in the CCI increases the probability of polypharmacy by 13.6 percentage points in northern countries compared to 11.4 percentage points in southern countries.

Figure E4 in the appendix shows the predicted probabilities and predicted counts for the analysed outcomes based on the age cohort, the TTD (differentiating between the two extremes of 0-12 months and 3+ years), and the CCI (considering only very low comorbidity profiles (CCI=0.1) and very high profiles (CCI=5, 6, or 7). The probability of hospitalisation and the hospital length of stay are higher for northern countries. The probability of a an outpatient visit with a doctor or nurse is higher for northern countries only when the CCI is low. It is higher for a TTD of 0-12 months and decreases slightly for both groups of countries for the 85+ age cohort. In contrast, the number of outpatient visits, it is higher for southern countries, and a high CCI increases the distance between both groups. Furthermore, for both countries, a greater proximity to death is associated with fewer outpatient visits. When we turn to home care, we find differences among northern countries for a TTD of more than three years, a high CCI, and after the age of 75. Finally, when we examine medication consumption, the picture is very different depending on morbidity controls.

6. Conclusion

This paper estimates the effect of ageing on health care utilization. We exploit longitudinal individual end of life data that measures the effect of TTD. We control and measure a number of comorbidities, and early health behaviours and consider the endogeneity of TTD. This has allowed us to disentangle the effect of ageing, from other determinants of health care utilization .

Our estimates suggest that time to death (TTD) increases hospitalizations, hospital length of stay, long-term care use (home and nursing home care) as well as outpatient use. More importantly, we document that the effect size of TTD exceeds that of an extra year of life. However, our estimates are heterogeneous across different types of health care. More specifically, we find that aging does not increase the utilisation of outpatient care, Furthermore, the effect of ageing is attenuated when we include comorbidity controls in explaining both the extensive and intensive margin of hospitalizations and medicine consumption. One potential explanation lies in that physicians discriminate patients based on their age[22]. Although we cannot directly observe such behavior in our data (e.g., we ignore access to elective surgical procedures, specific diagnosis, decisions to manage patients on intensive care units or on general wards), our results are not consistent with 'ageist practices'[23].

[22] Some studies (Pilote et al., 1996; Stone et al., 1996; Norman et al., 1998; Munro et al., 2012) find that older people are more likely to undergo medical care rather than surgery and they are prematurely discharged from intensive care units if there is no quick response to treatment.

[23] The effect of age over length of stay at hospital is positive (although only significant at 10%), and it is not significant for the number of outpatient visits with doctor/nurse, whereas for the subgroup of Northern and Southern countries, the effect of age is positive and significant at 5% which contradicts the hypothesis of early discharged related to ageing (each year of life increases the probability that length of stay rises 1 day by 11-13%).

These results taken together indicate that estimates of the effect of ageing on health care utilisation are affected by alternative influences (so called 'red herrings'), as well as omitted variable bias that, when accounted for, attenuate its effect.

References

Allison, P.D., Waterman, R.P. (2002). Fixed-effects negative binomial regression models. *Sociological Methodology* 32, 247-265.

Atella, V., Conti, V. (2014). The effect of age and time to death on primary care costs: the Italian experience. *Social Science and Medicine* 114, 10-17.

Blundell, R., Griffith, R., Windmeijer, F. (2002). Individual effects and dynamics in count data models. *Journal of Econometrics* 108, 113–131.

Breyer, F., Costa-Font, J., Felder, S. (2010). Ageing, health, and health care. *Oxford Review of Economic Policy* 26(4), 674-690.

Breyer, F., Lorenz, N., Niebel, T. (2012). Health care expenditures and longevity: is there a Eubie Blake effect? DIW Berlin Discussion Papers No. 1226.

Breyer, F., Ihle, P., Lorenz, N. (2017). The death of the red herring: ageing and health care expenditures in large German sickness fund. CESifo Area Conferences. Employment and Social Protection. Munich, 26-27 May.

Cameron, A.C., Trivedi, P.K. (2013). *Regression analysis of count data*. 2nd edition. Cambridge: Cambridge University Press.

Card, D. (1999). The causal effect of education on earnings. In O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, vol 3A. Amsterdam: Elsevier, 1999.

Chamberlain, G. (1980). Analysis of covariance with qualitative data. *Review of Economic Studies* 47, 225-238.

Carreras, M., Ibern, P., Inoriza, J. (2018). Ageing and healthcare expenditures: exploring the role of individual health status. *Health Economics* 27, 865-876.

Charlson, M., Pompei, P., Ales, K., MacKenzie, C. (1987). A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *Journal of Chronic Diseases* 40(5), 373-383.

Conley, T., Hansen, C., Rossi, P. (2012). Plausible exogenous. *Review of Economics and Statistics* 94, 260-272.

Clarke, D. (2014). PLAUSEXOG: Stata module to implement Conley et al's plausibly exogenous bounds. Statistical Software Components S457832, Boston College Department of Economics, revised 18 May 2019.

Costa-Font, J., Jimenez-Martin, S., Vilaplana, C. (2018). Does LTC subsidization reduce hospital admissions and utilization?. *Journal of Health Economics* 58, 43-66.

De Meijer, C., Koopmanschap, M., d'Uva, T., van Doorslaer, E. (2011). Determinants of long-term care spending: age, time to death or disability? *Journal of Health Economics* 30(3) 425-438.

Dormont, B., Huber, H. (2006). Causes of health expenditure growth: the predominance of changes in medical practices over population ageing. *Annales d'Èconomie et de Statistique. 83/84 (Health, Insurance, Equity),* 187-217.

Dormont, B., Grignon, M., Huber, H. (2006). Health expenditure growth: the threat of ageing. *Health Economics* 15(9), 947-963.

Drukker, D. (2017). Two-part models are robust to endogenous selection. *Economic Letters* 152, 71-72.

European Union (2016). Health expenditures by diseases and conditions. Luxembourg: Publications Office of the European Union. Available at: https://ec.europa.eu/eurostat/documents/3888793/7605571/KS-TC-16-008-EN-N.pdf

French, E., McCauley, J., Aragón, M., Bakx, P., Chalkley, M. et al (2017). End-of-life medical spending in the last twelve months of life is lower than previously reported. *Health Affairs* 36(7), 1211-1217.

Felder, S., Werblow, A., Zweifel, P. (2010). Do red herrings swim in circles? Controlling for the endogeneity of time-to-death. *Journal of Health Economics* 29(2), 205-212.

French, E., McCauley, J., Aragón, M., Bakx, P., Chalkley, M. et al (2017). End-of-life medical spending in the last twelve months of life is lower than previously reported. *Health Affairs* 36(7), 1211-1217.

Geue, C., Lorgelly, P., Lewsey, J., Hart, C., Briggs, A. (2015). Hospital expenditure and the end-of-life: what are the impacts of health status and health risks? *PLos ONE* 10(3), e0119035.

Gilles, R., Kim, S. (2017). Distribution-free estimation of zero-inflated models with unobserved heterogeneity. *Statistical Methods in Medical Research*, 26, 1532–1542.

Gillingham, K., Tsvetanov, T. (2019). Hurdles and steps: Estimating demand for solar photovoltaics. *Quantitative Economics* 10(1), 275-310.

Gjonca, E., Zaninotto, P. (2008). Blame the parents? the association between parental longevity and successful ageing. *Demographic Research* 19(38), 1435–1450.

Goldberg, R., Larson, M, Levy, D. (1996). Factors associated with survival to 75 years of age in middle-aged men and women: the Framingham study. *Archives of Internal Medicine* 156(5), 505–509.

Goldman, D., Shang, B., Bhattahcarya, J., Garber, A., Hurd, M., Joyce, G. (2005). Consequences of health trends in medical innovation for the future elderly. *Health Affairs* 24, W5R5-17.

Guo, Z., Small, D. (2016). Control function instrumental variable estimation of nonlinear causal effect models. *Journal of Machine Learning Research* 17, 1-35.

Hall, R. E., Jones, C. I- (2007), The value of life and the rise in health spending, *The Quarterly Journal of Economics*, 122(1):39-72.

Hausman, J.A., Hall, B.H., Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* 524, 909-938.

Hazra, N., Rudisill, C., Gulliford, M. (2018). Determinants of health care costs in the senior elderly: age, comorbidity, impairment or proximity to death? *European Journal of Health Economics* 19(6), 831-842.

Howdon, D., Rice, N. (2018). Health care expenditures, age, proximity to death and morbidity: implications for an ageing population. *Journal of Health Economics* 57, 60-74.

Ikeda, A., Iso, H., Toyoshima, H., Kondo, T., Mizoue, T., Koizumi, A., Inaba, Y., Tamakoshi, A. (2006). Parental longevity and mortality amongst Japanese men and women: the JACC Study. *Journal of Internal Medicine*, 259(3), 285–95.

Imbens, G., Wooldridge, J. M. (2007). What's New in Econometrics? Summer Institute 2007 Methods Lectures. Available at: https://www.nber.org/minicourse3.html

Ishizaki, T., Shimmei, M., Fukuda, H. et al. (2016). Cumulative number of hospital bed days among older adults in the last year of life: a retrospective cohort study. *Geriatrics and Gerontology International* 17, 737-743.

Karlsson, M., Klohn, F. (2011). Some notes on how to catch a red herring. Ageing, time-to-death and care costs for older people in Sweden. Darmstadt Discussion Papers in Economics 207, Darmstadt University of Technology, Department of Law and Economics.

Karlsson, M., Klohn, F. (2014). Testing the red herring hypothesis on an aggregated level: ageing, time-to-death and care costs for people in Sweden. The *European Journal of Health Economics* 15(5), 533-551.

Kelley, A., McGarry, K., Fahle, S., Marshall, S., Du, Q., Skinner, J. (2013). Out-of-pocket spending in the last five years of life. *Journal of General Internal Medicine* 28(2), 304-309.

Kusumastuti, S., Gerds, T.A., Lund, R., Mortensen, E.L., Westendorp, R.G.J. (2017). Discrimination ability of comorbidity, frailty, and subjective health to predict mortality in community-dwelling older people: Population based prospective cohort study. *European Journal of Internal Medicine* 42, 29-38

Lafortune G, Balestat G, Disability study expert group members (2007). Trends in severe disability among elderly people: assessing the evidence in 12 OECD countries and the future implications. Paris: OECD, 2007

Larsson , K. (2008). Care utilization in the last year of life in relation to age and time to death: results from a Swedish urban population of the oldest old. *European Journal of Ageing* 5, 349-357.

Lichtenberg, F. R. (2012). The effect of pharmaceutical innovation on longevity: patient level evidence from the 1996–2002 medical expenditure panel survey and linked mortality public-use files. *Forum for Health Economics and Policy*, 16(1), 1–33.

Lin, W., Wooldridge, J. (2019). Testing and correcting for endogeneity in nonlinear unobserved effect models. Panel Data Econometrics. Chapter 2. Pp. 21-43.

Majo M.C., van Soest A.H. (2011). The fixed effects zero-inflated Poisson model with an application to health care utilization. Tilburg University Discussion Paper 2011-083.

Marino, A., Morgan, D., Lorenzoni, L., James, C. (2017). Future trends in health care expenditure. OECD Health Working Paper No. 95

Modig K., Talbäck M., Torssander J., Ahlbom, A. (2017). Payback time? Influence of having children on mortality in old age. *Journal of Epidemiology and Community Health* 71, 424-430.

Munro, P., Smith, R., Parke, T. (2002). Effect of patients' age on management of acute intracranial haematoma: prospective national study. *British Medical Journal* 325, 1001-1006.

Neyman, J., Scott, E.L. (1948). Consistent estimates based on partially consistent observations. *Econometrica* 16, 1-36.

Norman, P., Semmens, J., Lawrence-Brown, M., Holman, C., D'Arcy, J. (1998). Long-term survival for abdominal aortic aneurysm in Western Australia: population-based study. *British Medical Journal* 317, 852-856.

Palladino, R., Lee, J., Ashworth, M., Triassi, M., Millet, C. (2016). Association between multimorbidity, healthcare utilization and health status: evidence from 16 European countries. *Age and Ageing* 45, 431-435.

Payne, R., Abel, G., Guthrie, B., Mercer, S. (2013). The effect of physical multimorbidity, mental health conditions and socioeconomic deprivation on unplanned admissions to hospital: a retrospective cohort study. *Canadian Medical Association Journal* 185, 221-228.

Pilote, L., Miller, D., Califf, R., Rao, J., Weaver, W., Topol, E. (1996). Determinants of the use of coronary angiography and revascularization after thrombosis for acute myocardial infarction. *New England Journal of Medicine* 335, 1198-205.

Rubin, D.B. (1987). *Multiple imputation for nonresponse in surveys*. Wiley: NewYork.

Salas, C., Raftery, J. (2001). Econometric issues in testing the age neutrality of health care expenditure. *Health Economics Letters* 10, 669-671.

Schneider, K., O'Donnell, B., Dean, D. (2009). Prevalence of multiple chronic conditions in the United States Medicare population. *Health and Quality of Life Outcomes* 7, 82.

Seshamani, M., Gray, A. (2004). Ageing and health-care expenditure: the red herring argument revisited. *Health Economics* 13(4), 303-314.

Shang, B., Goldman, P. (2007). Prescription drug coverage and elderly Medicare spending. NBER Working Paper No. 13358.

Stearns, S., Norton, E. (2004). Time to include time to death? The future of health care expenditure predictions. *Health Economics* 13, 315-327.

Steinmann, L., Telser, H., Zweifel, P. (2007). Aging and future healthcare expenditure: a consistent approach. *Aging and Medical Care Costs* 10(2), 1-26.

Stessman, J. , Yakir Rottenberg, Y., Shimshilashvili, I., Ein-Mor, E., Jacobs, J. (2014). Loneliness, health and longevity. *The Journals of Gerontology: Series A* 69(6), 744–750.

Stone, P., Thompson, B., Anderson, H. (1996). Influence of race, sex and age on management of unstable angina and non-Q wave myocardial infarction. The TIMI III registry. *Journal of the American Medical Association* 275, 1104-1112.

Vella, F. (1998). Estimating models with sample selection bias: a survey. *Journal of Human Resources* 33 (1), 127–169.

Verbeek, M., Nijman, T. (1992) Testing for selectivity bias in panel data models. *International Economic Review* 33, 681–703.

Werblow, A., Felder, S., Zweifel, P. (2007). Population ageing and health care expenditure: a school of "red herrings"? *Health Economics* 16(10), 1109-1126.

Winkelmann, R. (2008). *Econometric analysis of count data*. 5th edition. Berlin: Springer Verlag.

Wong, A., Wouterse, B., Slobbe, L., Boshuizen, H. (2012). Medical innovation and age-specific trends in health care utilization: findings and implications. *Social Science Medicine* 74(2), 263-272.

Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*. MIT Press.

WHO (2015). World report on ageing and health. World Health Organization.

Zweifel, P., Felder, S., Meiers, M. (1999). Ageing of population and health care expenditure: a red herring? *Health Economics* 8(6), 379-400.

Zweifel, P., Felder, S., Werblow, A. (2004). Population ageing and health care expenditure: new evidence on the "red herring". Geneva Papers on Risk and Insurance 29(4), 652-666.

Tables and Figures

Table 1. Description of the sample

	Initial sample	After merging consecutive waves			Registered in at least three waves					
		Number of observations			Number of observations			Number of individuals		
		Survivors	Deceased	Total	Survivors	Deceased	Total	Survivors	Deceased	Total
Austria	19,193	11,664	583	12,247	10,216	333	10,549	3,364	160	3,524
Belgium	28,931	17,902	783	18,685	15,712	530	16,242	4,776	223	4,999
Czech Rep.	23,302	13,627	897	14,524	12,574	461	13,035	4,418	217	4,635
Denmark	17,912	11,355	701	12,056	10,475	413	10,888	3,419	180	3,599
Estonia	23,747	14,760	963	15,723	13,083	515	13,598	4,571	256	4,827
France	23,938	14,053	674	14,727	12,313	385	12,698	3,885	175	4,060
Germany	21,357	12,071	405	12,476	10,757	211	10,968	4,156	100	4,256
Greece	14,59	5,289	725	6,014	3,061	453	3,514	1,533	224	1,757
Italy	24,005	14,187	800	14,987	12,559	516	13,075	3,913	226	4,139
Luxembourg	4,463	2,187	47	2,234	1,605	27	1,632	798	18	816
Netherlands	12,608	5,724	277	6,001	4,259	118	4,377	1,622	61	1,683
Poland	10,842	4,321	528	4,849	3,754	215	3,969	1,346	97	1,443
Portugal	4,233	1,989	144	2,133	860	24	884	427	15	442
Slovenia	13,814	7,769	333	8,102	5,954	168	6,122	2,266	84	2,350
Spain	25,958	15,455	1,434	16,889	14,198	848	15,046	4,881	403	5,284
Sweden	19,624	11,786	824	12,610	10,737	455	11,192	3,619	235	3,854
Switzerland	14,628	9,645	292	9,937	9,007	183	9,190	2,795	86	2,881
Total	288,555	175,807	10,529	186,336	151,124	5,855	156,979	51,789	2,760	54,549

Source: SHARE waves (1, 2, 4, 5, 6, and 7).

Table 2. Dependent variables

	N	Mean	Std. Dev	Min	Max
Hospitalization during last year	156,979	0.153	0.36	0	1
Length of stay at hospital (days per year) [a]	24,020	11.83	20.07	1	365
Consultations with doctor/nurse during last year	156,979	0.889	0.31	0	1
Number of consultations with doctor/nurse	140,139	7.60	9.74	1	98
Stayed at nursing home	156,979	0.005	0.07	0	1
Length of stay at nursing home (weeks per year)	668	27.61	23.13	1	52
Received formal care for personal care	156,979	0.013	0.12	0	1
Hours receiving formal care for personal care (per year)	2,095	257.83	772.01	1	8,736
Consumed any prescribed drug (during a week) [b]	118,159	0.749	0.43	0	1
Number of prescribed drugs consumed (during a week)	118,159	2.33	1.51	1	14
Polypharmacy (5 or more prescribed drugs)	118,159	0.144	0.35	0	1

[a] Considering all hospitalizations.

[b] The following categories of prescribed drugs are considered: (1) high blood cholesterol, (2) high blood pressure, (3) coronary or cerebrovascular diseases, (4) other heart diseases, (5) asthma, (6) diabetes, (7) joint pain or for joint inflammation, (8) other pain (e.g. headache, back pain, etc.), (9) drugs for sleep problems, (10) anxiety or depression, (11) osteoporosis (hormonal), (12) osteoporosis (other than hormonal), (13) stomach burns, (14) chronic bronchitis, (15) suppressing inflammation (only glycocorticoids or steroids), (16) other drugs, not yet mentioned.

Source: SHARE waves (1, 2, 4, 5, 6, and 7).

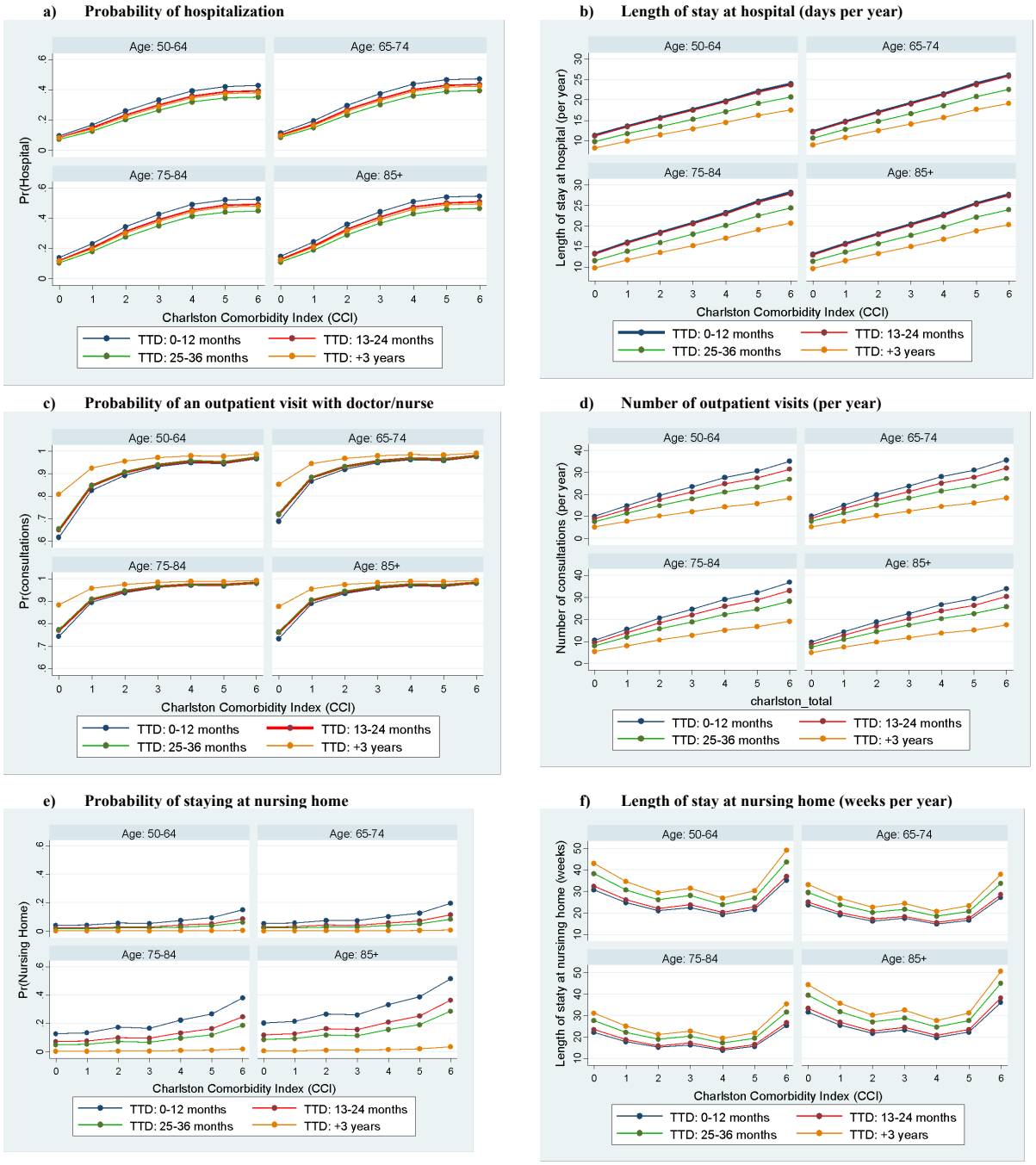
Table 3. Marginal effects reported for logit part; incidence rate ratios reported (Truncated Poisson model).

	Logit (marginal effects)					Truncated Poisson (IRR)				
	Exogenous TTD			TTD (IV)		Exogenous TTD			TTD (IV)	
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Hospitalization	**Hospitalization (extensive margin)**					**Length of stay at hospital (days per year)**				
Age	0.001	0.005***	0.0001	0.117***	0.014***	1.031**	1.054***	1.034***	1.053***	1.023*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age^2	0.000***	-0.000**	0.0001*	-0.001***	-0.000**	1.000	1.000***	1.000**	1.000***	1.000
	(0.000)	(0.000)	(0.0005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		-0.016***	-0.013***	-0.376***	-0.054***		0.828***	0.847***	0.840***	0.951***
		(0.000)	(0.000)	(0.004)	(0.015)		(0.008)	(0.009)	(0.035)	(0.034)
CCI			0.074***		0.066***			1.146***		1.153***
			(0.001)		(0.003)			(0.013)		(0.013)
Resid 1st stage				0.363***	0.042***					
				(0.004)	(0.015)					
Constant	-0.013	0.019	0.159***	0.704***	0.223***	2.674**	2.962**	4.619***	2.911**	4.055***
	(0.030)	(0.030)	(0.029)	(0.031)	(0.037)	(1.213)	(1.347)	(2.119)	(1.361)	(1.893)
N	156,979	156,979	156,979	156,979	156,979	24,020	24,020	24,020	24,020	24,020
Log-likelihood	-62,829.0	-61,333.0	-59,872.7	-58,447.2	-57,055.6	-218,658.6	-213,452.4	-208,370.2	-203,409.0	-198,566.0
AIC	125,737.9	122,744.1	119,821.7	116,968.8	114,183.8	437,397.2	426,983.0	416,816.7	406,892.5	397,204.6
BIC	126,136.5	123,133.3	120,201.5	117,339.6	114,545.8	437,720.7	427,298.8	417,125.0	407,193.5	397,498.4
Chi2	259.069	376.764	981.128	935.454	906.317	111.811	483.975	773.145	487.113	757.891
Outpatient visit	**Doctor/nurse outpatient visit (extensive margin)**					**Doctor/nurse outpatient visit (intensive margin)**				
Age	0.014***	0.014***	0.010***	0.089***	-0.003	1.015**	1.030***	1.004	1.057***	0.999
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.007)	(0.007)	(0.006)	(0.008)	(0.006)
Age^2	-0.000***	-0.000***	-0.000***	-0.001***	0.000	1.000	1.000***	1.000	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		-0.001**	0.001***	-0.241***	0.042***		0.876***	0.911***	0.658***	0.953**
		(0.000)	(0.000)	(0.004)	(0.013)		(0.006)	(0.006)	(0.026)	(0.018)
CCI			0.051***		0.058***			1.307***		1.310***
			(0.001)		(0.003)			(0.011)		(0.011)
Resid 1st stage				0.242***	-0.041***					
				(0.004)	(0.013)					
Constant	0.292***	0.293***	0.389***	0.750***	0.327***	3.078***	3.375***	6.559***	4.992***	6.189***
	(0.026)	(0.026)	(0.026)	(0.027)	(0.033)	(0.688)	(0.767)	(1.349)	(1.164)	(1.270)
N	156,979	156,979	156,979	156,979	156,979	140,139	140,139	140,139	140,139	140,139
Log-likelihood	-48,406.3	-47,253.8	-46,128.7	-45,030.4	-43,958.3	-664,679.6	-648,853.9	-633,405.0	-618,323.9	-603,601.9
AIC	96,892.7	94,585.7	92,333.7	90,135.2	87,989.2	1,329,439.0	1,297,785.7	1,266,886.0	1,236,722.1	1,207,276.3
BIC	97,291.2	94,974.8	92,713.5	90,506.0	88,351.1	1,329,833.0	1,298,170.3	1,267,261.5	1,237,088.6	1,207,634.1
Chi2	267.389	243.466	599.165	555.220	553.854	305.588	498.450	1.048.862	700.224	1.075.492
Stays nursing home	**Nursing home stays (extensive margin)**					**Nursing home stays (weeks per year)**				
Age	-0.004***	-0.003***	-0.003***	-0.001***	-0.002*	0.865***	0.867***	0.884***	0.859***	0.877***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age^2	0.000***	0.000***	0.000***	0.000***	0.000*	1.001***	1.001***	1.001***	1.001***	1.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		-0.002***	-0.002***	-0.008***	-0.006**		0.967***	0.963***	1.073***	1.034**
		(0.000)	(0.000)	(0.001)	(0.003)		(0.004)	(0.004)	(0.014)	(0.014)
CCI			0.001***		0.0003**			0.910***		0.914***
			(0.000)		(0.001)			(0.005)		(0.005)
Resid 1st stage				0.006***	0.004					
				(0.001)	(0.003)					
Constant	0.111***	0.115***	0.117***	0.126***	0.124***	5,740***	6,133***	3,323***	5,542***	3,193***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(1,222.08)	(1,307.23)	(717.62)	(1,182.57)	(690.08)
N	156,979	156,979	156,979	156,979	156,979	668	668	668	668	668
Log-likelihood	-3,734.2	-3,645.3	-3,558.5	-3,473.8	-3,391.1	-7,647.2	-7,465.1	-7,287.3	-7,113.8	-6,944.5
AIC	7,548.5	7,368.8	7,193.3	7,022.0	6,854.9	15,374.3	15,008.3	14,650.9	14,302.1	13,961.6
BIC	7,947.0	7,757.8	7,573.1	7,392.8	7,216.8	15,553.5	15,183.1	14,821.6	14,468.7	14,124.2
Chi2	189.305	236.533	220.782	220.925	203.962	572.234	623.327	917.038	690.499	947.197
Personal care	**Home care (extensive margin)**					**Home care (hours per year)**				
Age	0.022***	0.020***	0.021***	0.026***	0.028***	1.092***	1.072***	1.072***	1.132***	1.136***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	0.000***	0.000***	0.000***	0.000***	0.000***	1.000***	1.000***	1.000***	0.999***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		-0.010***	-0.009***	-0.095***	-0.049***		1.237***	1.237***	0.706***	0.696***
		(0.000)	(0.000)	(0.002)	(0.008)		(0.001)	(0.001)	(0.002)	(0.002)
CCI			0.017***		0.009***			1.003***		1.080***
			(0.000)		(0.001)			(0.001)		(0.001)
Resid 1st stage				0.086***	0.040***					
				(0.002)	(0.008)					
Constant	0.670***	0.706***	0.734***	0.864***	0.794***	2.888***	2.347***	2.363***	4.407***	4.234***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.020)	(0.112)	(0.091)	(0.092)	(0.172)	(0.165)
N	156,979	156,979	156,979	156,979	156,979	2,095	2,095	2,095	2,095	2,095
Log-likelihood	-7,964.6	-7,774.9	-7,589.8	-7,409.1	-7,232.7	-232,886.3	-227,341.4	-221,928.5	-216,644.5	-211,486.3
AIC	16,001.1	15,620.2	15,248.3	14,885.2	14,530.8	465,832.7	454,741.4	443,914.3	433,344.9	423,027.1
BIC	16,334.1	15,945.1	15,565.5	15,194.9	14,833.1	465,984.6	454,889.7	444,059.0	433,486.2	423,165.1
Chi2	1,007.573	1,078.357	1,114.884	1,113.728	1,031.372	330,768.242	385,346.242	385,358.220	439,649.931	440,320.107
Any prescribed drug	**Prescription drug consumption(extensive margin)**					**Prescription drug consumed (drugs per week)**				
Age	0.048***	0.049***	0.041***	0.236***	0.185***	1.066***	1.072***	1.039***	1.125***	1.039***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age^2	-0.000***	-0.000***	-0.000***	-0.002***	-0.001***	1.000***	1.000***	1.000***	0.999***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		-0.005***	0.000	-0.007***	-0.009***		0.951***	0.998	0.562***	0.990
		(0.000)	(0.000)	(0.005)	(0.017)		(0.003)	(0.003)	(0.006)	(0.009)
CCI			0.117***		0.032***			1.395***		1.394***
			(0.001)		(0.003)			(0.002)		(0.002)
Resid 1st stage				0.607***	0.449***					

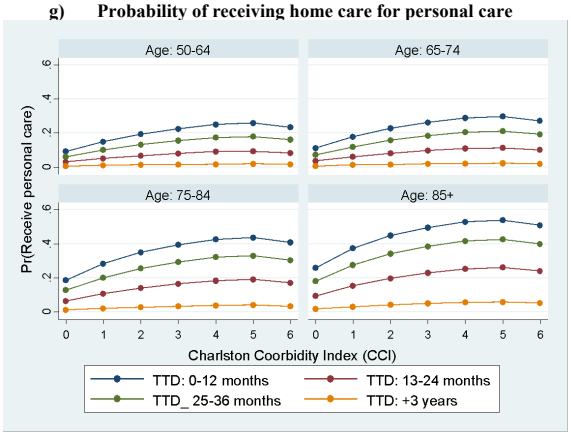
				(0.005)	(0.017)					
Constant	-1.273***	-1.264***	-1.043***	-0.118***	-0.355***	0.122***	0.124***	0.253***	0.248***	0.256***
	(0.035)	(0.035)	(0.034)	(0.035)	(0.042)	(0.011)	(0.011)	(0.023)	(0.022)	(0.023)
N	156,979	156,979	156,979	156,979	156,979	118,159	118,159	118,159	118,159	118,159
Log-likelihood	-72,245.1	-70,525.0	-68,845.8	-67,206.6	-65,606.5	-170,029.2	-165,980.9	-162,029.0	-158,171.1	-154,405.1
AIC	144,570.2	141,128.1	137,767.9	134,487.7	131,285.6	340,138.3	332,039.8	324,134.1	316,416.6	308,882.9
BIC	144,968.7	141,517.1	138,147.6	134,858.4	131,647.5	340,525.5	332,417.8	324,503.0	316,776.8	309,234.5
Chi2	1,783.305	1,631.050	2,793.264	2,854.246	2,643.527	12,103.814	12,449.715	48,742.386	15,111.931	48,743.353
Polypharmacy	**Probability of consuming 5 or more prescribed drugs**									
Age	0.011***	0.012***	0.004***	0.024***	0.004***					
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)					
Age^2	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
TTD		-0.015***	0.001	-0.147***	-0.002					
		(0.001)	(0.001)	(0.004)	(0.004)					
CCI			0.126***		0.126***					
			(0.001)		(0.001)					
Resid 1st stage				0.042***	0.001					
				(0.001)	(0.001)					
Constant	-0.406***	-0.390***	-0.216***	-0.208***	-0.213***					
	(0.037)	(0.037)	(0.034)	(0.037)	(0.035)					
N	118,159	118,159	118,159	118,159	118,159					
Log-likelihood	-42,410.5	-41,400.8	-40,415.0	-39,452.8	-38,513.4					
AIC	84,901.1	82,879.6	80,906.3	78,979.9	77,099.5					
BIC	85,299.6	83,268.7	81,286.1	79,350.7	77,461.4					
Chi2	225.750	216.604	1.990.125	289.298	1.837.066					

Note: This table reports different specifications of age, TTD and morbidity effect on health care use on both the intensive and extensive margin. M1 includes as explanatory variables age, age squared, marital status, income and wealth adjusted by the number of household members, municipality size, healthcare resources by NUTS and year fixed effects. TTD is included in the M2 model. CCI is included in the M3 model. M4 and M5 contain the same explanatory variables as M2 and M3, except that IV is used for TTD (CF for logit with fixed effects and a GMM truncated Poisson). Marginal effects are offered for the logit models, and the incidence risk ratio are shown for the truncated Poisson models. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

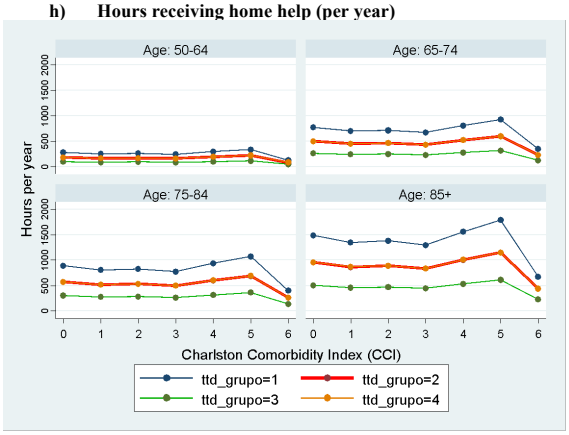
Figure 1. Predicted outcomes conditioned on age, time to death and Charlston Comorbidity Index (CCI).



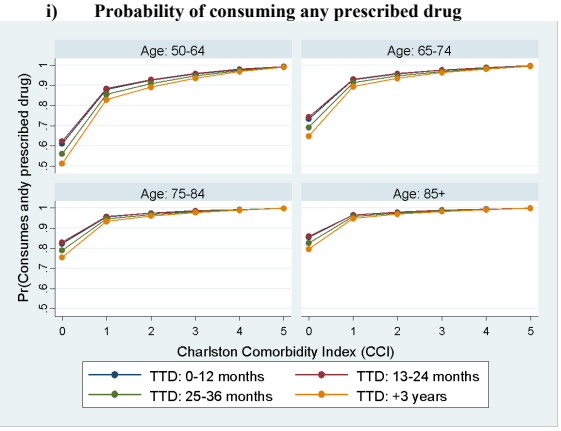
g) Probability of receiving home care for personal care



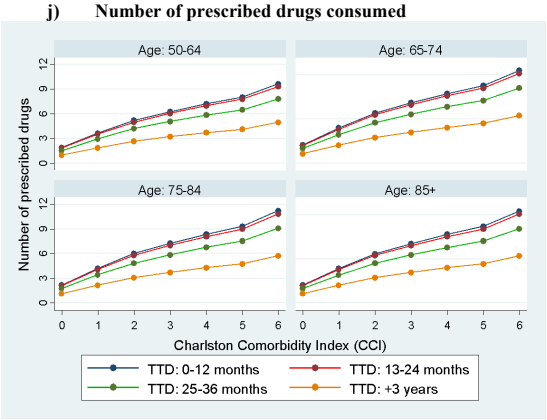
h) Hours receiving home help (per year)



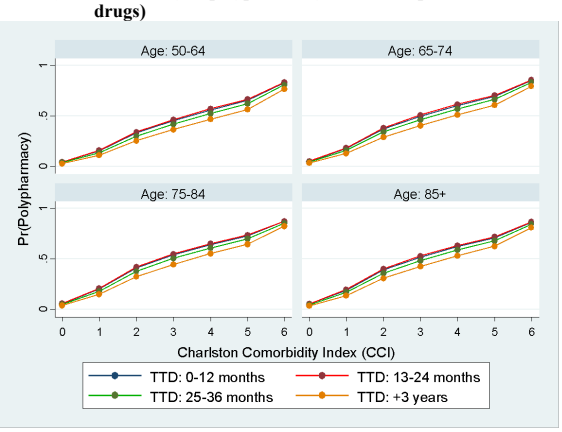
i) Probability of consuming any prescribed drug



j) Number of prescribed drugs consumed



k) Probability of polypharmacy (5 or more prescribed drugs)



Charlston Comorbidity Index: level 6 also includes level 7. In the graphs for the probability of hospitalization: the probability for TTD (13-24 months) overlaps with probability for TTD (+3 years). In the graphs for length of stay at hospital: length of stay for TTD (0-12 months) overlaps with length of stay for TTD (13-24 months). In the graphs for the predicted probability of consultation: the probability for TTD (13-24 months) overlaps with the probability for TTD (25-36 months).

Online Appendix

Appendix A

Table A1. Description of the sample

	Total sample	Deceased	Survivors
N	156,979	5,855	151,124
Age group			
50-64	46.26	14.58	48,19
65-74	16.68	9.75	17.10
75-84	32.18	50.50	31.06
85+	4.89	25.17	3.65
Time to death (TTD)			
0-12 months	1.70	30.07	0.00
13-24 months	1.76	31.22	0.00
25-36 months	0.57	10.05	0.00
+3 years	95.97	28.66	100.00
Man	43.73	52.98	43.26
Marital status			
Married/cohabiting	69.92	55.87	70.76
Single	5.60	5.58	5.61
Separated/divorced	9.34	6.39	9.52
Widow	15.14	32.16	14.12
Level of education (ISCED classification)			
Pre-primary education and primary education	24.95	46.29	23.67
Lower secondary education	17.86	17.08	17.91
Upper secondary education	31.90	22.80	32.45
Post-secondary non-tertiary education	4.19	2.80	4.28
First stage of tertiary education	20.33	10.68	20.91
Second stage of tertiary education	0.76	0.35	0.79
Size of municiaplity			
Big city	23.90	23.91	23.89
Large town	15.55	16.98	15.46
Small town	24.82	23.78	24.88
Rural area	31.43	28.23	31.62
Income (1,000PPP, 2015; adjusted by household size)	22.85	16.30	23.24
	(62.81)	(23.86)	(64.38)
Wealth (1,000PPP, 2015; adjusted by household size)	180.52	121.80	184.03
	(312.40)	(256.11)	(315.10)
Charlston Comorbidity Index: Items			
Item 1: A heart attack, myocardial infarction or coronary thrombosis (1 point)	12.30	25.75	11.49
Item 2: A stroke or cerebral vascular disease (1 point)	3.98	10.98	3.56
Item 3: Chronic lung disease such as chronic bronchitis or emphysema (1 point)	6.18	12.25	5.82
Item 4: Arthritis, including osteoarthritis, or rheumatism (1 point)	26.75	28.07	26.67
Item 4: Stomach or duodenal ulcer, peptic ulcer (1 point)	4.66	6.30	4.57
Item 6: Diabetes or high blood sugar (1 point)	12.24	19.93	11.78
Item 7: Cancer or malignant tumour, including leukaemia or lymphoma, but excluding minor skin cancers (2 points)	10.18	25.99	9.23
Charlston Comorbidity Index (final score)	0.76	1.29	0.73
	(0.98)	(1.20)	(0.96)
Charlston Comorbidity Index =0	51.03	50.12	30.07

Source: Own work using SHARE (waves 1, 2, 4, 5, 6 and 7)
Charlston Comorbidity Index: Charslton et al. (1987) adapted for SHARE by Kusumastuti et al. (2017)

The percentage of people who have been seen by a medical doctor or a qualified nurse in the last year increases from 86% for the cohort of 50–64 years to 94% for the cohort of 85 years and older and differences for survivors and deceased are not significant (Table A2). In contrast, *the average number of visits in the last year is lower for the sample of survivors (8.02) relative to the deceased (13.11).* For these, there is a slight increase as TTD decreases.

The percentage of people who have been *hospitalized in the last year is not significantly different in the survivor and in the deceased sample (31.02%) and increases progressively with age among survivors* (14.56%) (Table A3). The external margin of hospitalizations strikingly exceeds 40% among the youngest deceased cohorts (50–64 years) and those 75–84 years of age, in both cases when TTD = 0–12 months. *The average length of stay at the hospital among the deceased is three times that of the survivors (6.30 days vs. 1.62 days*). Importantly, the average stay increases as TTD decreases (4.98 days for TTD = +3 years vs. 7.86 days for TTD = 0–12 months). Significantly, stays longer than 10 days do not correspond to the older cohort.

The percentage of people who have taken any drug at least once a week is much higher among the deceased sample (89.13% vs. 73.69%) (Table A4). For both survivors and deceased, a progressive increase is observed with increasing age, and these increases are greater in the sample of survivors (e.g. 15.94 pp for survivors and 11.08 pp for deceased when going from the 50–64 to 65–74 years age bracket). In the deceased sample, the percentage of a drug consumed increases as TTD decreases, except for the youngest and oldest cohorts.

The average number of drugs consumed is higher among all age cohorts for the deceased sample (2.82 vs. 2.28 for survivors). We document an increasing pattern of consumption as TTD decreases, with the maximum consumption corresponding to the cohort of 85+ years and TTD = 0–12 months (3.29 drugs) and the cohort of 75–84 years and TTD = 13–24 months (3.04 drugs). Consistently, the percentage of polypharmacy (consumption of 5 or more drugs at least once a week) is 8 percentage points higher in the deceased sample, increasing from 15.13% to 22.21% as TTD decreases and reaches 25% for the two aforementioned groups.

Finally, we have examined the use of long-term care, *the percentage of people who have been in a nursing home during the last year is 7.5 times higher among the deceased sample (2.73% vs. 0.36%)* (Table A5). Considering TTD, this figure remains stable at approximately 2% when TTD is greater than one year and increases to 4.12% for TTD = 0–12 months. The cohort of 85+ years is the most common age of entry into nursing homes (5.37%). The analysis of the average length of stay reveals some interesting characteristics: (i) no significant differences are observed between survivors and deceased (27.57 weeks vs. 28.67 weeks) and (ii) the longest duration corresponds to the cohort of 65–74 years and TTD = 25–36 years (48.68 weeks).

Table A6 reports the percentage that receives personal care at home which we find it increases with age for both survivors and deceased, with the increase becoming steeper among 75–84 years to 85+ years. We document an increase as the TTD declines (from 14.14% to 24.42% for TTD = 0–12 months). Two significant cases are the result of the largest number of hours of care received throughout the year: (i) when TTD = 0–12 months, the largest number of hours corresponds to the youngest cohort and (ii) for the cohort of 85+ years, the average number of hours is higher among survivors.

Table A2. Doctor consultations

- **Has seen or talked to a medical doctor or qualified nurse about his/her health during last year (%). Include emergency room or outpatient clinic visits. Exclude dentist visits and hospital stays.**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	86.53	86.99	87.34	86.92	86.89	86.54
65-74	94.95	96.25	91.05	91.20	93.22	91.45
75-84	95.28	95.00	90.75	93.32	93.90	94.02
85+	95.13	93.75	91.33	93.80	93.97	94.48
Total	93.92	93.81	90.33	92.19	92.85	89.76

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 156,979.

- **Average number of times has seen or talked to a medical doctor or qualified nurse about his/her health during last year (conditioned on having talked to a medical doctor or qualified nurse during last year)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	16.63	16.09	12.64	12.13	14.13	7.06
	19.48	*20.65*	*13.26*	*16.33*	*17.88*	*9.37*
65-74	16.47	11.26	14.09	15.44	14.36	8.02
	17.02	*12.63*	*19.42*	*18.69*	*17.11*	*9.35*
75-84	15.11	13.33	12.58	12.83	13.45	9.33
	19.01	*15.52*	*15.94*	*14.35*	*15.99*	*10.51*
85+	12.52	10.98	11.59	11.12	11.55	9.94
	13.30	*13.85*	*16.05*	*10.70*	*13.06*	*10.81*
Total	14.54	12.67	12.52	12.64	13.11	8.02
	17.27	*15.47*	*15.95*	*14.54*	*15.67*	*9.87*

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 140,139. Standard errors in italics.

Table A3. Hospitalizations

- **Hospitalizations during last year (%). Include stays in medical, surgical or psychiatric wards.**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	41.05	35.31	25.09	22.91	30.28	11.64
65-74	35.40	28.97	34.77	29.20	30.99	14.53
75-84	41.73	32.48	23.81	27.20	31.40	18.84
85+	37.32	26.96	32.12	27.44	30.71	22.40
Total	39.70	30.71	27.03	26.78	31.02	14.56

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 156,979.

- **Average length of stay at hospital (conditioned on having stayed at hospital last year)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	9.90	10.87	4.80	5.24	7.51	1.17
	23.62	*27.71*	*13.01*	*16.92*	*21.08*	*6.65*
65-74	10.60	6.84	12.58	7.19	8.40	1.53
	23.57	*20.98*	*57.14*	*27.86*	*30.74*	*6.98*
75-84	8.66	7.76	3.52	4.80	6.28	2.27
	19.39	*26.18*	*10.28*	*16.79*	*19.75*	*8.59*
85+	5.31	5.22	5.67	4.13	4.97	3.10
	12.58	*26.10*	*15.27*	*12.31*	*18.08*	*10.35*
Total	7.86	7.22	5.16	4.98	6.30	1.62
	18.60	*25.95*	*21.82*	*17.53*	*20.81*	*7.51*

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 24,020. Standard errors in italics.

Table A4. Drugs consumption

- **Percentage taking any drug at least once a week (%).**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	76.58	72.95	74.98	73.36	74.28	62.84
65-74	90.65	85.94	82.00	83.57	85.36	78.78
75-84	94.46	94.39	90.55	90.66	92.44	88.17
85+	92.96	91.98	91.22	92.25	92.29	93.11
Total	91.07	90.44	87.19	87.54	89.13	73.69

We consider the following drug categories: (1) high blood cholesterol, (2) high blood pressure, (3) coronary or cerebrovascular diseases, (4) other heart diseases, (5) asthma, (6) diabetes, (7) joint pain or for joint inflammation, (8) other pain (e.g. headache, back pain, etc.), (9) drugs for sleep problems, (10) anxiety or depression, (11) osteoporosis (hormonal), (12) osteoporosis (other than hormonal), (13) stomach burns, (14) chronic bronchitis, (15) suppressing inflammation (only glycocorticoids or steroids), (16) other drugs, not yet mentioned.
Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 156,979.

- **Average number of drugs consumed (conditioned on having consumed any drug during last week)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	2.56	2.25	2.44	2.32	2.38	1.98
	1.93	*1.48*	*1.55*	*1.57*	*1.66*	*1.35*
65-74	2.98	2.73	2.44	2.63	2.71	2.28
	1.88	*1.66*	*1.74*	*1.70*	*1.74*	*1.49*
75-84	3.08	3.04	2.93	2.72	2.91	2.58
	1.82	*1.73*	*1.75*	*1.64*	*1.73*	*1.56*
85+	3.29	2.86	2.46	2.67	2.90	2.74
	1.90	*1.76*	*1.71*	*1.46*	*1.74*	*1.64*
Total	3.08	2.88	2.70	2.65	2.82	2.28
	1.88	*1.73*	*1.72*	*1.60*	*1.73*	*1.49*

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 118,159.

- **Consumption of 5 or more drugs (polypharmacy) at least once a week**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	13.12	9.63	9.45	8.45	9.98	5.73
65-74	20.11	22.47	18.10	19.76	20.34	10.90
75-84	23.37	25.27	19.98	17.23	20.95	16.11
85+	25.07	19.35	15.13	12.48	18.70	18.29
Total	22.21	21.36	16.90	15.13	18.71	10.02

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Source: own work using waves 1, 2, 4, 5, 6 and 7 of SHARE. Number of observations = 118,159.

Table A5. Stays in nursing homes

- **Has stayed in a nursing home during last year (%)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	1.77	0.01	0.17	1.69	1.17	0.18
65-74	2.53	0.31	2.66	0.48	1.09	0.18
75-84	2.92	1.86	2.68	1.53	2.05	0.60
85+	7.10	3.91	3.32	5.77	5.37	1.64
Total	4.12	2.17	2.39	2.32	2.73	0.36

A nursing home provides all of the following services for its residents: dispensing of medication, available 24-hour personal assistance and supervision (nor necessarily a nurse), room and meals.
Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 156,979.

- **Average number of weeks stayed in a nursing home (conditioned on having stayed in a nursing home during last year)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	38.15	21.00	19.00	16.34	24.29	36.58
	22.92	*19.88*	*21.13*	*25.15*	*24.98*	*21.95*
65-74	3.57	11.42	48.68	43.26	24.90	28.45
	9.18	*3.00*	*17.80*	*22.98*	*25.32*	*24.12*
75-84	17.26	27.80	32.11	25.62	24.37	22.29
	19.49	*22.77*	*21.26*	*24.64*	*22.49*	*22.66*
85+	35.21	22.44	33.17	35.70	32.37	28.81
	22.54	*23.91*	*25.33*	*22.90*	*23.46*	*23.01*
Total	28.29	24.51	33.97	30.25	28.67	27.57
	23.23	*23.29*	*22.03*	*24.18*	*23.47*	*23.36*

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 668. Standard errors in italics.

Table A6. Home care for personal care

- **Has received in his/her home professional or paid services for personal care due to physical, mental, emotional or memory problems (%)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	11.64	7.86	1.83	6.16	7.33	1.47
65-74	10.48	9.12	10.55	9.48	9.69	2.05
75-84	22.09	20.72	12.94	12.81	16.72	5.30
85+	36.71	27.24	30.44	26.36	29.94	18.53
Total	24.42	20.09	14.85	14.14	18.05	3.38

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Using calibrated sampling weights. Number of observations = 156,979.

- **Average number of hours (per year) that has received professional paid services for personal care (conditioned on receiving paid services for personal care)**

	Deceased (time to death)					Survivors
Age at interview	0-12 months	13-24 months	25-36 months	+3 years	Total	
50-64	338.10	222.44	24.65	54.60	144.27	52.09
	663.43	*396.08*	*17.46*	*163.00*	*375.62*	*348.76*
65-74	240.34	22.09	63.71	459.20	328.52	95.03
	205.32	*25.39*	*161.85*	*954.38*	*799.60*	*534.33*
75-84	104.02	111.46	127.18	344.56	251.68	81.85
	203.11	*283.83*	*176.08*	*892.46*	*713.69*	*343.91*
85+	127.76	808.40	253.08	494.56	476.34	556.75
	241.85	*1438.04*	*913.49*	*1482.45*	*1346.08*	*1618.10*
Total	152.05	347.54	161.68	387.46	329.33	121.33
	328.09	*907.42*	*555.85*	*1126.85*	*982.39*	*639.00*

Time to death = Age at decease (in years and months) – Age at last interview (years and months)
Average number of hours per year is obtained multiplying average number of weeks times average hours per week.
Records of home care hours are only observed for years 2004, 2005, 2006, 2007, 2009 and 2010.
Using calibrated sampling weights. Number of observations = 2,095.

Table A7. Regional healthcare indicators

	2004	2005	2006	2007	2009	2010	2011	2012	2013	2015	2017
Beds in hospitals (per hundred thousand inhabitants)											
Mean	584.3	577.4	570.9	563.2	551.0	547.5	541.9	546.9	533.8	527.7	524.17
Std.Dev	204.9	200.8	195.2	193.6	195.1	236.6	237.6	251.3	238.8	240.5	201.52
Max.	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg	Mecklenburg
	1,231.39	1,223.49	1,221.63	1,241.58	1,252.69	1,268.18	1,272.73	1,276.27	1,290.28	1,301.57	1.282.89
Min.	Alentejo	Alentejo	Alentejo	Alentejo	Alentejo	Alentejo	Alentejo	Ceuta	Ceuta	Ceuta	Melilla
	225.89	230.43	225.71	223.18	208.28	211.80	225.00	216.17	212.75	210.21	189.74
Beds in nursing and residential care facilities (per hundred thousand inhabitants)											
Mean	700.5	706.6	718.3	722.6	741.1	702.4	775.2	806.5	788.3	817.7	821.4
Std.Dev	489.4	482.7	483.5	469.7	488.7	491.9	468.8	492.7	496.0	487.5	495.5
Max.	Övre Norrland	Övre Norrland	Övre Norrland	Övre Norrland	Övre Norrland	Mellersta Norrland	Mellersta Norrland	Mellersta Norrland	Castilla y León	Castilla-la Mancha	Castilla-la Mancha
	1,569.22	1,521.35	1,494.39	1,471.38	1,441.59	1,904.94	1,832.55	1,798.45	1,780.84	2,226.85	2,228.81
Min.	Campania	Campania	Campania	Campania	Campania	Greece	Kriti	Greece	Greece	Greece	Greece
	27.34	25.27	34.04	34.91	36.64	13.29	5.70	14.92	17.49	16.75	17.01
Medical doctors											
Mean	331.9	330.4	336.2	339.0	351.4	356.4	364.0	364.4	367.5	375.4	376.49
Std.Dev	92.3	93.4	96.6	102.2	120.0	130.4	127.3	115.8	115.3	116.4	112.20
Max.	Praha	Praha	Attiki	Attiki	Attiki	Ceuta	Ceuta	Attiki	Attiki	Attiki	Attiki
	662.97	669.08	684.73	712.79	845.41	976.25	959.81	867.30	867.27	865.00	791.92
Min.	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland	Flevoland
	131.72	134.96	132.87	126.94	126.28	129.77	134.60	135.02	132.28	127.32	124.96
Nurses											
Mean	770.96	795.42	835.03	823.11	850.31	869.20	880.89	890.83	876.51	852.77	847.31
Std.Dev	326.10	336.05	354.45	372.72	373.04	377.10	384.54	386.47	395.86	389.88	366.04
Max.	Denmark	Denmark	Switzerland	Nordjylland	Syddanmark	Midtjylland	Midtjylland	Syddanmark	Switzerland	Syddanmark	Switzerland
	1.423.16	1.463.40	1.478.46	1.548.70	1.621.87	1.623.54	1.612.07	1.729.43	1.767.10	1.797.58	1.826.62
Min.	Sterea Ellada	Sterea Ellada	Sterea Ellada	Luxembourg	Sterea Ellada	Sterea Ellada	Sterea Ellada	Sterea Ellada	Sterea Ellada	Sterea Ellada	Sterea Ellada
	130.61	135.5	131.44	34.17	143.07	150.18	149.73	139.76	145.8	151.66	137.57

Source: own work using data from Eurostat. Regional healthcare indicators.
Data for the number of beds in nursing and residential care facilities are not disaggregated by region in Greece.

Table A8. Dependent variables for men and women

	Men		Women		Test equality of means	
	N	Mean	N	Mean	t	p-value
Hospitalization during last year	68,647	0.161	88,332	0.147	t = -7.2336	0.0000
Length of stay at hospital (days per year)[a]	11,022	11.457	13,006	11.456	t = -0.0037	0.9970
		(18.461)		(19.239)		
Outpatient visit with doctor/nurse during last year	68,647	0.875	88,332	0.907	t = 19.8880	0.0000
Number of outpatient visit with doctor/nurse	60,045	7.308	80,077	7.757	t = 8.7435	0.0000
		(9.393)		(9.623)		
Stayed at nursing home	68,647	0.003	88,332	0.005	t = 4.7061	0.0000
Length of stay at nursing home (weeks per year)	233	25.579	434	26.158	t = 0.3088	0.7576
		(22.639)		(23.203)		
Received formal care for personal care	68,647	0.011	88,332	0.015	t = 6.4934	0.0000
Hours receiving formal care for personal care (per year)	771	114.798	1,322	157.004	t = 1.1688	0.2428
		(550.394)		(664.638)		
Consumed any prescribed drug (during a week) [b]	68,647	0.729	88,332	0.771	t = 18.8861	0.0000
Number of prescribed drugs consumed (during a week)	50,048	2.190	68,088	2.426	t = 27.1876	0.0000
		(1.391)		(1.578)		
Polypharmacy (5 or more prescribed drugs)	50,048	0.089	68,088	0.123	t = 21.6998	0.0000

Northern countries: Denmark, Sweden and Poland
Southern countries: Greece, Italy and Spain.
[a] Considering all hospitalizations.
[b] The following categories of prescribed drugs are considered: (1) high blood cholesterol, (2) high blood pressure, (3) coronary or cerebrovascular diseases, (4) other heart diseases, (5) asthma, (6) diabetes, (7) joint pain or for joint inflammation, (8) other pain (e.g. headache, back pain, etc.), (9) drugs for sleep problems, (10) anxiety or depression, (11) osteoporosis (hormonal), (12) osteoporosis (other than hormonal), (13) stomach burns, (14) chronic bronchitis, (15) suppressing inflammation (only glycocorticoids or steroids), (16) other drugs, not yet mentioned.
Source: SHARE waves (1, 2, 4, 5,6, and 7). Standard errors between parenthesis.
T-test assuming unequal variances. Satterthwaite's degrees of freedom is an alternative way to calculate the degrees of freedom that takes into account that the variances are assumed to be unequal.

Table A9. Dependent variables for Northern and Southern samples

	Northern countries		Southern countries		Test equality of means	
	N	Mean	N	Mean	t	p-value
Hospitalization during last year	39,647	0.143	39,009	0.126	t = -5.8626	0.0000
Length of stay at hospital (days per year)[a]	5,667	10.190	4,924	11.139	t = 4.8632	0.0000
		(17.681)		(19.367)		
Consultations with doctor/nurse during last year	39,647	0.846	39,009	0.792	t = 20.7815	0.0000
Number of consultations with doctor/nurse	33,550	6.083	30,883	7.963	t = 34.0262	0.0000
		(7.945)		(10.206)		
Stayed at nursing home	39,647	0.005	39,009	0.005	t = 0.4103	0.6816
Length of stay at nursing home (weeks per year)	219	29.828	215	30.823	t = -0.5004	0.6172
		(23.149)		(22.744)		
Received formal care for personal care	39,647	0.015	39,009	0.0008	t = 7.4364	0.0000
Hours receiving formal care for personal care (per year)	596	181.121	329	152.067	t = -0.3628	0.7171
		(732.167)		(592.526)		
Consumed any prescribed drug (during a week) [b]	39,647	0.818	39,009	0.734	t = 19.6768	0.0000
Number of prescribed drugs consumed (during a week)	32,448	2.289	28,605	2.358	t = 11.4097	0.0000
		(1.471)		(1.558)		
Polypharmacy (5 or more prescribed drugs)	32,448	0.097	28,605	0.114	t = 14.1277	0.0000

Northern countries: Denmark, Sweden and Poland

Southern countries: Greece, Italy and Spain.

[a] Considering all hospitalizations.

[b] The following categories of prescribed drugs are considered: (1) high blood cholesterol, (2) high blood pressure, (3) coronary or cerebrovascular diseases, (4) other heart diseases, (5) asthma, (6) diabetes, (7) joint pain or for joint inflammation, (8) other pain (e.g. headache, back pain, etc.), (9) drugs for sleep problems, (10) anxiety or depression, (11) osteoporosis (hormonal), (12) osteoporosis (other than hormonal), (13) stomach burns, (14) chronic bronchitis, (15) suppressing inflammation (only glycocorticoids or steroids), (16) other drugs, not yet mentioned.

Source: SHARE waves (1, 2, 4, 5,6, and 7). Standard errors between parenthesis.

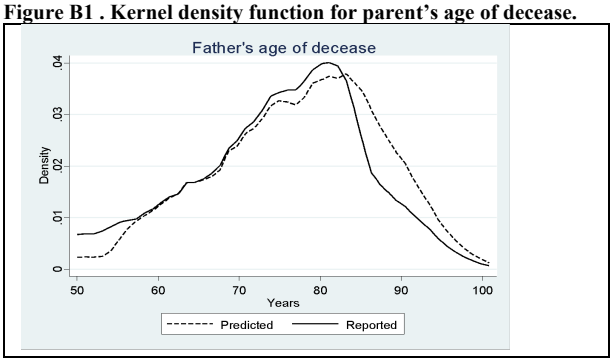
T-test assuming unequal variances. Satterthwaite's degrees of freedom is an alternative way to calculate the degrees of freedom that takes into account that the variances are assumed to be unequal.

Appendix B

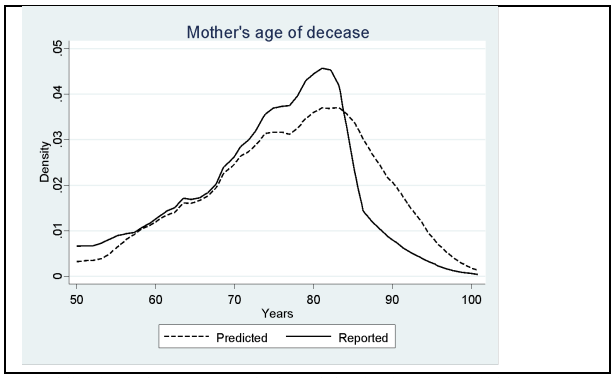
We have selected characteristics of the deceased respondents (EoLQ) that are also seen in the parents of respondents (MQ) who are still alive. These variables are the following: (a) sex, (b) age at death of respondent at the time of death (EoLQ) and age of the father/mother (MQ), (c) number of children of a deceased respondent (EoLQ) and the number of children of a father/mother (MQ), (d) frequency of contact of a deceased respondent with their children (EoLQ) and frequency of contact of a father/mother with the respondent (MQ), (e) distance between a deceased respondent's home and his/her children (EoLQ) and distance of a father/mother from his/her children (MQ), and (f) country and year fixed effects. The reason for including whether or not a person has children is based on evidence that indicates greater longevity for people with children (Modig et al., 2017). The reason for including the spatial distance between parents and children and the frequency of contact is because loneliness has been positively correlated with morbidity and mortality (Stressman et al., 2014). Although it is perfectly plausible that a father or mother could have other relatives, the parent/child link is the only one for which information is available in both the EoLQ and the MQ. Five different random seed values have been selected that produce five different allocations and yield very similar results[24].

Figure B1 presents the density function corresponding to the reported age at death (for parents who died prior to the survey) and the imputed age at death (for parents who were still alive at the time of the survey). Their age at death has been imputed using the procedure that was described above. The figure shows that for both fathers and mothers, the density function for the imputed age at death is to the right of the density function for the reported age at death. The table B1 separately presents (by interviewee gender) the descriptive statistics for the reported and imputed age at death of parents. For both men and women, the imputed age at death is two to three years older than the reported age at death of fathers and mothers.

Figure B1 . Kernel density function for parent's age of decease.



[24] The percentage of imputations amounts to 53.09% for mother's age of decease and 47.15% for father's age of decease (see Table B1).



Dashed line is used to represent the kernel density function of father's (mother's) age of decease for those fathers (mothers) who have died at the time of the survey. Straight line is used to represent the kernel density function of father's (mother's) age of decease for those fathers (mothers) who are still alive at time of the survey, and for whom age of decease has been predicted using multiple imputation.

Table B1. Parent's age of decease

	All sample		Men		Women	
	N	Age	N	Age	N	Age
Mother's age of decease						
Reported	73,638	81.54	32,988	81.68	40,650	81.42
		(8.76)		(8.61)		(8.88)
Predicted	83,341	83.28	35,659	83.79	47,682	82.88
		(6.52)		(6.31)		(6.66)
Father's age of decease						
Reported	82,960	78.96	37,113	79.30	45,847	78.69
		(9.08)		(8.96)		(9.18)
Predicted	74,019	82.37	31,534	83.01	42,485	81.90
		(5.63)		(5.33)		(5.80)

Own work using SHARE data and imputation procedure proposed by Rubin (1987).

Table B2. First stage regression for time to death (TTD, in years)

	Coef.		Coef.
Man & Father's age of decease	0.00061***	Large town	0.10919***
	(0.00019)		(0.01276)
Woman & Father's age of decease	0.00026***	Small town	0.10863***
	(0.00006)		(0.01229)
Man & Mother's age of decease	0.00080***	Rural area	0.11149***
	(0.00020)		(0.01213)
Woman & Mother's age of decease	0.00046**	Income	0.00008*
	(0.00019)		(0.00005)
Man	-0.11706***	Wealth	0.00002***
	(0.02354)		(0.00001)
Age	0.10036***	Married	0.00840
	(0.00284)		(0.00822)
Age squared	-0.00081***	Single	0.00611
	(0.00002)		(0.01251)
Pre-primary education and primary education	-0.09402***	Widow	0.01061
	(0.02701)		(0.00996)
Lower secondary education	-0.07280***	Constant	1.39242***
	(0.02715)		(0.10684)
Upper secondary education	-0.05795**	N	156,979
	(0.02687)	R2	0.27607
Post-secondary non-tertiary education	-0.06828**	F	202.81
	(0.02893)	p	0.0000
First stage of tertiary education	-0.04153		

Omitted categories: second stage of tertiary education, separated/divorce, living in big city. Standard errors between parenthesis. Income and wealth: 1,000PPP, 2015; adjusted by household size. Clusters by NUTS. Robust standard errors. Regression includes time fixed effects. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Table B3. Effect of the instrumental variables over outcome variables

	Probability of hospitalization	Length of stay at hospital (days per year)	Probability of Outpatient visit with doctor/nurse	Number of Outpatient visit with doctor/nurse (per year)
Man & Father's age at death	-0.00169**	-0.00066	0.00137	-0.00165
	(0.00082)	(0.00051)	(0.00101)	(0.00111)
Woman & Father's age at death	-0.00004	-0.00014	0.00185*	-0.00031
	(0.00074)	(0.00019)	(0.00099)	(0.00110)
Man & Mother's age at death	0.00074	-0.00017	0.00030	-0.00072
	(0.00091)	(0.00023)	(0.00112)	(0.00112)
Woman & Mother's age at death	-0.00106	0.00027	0.00208	-0.00117
	(0.00085)	(0.00022)	(0.00144)	(0.00111)
N	156.979	24.020	156.979	140.139
Loglikelihood	-29,600.63	-101,949.70	-20,896.83	-30,9412.85
Chi2	4,347.32	16,588.63	4,659.23	76,639.46
p	0.00000	0.00000	0.00000	0.00000
	Probability of staying at other institutions	**Days stayed at other institutions (per year)**	**Probability of staying at a nursing home**	**Weeks stayed at a nursing home (per year)**
Man & Father's age at death	-0.00240	-0.00346	-0.00090	-0.00200
	(0.00184)	(0.00233)	(0.00479)	(0.00151)
Woman & Father's age at death	-0.00227	-0.00169	-0.00220	0.00045
	(0.00153)	(0.00128)	(0.00304)	(0.00065)
Man & Mother's age at death	-0.00339*	-0.00499	0.00124	-0.00267
	(0.00204)	(0.00335)	(0.00496)	(0.00203)
Woman & Mother's age at death	-0.00038	-0.00401	-0.00375	-0.00703
	(0.00186)	(0.00331)	(0.00322)	(0.00570)
N	156.979	3.850	156.979	668
Loglikelihood	-7,994.72	-27,376.14	-1,908.44	-4,045.95
Chi2	1,478.61	7,465.01	604.70	1,589.02
p	0.00000	0.00000	0.00000	0.00000
	Probability of receiving formal care for personal care	**Number of hours receiving personal care (per year)**	**Probability of consuming any prescribed drug**	**Number of prescribed drugs consumed (per week)**
Man & Father's age at death	-0.00335	-0.00600	-0.00166	-0.00134
	(0.00239)	(0.00432)	(0.00103)	(0.00097)
Woman & Father's age at death	-0.00008	-0.00979	-0.00163	-0.00070
	(0.00183)	(0.00718)	(0.00179)	(0.00051)
Man & Mother's age at death	-0.00624*	0.00658	-0.00093	-0.00038
	(0.00359)	(0.00532)	(0.00093)	(0.00029)
Woman & Mother's age at death	0.00005	-0.00879	-0.00126	-0.00043
	(0.00202)	(0.00618)	(0.00094)	(0.00054)
N	156.979	2.095	156.979	118.159
Loglikelihood	-5,026.17	-116,538.79	-30,790.157	-82,085.43
Chi2	1,767.84	149,356.63	13,124.85	20,681.53
p	0.00000	0.00000	0.00000	0.00000
	Probability of consuming 5 or more prescribed drugs			
Man & Father's age at death	-0.00473			
	(0.00305)			
Woman & Father's age at death	-0.00221			
	(0.00182)			
Man & Mother's age at death	-0.00145			
	(0.00113)			
Woman & Mother's age at death	-0.00124			
	(0.00093)			
N	118.159			
Loglikelihood	-20,927.45			
Chi2	10,777.22			
p	0.00000			

Logit with fixed effects for binary variables. Truncated Poisson for count data variables. Other variables included in all the regressions: age, age squared, marital status, size of municipality, income and wealth (1,000PPP, 2015; adjusted by household size), Charlston Comorbidity Index and year fixed effects. Standard errors between parenthesis. Income and wealth:. Clusters by NUTS. Robust standard errors. Regression includes time fixed effects. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Table B4. Effect of instrumental variables over respondent's lifestyle variables. Marginal effects.

	Sedentary lifestyle	Overweight	Obese	Ever smoked daily	Smoke at present time	At least one alcoholic beverage the last 7 days
Man & Father's age of decease	-0.0008	0.0003*	-0.0004	0.0003	0.0000	0.0002*
	(0.0007)	(0.0002)	(0.0005)	(0.0011)	(0.0001)	(0.0001)
Woman & Father's age of decease	-0.0010	0.0006	-0.0003*	0.0002	-0.0001	0.0004
	(0.0008)	(0.0007)	(0.0001)	(0.0001)	(0.0001)	(0.0005)
Man & Mother's age of decease	-0.0007	0.0002	-0.0006	-0.0002	-0.0005	0.0002*
	(0.0005)	(0.0001)	(0.0008)	(0.0008)	(0.0007)	(0.0001)
Woman & Mother's age of decease	-0.0006	0.0004	-0.0002	-0.0004	-0.0004	0.0003*
	(0.0005)	(0.0006)	(0.0010)	(0.0005)	(0.0006)	(0.0002)
Male	-0.0169	0.0755***	-0.0403***	0.1273***	0.0625***	0.1054***
	(0.0120)	(0.0188)	(0.0154)	(0.0133)	(0.0122)	(0.0132)
Age	-0.0463***	0.0226***	0.0293***	-0.0387***	-0.0250***	0.0087***
	(0.0014)	(0.0023)	(0.0019)	(0.0016)	(0.0015)	(0.0016)
Age^2	0.0004***	-0.0002***	-0.0002***	0.0002***	0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Married	-0.0087**	0.0032	-0.0177***	-0.0099**	-0.0369***	0.0078**
	(0.0035)	(0.0055)	(0.0045)	(0.0039)	(0.0035)	(0.0038)
Separated	-0.0110**	-0.0336***	-0.0165**	0.0122**	0.0291***	-0.0033
	(0.0051)	(0.0079)	(0.0065)	(0.0056)	(0.0051)	(0.0056)
Single	0.0124**	-0.0572***	-0.0322***	-0.0254***	-0.0028	-0.0057
	(0.0060)	(0.0093)	(0.0077)	(0.0066)	(0.0060)	(0.0066)
Big city	-0.0078**	0.0071	-0.0180***	0.0387***	0.0294***	0.0093***
	(0.0031)	(0.0049)	(0.0040)	(0.0035)	(0.0032)	(0.0034)
Large town	-0.0043	0.0117**	-0.0121***	0.0318***	0.0202***	-0.0039
	(0.0035)	(0.0055)	(0.0045)	(0.0039)	(0.0036)	(0.0039)
Small town	-0.0072**	0.0072	-0.0067*	0.0099***	0.0038	0.0081**
	(0.0031)	(0.0048)	(0.0039)	(0.0034)	(0.0031)	(0.0034)
Pre-primary education and primary education	0.0809***	0.0589***	0.0869***	0.0384**	0.0278**	-0.0107
	(0.0138)	(0.0215)	(0.0177)	(0.0153)	(0.0139)	(0.0152)
Lower secondary education	0.0320**	0.0621***	0.0752***	0.0377**	0.0465***	-0.0253*
	(0.0138)	(0.0217)	(0.0178)	(0.0154)	(0.0140)	(0.0152)
Upper secondary education	0.0101	0.0540**	0.0603***	0.0319**	0.0280**	-0.0331**
	(0.0137)	(0.0214)	(0.0176)	(0.0152)	(0.0139)	(0.0151)
Post-secondary non-tertiary education	-0.0062	0.0455**	0.0517***	0.0305*	0.0237	-0.0769***
	(0.0148)	(0.0231)	(0.0190)	(0.0164)	(0.0149)	(0.0163)
First stage of tertiary education	-0.0052	0.0355*	0.0051	0.0207	0.0010	-0.0177
	(0.0138)	(0.0215)	(0.0177)	(0.0153)	(0.0139)	(0.0152)
Income (1,000PPP, 2015; adjusted by household size)	-0.0001***	0.0000	-0.0002***	0.0003***	0.0000	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wealth (1,000PPP, 2015; adjusted by household size)	-0.0000***	-0.0000***	-0.0001***	-0.0000***	-0.0000***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1.5652***	-0.4815***	-0.6275***	1.6281***	1.2251***	-0.2350***
	(0.0517)	(0.0809)	(0.0665)	(0.0575)	(0.0524)	(0.0570)
N	156,979	156,979	156,979	156,979	156,979	156,979
Log likelihood	-23,514.304	-47,698.893	-35,557.054	-25,406.613	-24,122.142	-26,712.771
chi2	6,471.095	1,277.353	1,573.318	9,854.335	4,192.877	5,230.457
p	0.000	0.000	0.000	0.000	0.000	0.000

Overweight: 1 if body mass index is between 25 and 30, 0 otherwise.
Obese: 1 if body mass index is higher than 30, 0 otherwise.
Sedentary lifestyle: 1 if engaged in vigorous physical activity, such as sports, heavy housework, or a job that involves physical labour less than once a week, 0 otherwise.
Omitted categories: widow, second stage of tertiary education, rural area or village. All models include country and year fixed effects as regressors. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Appendix C

Table C1. Estimations for the intensive margin using a truncated Poisson or a truncated negative binomial.

	Truncated Negative Binomial (IRR)					Truncated Poisson (IRR)				
	Exogenous TTD			TTD (IV)		Exogenous TTD			TTD (IV)	
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Hospitalization	**Length of stay at hospital (days per year)**					**Length of stay at hospital (days per year)**				
Age	1.020	1.032*	1.010	1.055***	1.009	1.031**	1.054***	1.034***	1.053***	1.023*
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age^2	1.000	1.000	1.000	1.000***	1.000	1.000	1.000***	1.000**	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		0.795***	0.812***	0.618***	0.818***		0.828***	0.847***	0.840***	0.951***
		(0.011)	(0.014)	(0.031)	(0.046)		(0.008)	(0.009)	(0.035)	(0.034)
CCI			1.200***		1.201***			1.146***		1.153***
			(0.016)		(0.017)			(0.013)		(0.013)
Constant	2.309	4.330**	7.218***	6.143***	7.150***	2.674**	2.962**	4.619***	2.911**	4.055***
	-1.507	-2.815	-4.752	-4.052	-4.764	(1.213)	(1.347)	(2.119)	(1.361)	(1.893)
Alpha	2.799***	2.635***	2.474***	2.622***	2.474***					
	(0.235)	(0.213)	(0.196)	(0.212)	(0.196)					
N	24,020	24,020	24,020	24,020	24,020	24,020	24,020	24,020	24,020	24,020
Log-likelihood	-279,567.2	-279,355.5	-279,107.8	-279,335.8	-279,107.8	-218,658.6	-213,452.4	-208,370.2	-203,409.0	-198,566.0
AIC	559,142.5	558,721.1	558,227.6	558,683.6	558,229.6	437,397.2	426,983.0	416,816.7	406,892.5	397,204.6
BIC	559,174.8	558,761.5	558,276.1	558,732.1	558,286.2	437,720.7	427,298.8	417,125.0	407,193.5	397,498.4
Chi2	97.769	280.956	536.155	329.821	547.260	111.811	483.975	773.145	487.113	757.891
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outpatient visit	**Outpatient visitwith doctor/nurse (intensive margin)**					**Outpatient visit with doctor/nurse (intensive margin)**				
Age	1.015*	1.026***	0.997	1.070***	0.995	1.015**	1.030***	1.004	1.057***	0.999
	(0.008)	(0.009)	(0.007)	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.006)
Age^2	1.000	1.000*	1.000	1.000***	1.000	1.000	1.000***	1.000	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		0.853***	0.894***	0.527***	0.915***		0.876***	0.911***	0.658***	0.953**
		(0.008)	(0.007)	(0.029)	(0.029)		(0.006)	(0.006)	(0.026)	(0.018)
CCI			1.407***		1.409***			1.307***		1.310***
			(0.015)		(0.015)			(0.011)		(0.011)
Constant	2.332***	3.185***	6.364***	6.489***	6.181***	3.078***	3.375***	6.559***	4.992***	6.189***
	(0.670)	(0.930)	-1.595	-1.912	-1.538	(0.688)	(0.767)	(1.349)	(1.164)	(1.270)
Alpha	1.337***	1.317***	1.076	1.293***	1.076					
	(0.065)	(0.063)	(0.049)	(0.062)	(0.049)					
N	140,139	140,139	140,139	140,139	140,139	140,139	140,139	140,139	140,139	140,139
Log-likelihood	-812,159.1	-811,738.8	-805,466.2	-811,224.1	-805,465.3	-664,679.6	-648,853.9	-633,405.0	-618,323.9	-603,601.9
AIC	1,824,326	1,823,487	1,810,944	1,822,460	1,810,944	1,329,439.0	1,297,785.7	1,266,886.0	1,236,722.1	1,207,276.3
BIC	1,824,365	1,823,536	1,811,003	1,822,519	1,811,013	1,329,833.0	1,298,170.3	1,267,261.5	1,237,088.6	1,207,634.1
Chi2	298.681	493.500	1,193.826	637.600	1,198.945	305.588	498.450	1.048.862	700.224	1.075.492
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stays nursing home	**Nursing home stays (weeks per year)**					**Nursing home stays (weeks per year)**				
Age	0.847***	0.850***	0.864**	0.846***	0.864**	0.865***	0.867***	0.884***	0.859***	0.877***
	(0.048)	(0.048)	(0.050)	(0.049)	(0.050)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age^2	1.001***	1.001***	1.001**	1.001***	1.001**	1.001***	1.001***	1.001***	1.001***	1.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		0.972	0.970	1.031	1.075 **		0.967***	0.963***	1.073***	1.034**
		(0.040)	(0.040)	(0.139)	(0.031)		(0.004)	(0.004)	(0.014)	(0.014)
CCI			0.925*		0.905***			0.910***		0.914***
			(0.038)		(0.009)			(0.005)		(0.005)
Constant	10177***	10317***	5965***	9209***	5920***	5,740***	6,133***	3,323***	5,542***	3,193***
	-21.098	-21.359	-12.421	-19.202	-12.370	(1,222.08)	(1,307.23)	(717.62)	(1,182.57)	(690.08)
	1.917***	1.914***	1.894***	1.913***	1.894***					
	(0.185)	(0.185)	(0.182)	(0.185)	(0.182)					
N	668	668	668	668	668	668	668	668	668	668
Log-likelihood	-12.716.1	-12.715.8	-12.714.1	-12.715.7	-12.714.1	-7,647.2	-7,465.1	-7,287.3	-7,113.8	-6,944.5
AIC	25,440.2	25,441.7	25,440.2	25,443.5	25, 442.2	15,374.3	15,008.3	14,650.9	14,302.1	13,961.6
BIC	25,458.1	25,464.1	25,467.1	25,470.3	25,473.5	15,553.5	15,183.1	14,821.6	14,468.7	14,124.2
Chi2	9.701	10.182	13.673	10.400	13,675	572.234	623.327	917.038	690.499	947.197
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Personal care	**Home care (hours per year)**					**Home care (hours per year)**				
Age	1.057***	0.777***	0.782***	0.666***	0.675***	1.092***	1.072***	1.072***	1.132***	1.136***
	(0.004)	(0.070)	(0.071)	(0.067)	(0.067)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	1.000***	1.002***	1.002***	1.003***	1.001***	1.000***	1.000***	1.000***	0.999***	0.999***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	0.936***	0.733***	0.730***	1.452*	0.613***		1.237***	1.237***	0.706***	0.696***
	(0.004)	(0.067)	(0.067)	(0.299)	(0.003)		(0.001)	(0.001)	(0.002)	(0.002)
CCI			0.947		1.145**			1.003***		1.080***
			(0.054)		(0.005)			(0.001)		(0.001)
Constant	0.092***	0.009	0.003	0.092	0.071	2.888***	2.347***	2.363***	4.407***	4.234***
	(0.012)	-2.658	(0.648)	-26.475	-20.663	(0.112)	(0.091)	(0.092)	(0.172)	(0.165)
Alpha	0.238***	2,64E+11	5,38E+11	2,54E+11	2,06E+11					
	(0.005)	-7,69E+13	-1,01E+14	-7,31E+13	-6,01E+13					
N	2,095	2,095	2,095	2,095	2,095	2,095	2,095	2,095	2,095	2,095
Log-likelihood	-276,748.4	-275,214.8	-275,214.4	-275,204.7	-275,204.6	-232,886.3	-227,341.4	-221,928.5	-216,644.5	-211,486.3
AIC	513,508.8	510,441.7	510,442.8	510,425.5	510,425.2	465,832.7	454,741.4	443,914.3	433,344.9	423,027.1
BIC	513,566.7	510,471.9	510,478.0	510,465.8	510,465.4	465,984.6	454,889.7	444,059.0	433,486.2	423,165.1
Chi2	71.343	83.680	84.564	103.882	104.231	330,768.242	385,346.242	385,358.220	439,649.931	440,320.107
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Prescribed drugs	**Prescription drug consumed (drugs per week)**					**Prescription drug consumed (drugs per week)**				
Age	1.068***	1.074***	1.038***	1.173***	1.041***	1.066***	1.072***	1.039***	1.125***	1.039***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Age^2	1.000***	1.000***	1.000***	0.999***	1.000***	1.000***	1.000***	1.000***	0.999***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD		0.941***	0.989***	0.357***	0.955		0.951***	0.998	0.562***	0.990
		(0.004)	(0.004)	(0.007)	(0.013)		(0.003)	(0.003)	(0.006)	(0.009)
CCI			1.425***		1.422***			1.395***		1.394***
			(0.003)		(0.003)			(0.002)		(0.002)
Constant	0.095***	0.101***	0.254***	0.373***	0.265***	0.122***	0.124***	0.253***	0.248***	0.256***
	(0.012)	(0.013)	(0.027)	(0.047)	(0.029)	(0.011)	(0.011)	(0.023)	(0.022)	(0.023)
	0.279***	0.277***	0.058***	0.220***	0.058***					
	(0.006)	(0.006)	(0.003)	(0.005)	(0.003)					
N	118,159	118,159	118,159	118,159	118,159	118,159	118,159	118,159	118,159	118,159
Log-likelihood	-384.198.4	-384,111.5	-371,443.4	-382,590.6	-371,439.9	-170,029.2	-165,980.9	-162,029.0	-158,171.1	-154,405.1
AIC	368,404.9	368,233.0	342,898.8	365,193.2	342,893.9	340,138.3	332,039.8	324,134.1	316,416.6	308,882.9
BIC	368,443.6	368,281.4	342,956.9	365,251.2	342,961.7	340,525.5	332,417.8	324,503.0	316,776.8	309,234.5
Chi2	24,235.8	24,409.7	29,745.9	27,451.5	29,752.8	12,103.814	12,449.715	48,742.386	15,111.931	48,743.353
p	0.000	0.000	0.000	0.000	0.000					

This table reports different specifications of age, TTD and morbidity effect on health care use on the intensive margin using truncated Poisson or a truncated negative binoimal. M1 includes age, age squared, marital status, income and wealth adjusted by the number of household members, municipality size, healthcare resources by NUTS, and the year fixed effects as regressors. TTD is included in the M2 model. CCI is included in the M3 model. M4 and M5 contain the same explanatory variables as M2 and M3, except that IV is used for TTD (CF for logit with fixed effects and a GMM truncated Poisson). Marginal effects are offered for the logit models, and the incidence risk ratio are shown for the truncated Poisson models . Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Table C2. Dependent variables for initial sample and final sample

	Initial sample		Final sample		Test equality of means	
	N	Mean	N	Mean	t	p-value
Hospitalization during last year	288,555	0.154	156,979	0.153	t = 0.6641	0.7466
Length of stay at hospital (days per year)[a]	44,423	12.045	24,020	11.83	t = 0.8424	0.7880
		(20.641)		(20.071)		
Outpatient visit with doctor/nurse during last year	288,555	0.885	156,979	0.889	t = 0.6022	0.7264
Number of Outpatient visits with doctor/nurse	255,253	7.68	140,139	7.60	t = 0.8560	0.8043
		(9.925)		(9.741)		
Stayed at nursing home	288,555	0.005	156,979	0.005	t = 0.5049	0.6931
Length of stay at nursing home (weeks per year)	1,585	27.44	668,000	27.61	t = 1.2923	0.1968
		(22.995)		(23.130)		
Received formal care for personal care	288,555	0.015	156,979	0.013	t = 0.6575	0.7445
Hours receiving formal care for personal care (per year)	4,481	256.22	2,095	257.83	t = 0.9823	0.8369
		(768.959)		(772.014)		
Consumed any prescribed drug (during a week) [b]	288,555	0.746	118,159	0.749	t = 0.2004	0.5792
Number of prescribed drugs consumed (during a week)	215,143	2.31	118,159	2.33	t = 0.5677	0.7156
		(1.508)		(1.513)		
Polypharmacy (5 or more prescribed drugs)	215,143	0.136	118,159	0.144	t = 0.5571	0.7088

[a] Considering all hospitalizations.

[b] The following categories of prescribed drugs are considered: (1) high blood cholesterol, (2) high blood pressure, (3) coronary or cerebrovascular diseases, (4) other heart diseases, (5) asthma, (6) diabetes, (7) joint pain or for joint inflammation, (8) other pain (e.g. headache, back pain, etc.), (9) drugs for sleep problems, (10) anxiety or depression, (11) osteoporosis (hormonal), (12) osteoporosis (other than hormonal), (13) stomach burns, (14) chronic bronchitis, (15) suppressing inflammation (only glycocorticoids or steroids), (16) other drugs, not yet mentioned.

Source: SHARE waves (1, 2, 4, 5,6, and 7). Standard errors between parenthesis.

T-test assuming unequal variances. Satterthwaite's degrees of freedom is an alternative way to calculate the degrees of freedom that takes into account that the variances are assumed to be unequal.

Table C3. Effect of attrition over dependent variables. Marginal effects for binary dependent variables after logistic regression.

	Hospitalization	Outpatient visit doctor/nurse	Stay at nursing homes	Receives formal care for personal care	Consumes any prescribed drug	Polypharmacy (at least 5 prescribed drugs)
Present in the final sample	0.998	1.002	1.013***	1.005	1.001	0.997
	(0.003)	(0.005)	(0.003)	(0.006)	(0.001)	(0.003)
Male	1.030**	0.992	0.993***	1.010**	0.979	0.981
	(0.015)	(0.011)	(0.003)	(0.005)	(0.015)	(0.012)
Age	0.998	1.014***	0.996***	0.993***	1.052***	1.013***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.002)
Age^2	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.981***	1.007*	0.998***	0.987***	0.994	0.986***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)
Separated	1.007	1.001	0.999	0.994***	0.989*	0.994
	(0.006)	(0.001)	(0.001)	(0.002)	(0.006)	(0.005)
Single	0.984**	0.979***	0.986***	0.996*	0.987*	0.980***
	(0.007)	(0.006)	(0.002)	(0.002)	(0.007)	(0.006)
Big city	0.988***	1.006*	1.004***	0.999	1.008**	1.004
	(0.004)	(0.003)	(0.001)	(0.001)	(0.004)	(0.003)
Large town	0.989***	0.990***	0.999	0.999	1.009**	1.010***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.005)	(0.004)
Small town	0.994	1.000	0.999	1.003**	1.020***	1.006*
	(0.004)	(0.003)	(0.001)	(0.001)	(0.004)	(0.003)
Pre-primary and primary education	0.985	0.977*	1.003	1.000	1.084***	1.052***
	(0.016)	(0.013)	(0.003)	(0.001)	(0.019)	(0.015)
Lower secondary education	0.988	0.976*	1.003	0.997	1.067***	1.022
	(0.016)	(0.013)	(0.003)	(0.006)	(0.019)	(0.015)
Upper secondary education	0.998	0.980	1.003	0.999	1.046***	1.003
	(0.016)	(0.013)	(0.003)	(0.005)	(0.018)	(0.014)
Post-secondary non-tertiary education	0.995	0.972**	1.001	0.993	1.026	0.982
	(0.017)	(0.014)	(0.003)	(0.006)	(0.019)	(0.015)
First stage of tertiary education	0.981	0.980	1.002	0.997	1.009	0.990
	(0.016)	(0.013)	(0.003)	(0.006)	(0.018)	(0.014)
Income (1,000PPP, 2015; adjusted by household size)	1.000	1.000*	1.000	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wealth (1,000PPP, 2015; adjusted by household size)	1.000**	1.000	1.000	1.000	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.153**	1.404***	1.142***	1.247***	0.281***	0.687***
	(0.071)	(0.070)	(0.013)	(0.026)	(0.019)	(0.037)
N	288,555	288,555	288,555	288,555	288,555	288,555
Log likelihood	-31,284.156	-22,754.008	-2,004.991	-5,504.347	-34,381.220	-25,090.709
chi2	980.288	944.896	411.612	811.504	5,942.734	2,450.704
p	0.000	0.000	0.000	0.000	0.000	0.000

Present in the final sample: 1 if the individual belongs to the final sample, 0 otherwise. Omitted categories: widow, second stage of tertiary education, rural area or village. All models include country and year fixed effects as regressors. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Table C4. Effect of attrition over dependent variables. Incidence risk ratios computed for truncated Poisson regression.

	Length of stay at hospital	Number of Outpatient visits	Length of stay at nursing home	Hours of personal care received	Number of prescribed drugs
Present in the final sample	1.022	1.047	1.144***	0.990	1.000
	(0.033)	(0.046)	(0.027)	(0.043)	(0.001)
Male	1.092***	1.056***	0.927	0.282***	0.965
	(0.027)	(0.014)	(0.072)	(0.007)	(0.029)
Age	1.033***	1.025***	0.921***	0.826***	1.063***
	(0.004)	(0.002)	(0.010)	(0.003)	(0.005)
Age^2	1.000***	1.000***	1.001***	1.001***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.855***	0.992**	1.064**	0.961***	0.970***
	(0.006)	(0.004)	(0.031)	(0.009)	(0.009)
Separated	0.977**	1.023***	1.248***	0.516***	1.046***
	(0.011)	(0.006)	(0.060)	(0.011)	(0.014)
Single	0.942***	1.037***	1.360***	1.689***	0.943***
	(0.013)	(0.007)	(0.059)	(0.020)	(0.016)
Big city	0.876***	1.023***	0.878***	1.314***	1.018**
	(0.006)	(0.004)	(0.026)	(0.011)	(0.009)
Large town	0.857***	0.945***	0.840***	0.693***	1.035***
	(0.007)	(0.004)	(0.030)	(0.008)	(0.010)
Small town	0.871***	0.980***	0.848***	0.590***	1.016*
	(0.006)	(0.004)	(0.026)	(0.006)	(0.009)
Pre-primary and primary education	1.018	1.131***	1.636*	11.737***	1.127***
	(0.033)	(0.020)	(0.442)	-1.501	(0.049)
Lower secondary education	1.001	1.071***	1.506	7.977***	1.016***
	(0.033)	(0.019)	(0.408)	-1.023	(0.003)
Upper secondary education	1.127***	1.042**	1.592*	9.382***	2.966***
	(0.007)	(0.018)	(0.430)	-1.201	(0.025)
Post-secondary non-tertiary education	0.862***	0.930***	2.619***	17.287***	0.903**
	(0.031)	(0.017)	(0.726)	-2.247	(0.042)
First stage of tertiary education	0.844***	0.974	1.928**	1.144***	0.915**
	(0.028)	(0.017)	(0.523)	-1.044	(0.040)
Income (1,000PPP, 2015; adjusted by household size)	0.999***	0.999***	0.979***	1.002***	0.999***
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
Wealth (1,000PPP, 2015; adjusted by household size)	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3.897***	2.925***	539.503***	11101.685***	0.192***
	(0.493)	(0.189)	-259.587	-1.939.813	(0.031)
N	288,555	288,555	288,555	288,555	288,555
chi2	5,016.805	11,930.938	470.527	92,356.235	5,900.108
p	0.000	0.000	0.000	0.000	0.000

Present in the final sample: 1 if the individual belongs to the final sample, 0 otherwise. Omitted categories: widow, second stage of tertiary education, rural area or village. All models include country and year fixed effects as regressors. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Appendix D

Plausible exogeneity of the instruments:

The departure point is equation (1) in which we explicitly distinguish between the potential endogenous variable (TTD) and the other explanatory variables:

$$Y_{it} = X_{it}\beta + \lambda TTD_{it} + \eta_i + \delta_t + \varepsilon_{it} \qquad (C.1)$$

The first method is the γ-Local-to-Zero (LTZ) approximation bounds method, which introduces some bias term (or exogeneity error) in the approximate distribution of $\hat{\lambda}$. In other words, it relaxes the exclusion restriction requirement by allowing for uncertainty in the priors about γ. According to Conley et al., (2012) this method provides robustness with respect to 2SLS approach under the assumption that the priors are correct.

$$\hat{\lambda} \sim N(\lambda, \Sigma_{2SLS}) + \Pi\gamma \qquad (C.2)$$

$$\gamma \sim \Upsilon$$

$$\Pi = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z$$

Where Υ is the distribution of γ, Σ_{2SLS} is the variance-covariance matrix for the estimation 2SLS and Z is the vector of instrumental variables. The distribution of the exogeneity error ($\widehat{\Pi\gamma}$) depends on the sample moments of the matrix Π, which shows a negative relationship between the strength of the instrumental variable and the exogeneity error, and the distribution Υ. This exogeneity error is an indicator of the deviations of $\hat{\lambda}$ from the asymptotic standard distribution of the 2SLS estimator due to non-fulfilment of the exclusion restriction assumption.

It is assumed that γ follows a normal distribution with mean μ_γ and variance-covariance matrix Ω_γ. Then, the asymptotic distribution $\hat{\lambda}$ of can be expressed as:

$$\hat{\lambda} \sim N\left(\lambda + \Pi\mu_\gamma, \Sigma_{2SLS} + \Pi\Omega_\gamma\Pi'\right) \qquad (C.3)$$

Following Conley et al. (2012), we implement the simplest form of priors for γ, that is, $\gamma \sim N(0, \delta^2)$ and computed the 95% confidence intervals for λ for different values of δ. Under the assumption that priors are correct, this approach provides valid inference and robustness with respect to normal 2SLS approach.

The second method is the Union Confidence Interval (UCI), which allows us to analyse the robustness of the estimations in case of a direct relationship between the instrumental variables (parent's age of decease) and the outcome variables. Following Conley et al. (2012) equation (1) can be modified as follows:

$$Y_{it} = X_{it}\beta + \lambda TTD_{it} + PAD_{it}\gamma_0 + \eta_i + \delta_t + \varepsilon_{it} \qquad (C.4)$$

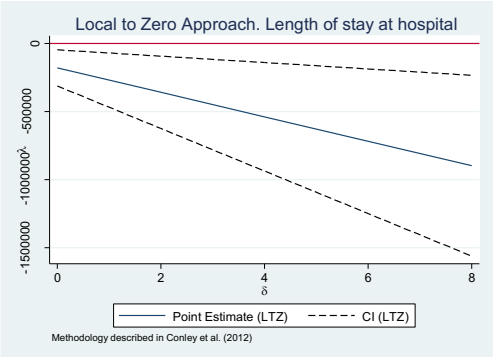
$$TTD_{it} = PAD_{it}\gamma_0 + X_{it}\beta + \zeta_i \qquad (C.5)$$

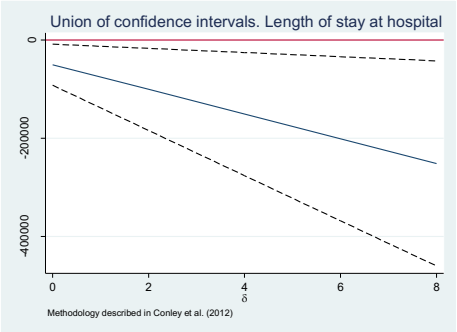
Where denotes PAD_{it} parent's age of decease. In a normal 2SLS estimation the term ($PAD_{it}\gamma_0$) would not be present in equation (C.4). If the strict exogeneity assumption is satisfied, parents' age of decease does not have any effect over outcome variables and thus $\gamma = 0$. The innovation proposed by Conley et a. (2012) consist in relaxing the strict exogeneity assumption ($\gamma \neq 0$) and checking its significance in the outcome equation. Then, allowing for non-zero γ, equation (C.4) can be expressed as (C.5) where we have assumed that $\gamma = \gamma_0$:

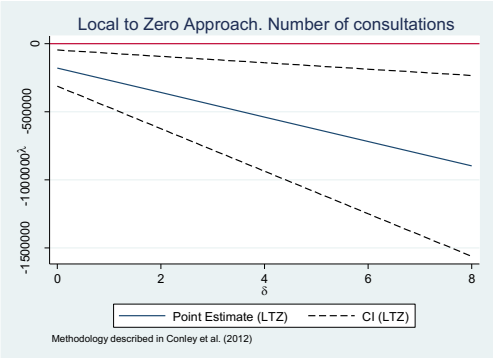
$$Y_{it} - PAD_{it}\gamma_0 = X_{it}\beta + \lambda TTD_{it} + \eta_i + \delta_t + \varepsilon_{it} \qquad (C.5)$$

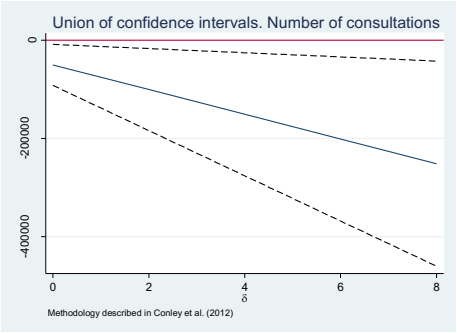
Considering that the outcome variable is now ($Y_{it} - PAD_{it}\gamma_0$), then λ can be consistently estimated using PAD as an instrument for TTD. Under the UCI approach, λ is estimated given any γ_0 belonging to the specific support interval for γ: $\gamma \in [-\delta, +\delta]$. Conley et al. (2012) notes that given that γ belongs to that interval, the union will contain the true parameter value for λ at least 95% of the time (if using a 95% confidence interval).

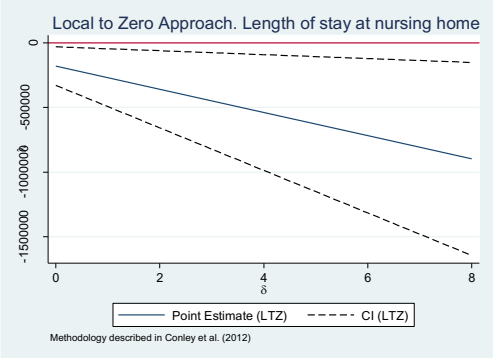
Figure D1. Local-to-Zero approximation and Union of Confidence Intervals. Test for instrument validity. [25]

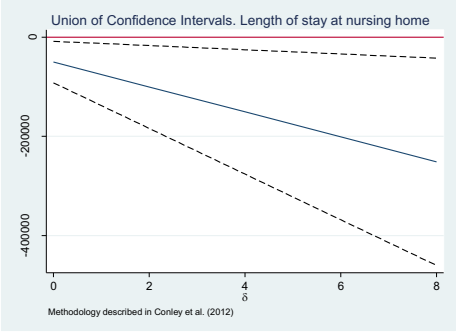


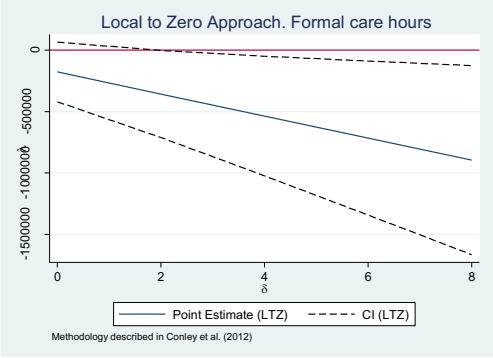


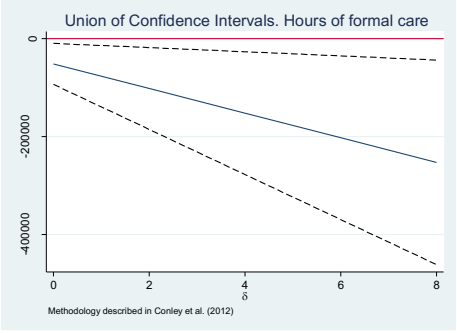




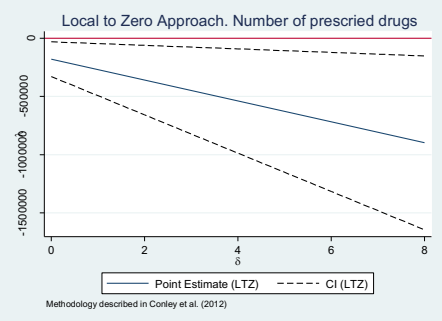


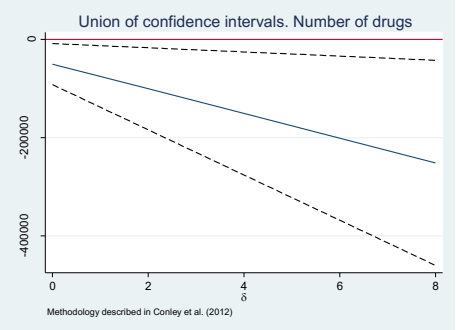






[25] These figures have been obtained using the command *plausexog* proposed by Clarke (2014) for STATA.



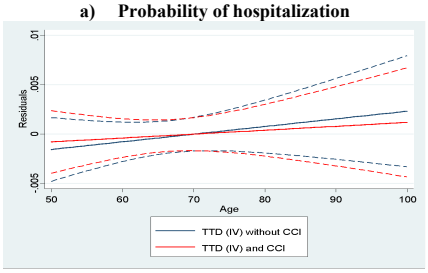


The γ -Local-to-Zero (LTZ) approximation bounds are drawn for different values of δ under the assumption that $\gamma \sim N(0, \delta^2)$. All the reported bounds are for the 95% confidence intervals generated with robust standard errors. The Union for Confidence Intervals (UCI) bounds are drawn for different values of δ, which define the support of γ (i.e., the true direct effect of parents' age of decease on TTD). Dash lines around the 2SLS estimation represent the upper and confidence intervals or the respective tests. The solid red line represents the value $\lambda = 0$. The solid black line in the γ -Local-to-Zero (LTZ) approximation represents the 2SLS class size effect estimate. Estimations performed using the command plausexog from STATA.

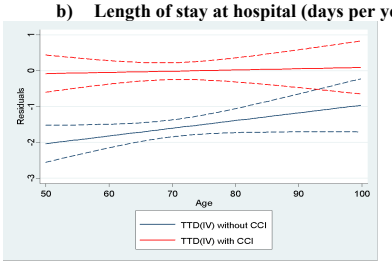
Appendix E

Figure E1. Comparison of residuals from logit and truncated Poisson models conditioned on including Charlston Comorbidity Index.

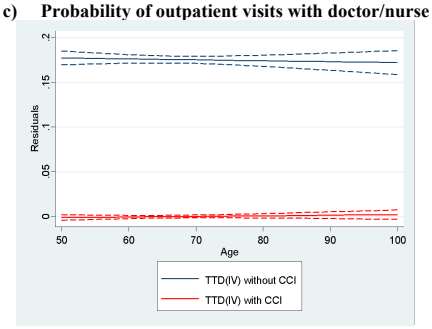
a) Probability of hospitalization



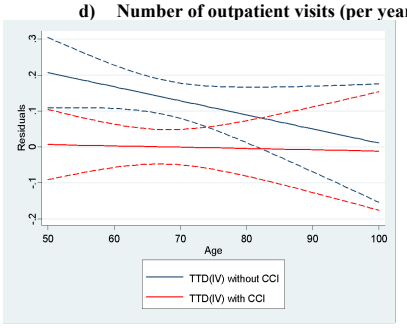
b) Length of stay at hospital (days per year)



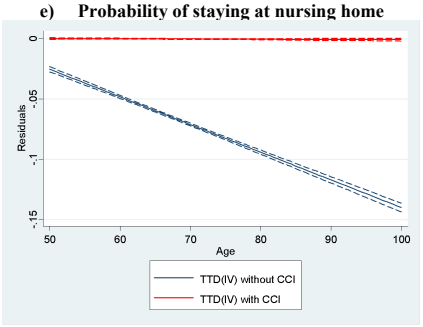
c) Probability of outpatient visits with doctor/nurse



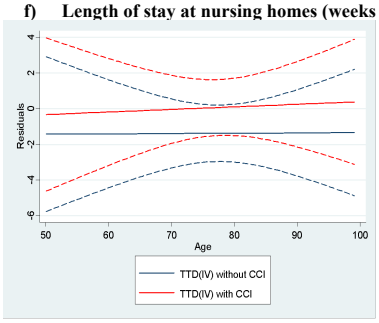
d) Number of outpatient visits (per year)



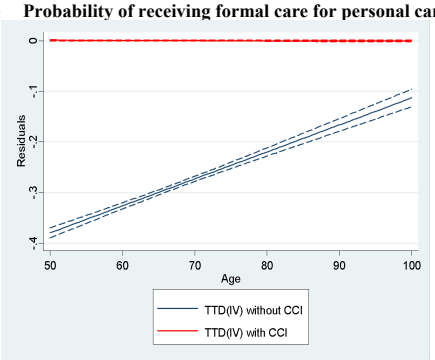
e) Probability of staying at nursing home



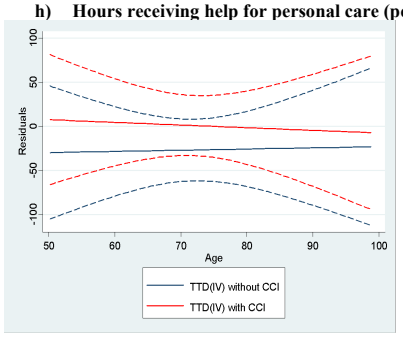
f) Length of stay at nursing homes (weeks per year)



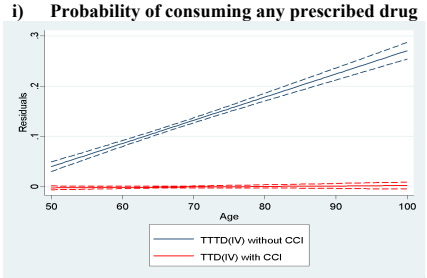
g) Probability of receiving formal care for personal care



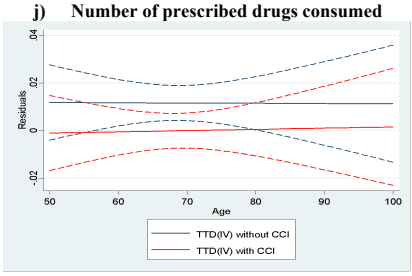
h) Hours receiving help for personal care (per year)



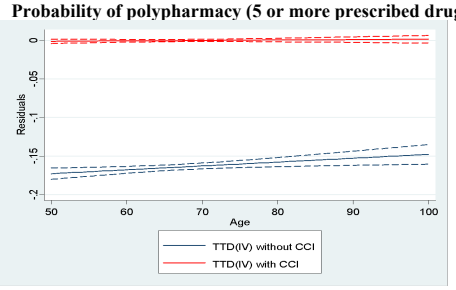
i) Probability of consuming any prescribed drug



j) Number of prescribed drugs consumed



k) Probability of polypharmacy (5 or more prescribed drugs)



Each graph compares residuals obtained from logit (binary outcomes) or truncated Poisson (count data outcomes) instrumenting time-to-death(TTD) with parent's age of decease. Blue straight line corresponds to residuals from regressions after including as explanatory variables age, age squared, marital status, income and wealth, size of municipality, healthcare provision by NUTS and year fixed effects. Red straight line corresponds to residuals from regressions that includes the same explanatory variables as before and also Charlston Comorbidity Index (CCI). Blue and red dashed lines corresponds to confidence intervals at 95% significance level.

Table E1. Gender Heterogeneity. Marginal effects reported for logit part; incidence rate ratios reported for truncated Poisson.

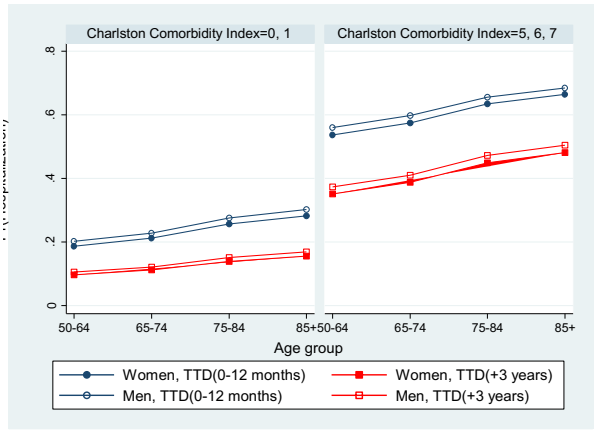
	Logit (marginal effects)				Truncated Poisson (IRR)			
	Men		Women		Men		Women	
	M4	M5	M4	M5	M4	M5	M4	M5
Hospital	**Hospitalization (extensive margin)**				**Length of stay at hospital (days per year)**			
Age	0.018***	0.003***	0.012***	0.005***	1.069***	1.028*	1.061***	1.022*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.023)	(0.021)	(0.019)	(0.010)
Age^2	-0.000***	0.000	-0.000***	0.000***	1.000***	1.000	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.175***	-0.039***	-0.172***	-0.025***	0.681***	0.848***	0.698***	0.869**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.047)	(0.049)	(0.057)	(0.061)
Resid 1st stage	0.035***	-0.004	0.039***	-0.005**				
	(0.002)	(0.003)	(0.002)	(0.002)				
CCI		0.081***		0.070***		1.160***		1.143***
		(0.002)		(0.001)		(0.019)		(0.020)
Constant	0.145**	0.135**	0.358***	0.294***	4.868**	6.473***	4.349**	5.245**
	(0.062)	(0.060)	(0.043)	(0.042)	(3.543)	(4.561)	(2.887)	(3.458)
N	68,647	68,647	88,332	88,332	11,022	11,022	13,006	13,006
Log-likelihood	-29,183.646	-28,024.289	-36,346.341	-35,185.103	-99,100.104	-97,089.482	-124,738.978	-122,860.428
AIC	58,393.292	56,076.577	72,718.682	70,398.207	198,210.207	194,190.963	249,487.957	245,732.855
BIC	58,511.962	56,204.375	72,840.820	70,529.740	198,246.704	194,234.759	249,525.354	245,777.732
Chi2	1,625.038	3,943.753	1,605.567	3,928.042	193.183	428.841	184.495	320,517
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outpatient visits	**Outpatient visits with doctor/nurse (extensive margin)**				**Number of Outpatient visits with doctor/nurse (intensive margin**			
Age	0.028***	0.016***	0.020***	0.009***	1.103***	1.023**	1.097***	0.998
	(0.002)	(0.002)	(0.001)	(0.001)	(0.013)	(0.010)	(0.017)	(0.008)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	0.999***	1.000	0.999***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.087***	-0.018**	-0.087***	-0.026 **	0.549***	0.952*	0.409***	0.899***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.036)	(0.027)	(0.054)	(0.034)
Resid 1st stage	0.026***	-0.002	0.027***	-0.001				
	(0.002)	(0.002)	(0.002)	(0.002)				
CCI		0.057***		0.044***		1.323***		1.306***
		(0.001)		(0.001)		(0.012)		(0.013)
Constant	0.112**	0.105*	0.526***	0.486***	2.253**	2.466***	12.523***	9.194***
	(0.056)	(0.055)	(0.035)	(0.035)	(0.752)	(0.732)	-3.579	-2.144
N	68,647	68,647	88,332	88,332	60,045	60,045	80,077	80,077
Log-likelihood	-1,397.064	-1,388.182	-2,391.422	-2,371.341	-3,000.164	-2,945.933	-5,807.251	-5,782.566
AIC	2,818.127	2,802.365	4,808.843	4,770.682	6,010.328	5,903.867	11,624.501	11,577.131
BIC	2,927.555	2,920.911	4,930.982	4,902.216	6,027.474	5,924.443	11,644.738	11,601.415
Chi2	289.638	307.401	734.587	774.749	204.699	313.159	355.307	404.677
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Nursing home	**Nursing home stays (extensive margin)**				**Nursing home stays (weeks per year**			
Age	-0.002***	-0.002***	-0.003***	-0.004***	0.839***	0.867***	0.879***	0.893***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.012)	(0.007)	(0.008)
Age^2	0.000***	0.000***	0.000***	0.000***	1.001***	1.001***	1.001***	1.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.006***	-0.004***	-0.011***	-0.008***	1.023***	1.011***	1.111***	1.069***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.031)	(0.031)	(0.025)	(0.025)
Resid 1st stage	0.000	-0.000	0.001*	-0.000				
	(0.000)	(0.000)	(0.000)	(0.000)				
CCI		0.001***		0.002***		0.879***		0.945***
		(0.000)		(0.000)		(0.011)		(0.008)
Constant	0.073***	0.073***	0.146***	0.145***	23862.13***	12623.54***	2054.28***	1457.18***
	(0.010)	(0.010)	(0.008)	(0.008)	-11.433.482	-6.093.186	-598.453	-430.630
N	68,647	68,647	88,332	88,332	233	233	434	434
Log-likelihood	-7,950.500	-7,746.013	-11,908.774	-11,642.072	-96,307.899	-96,275.428	-204,258.815	-201,662.700
AIC	15,927.000	15,520.026	23,843.549	23,312.143	192,625.797	192,562.856	408,527.629	403,337.400
BIC	16,045.152	15,647.267	23,965.164	23,443.113	192,646.070	192,587.182	408,550.696	403,365.080
Chi2	1,842.910	2,251.883	4,022.220	4,555.625	19,849.303	19,914.245	72.548.750	77,740.980
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Personal home care	**Home care (extensive margin)**				**Home care (hours per year)**			
Age	0.013***	0.017***	0.019***	0.023***	1.055***	1.082***	1.052***	1.102***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age^2	0.000***	0.000***	0.000***	0.000***	0.994***	0.991***	0.991***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.002)	(0.002)
TTD	-0.068***	-0.038***	-0.078***	-0.036***	0.887***	0.788***	0.774***	0.678***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)
Resid 1st stage	0.011***	0.002	0.012***	-0.001				
	(0.001)	(0.001)	(0.001)	(0.001)				
CCI		0.016***		0.018***		1.030***		1.106***
		(0.001)		(0.001)		(0.004)		(0.002)
Constant	0.681***	0.673***	0.870***	0.846***	29486.75***	32933.06***	90090.6***	28921.06***
	(0.029)	(0.029)	(0.024)	(0.023)	-3.958.839	-4.439.789	-7.757.116	-2.536.271
N	68,647	68,647	88,332	88,332	771	771	1,322	1,322
Log-likelihood	-36,578.437	-33,027.169	-43,412.597	-39,846.821	-81,436.507	-77,291.402	-118,716.483	-112.954.505
AIC	73,182.874	66,082.337	86,851.193	79,721.641	162,883.014	154,594.803	237,442.965	225.921.011
BIC	73,301.544	66,210.136	86,973.331	79,853.175	162,927.076	154,647.678	237,488.640	225.975.821
Chi2	6,388.081	13,490.617	8,880.347	16,011.899	2,044.261	10,334.472	5,479.226	1,003.181
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Medication	**Prescription drug consumption(extensive margin)**				**Prescription drug consumed (drugs per week)**			
Age	0.076***	0.049***	0.071***	0.045***	1.148***	1.026***	1.229***	1.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.006)	(0.005)	(0.004)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	0.999***	1.000***	0.998***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.212***	-0.005**	-0.258***	-0.036***	0.811***	0.996	0.756***	0.930***

	(0.009)	(0.001)	(0.009)	(0.009)	(0.010)	(0.018)	(0.007)	(0.016)
Resid 1st stage	0.059***	-0.002	0.078***	0.011***				
	(0.003)	(0.003)	(0.003)	(0.003)				
CCI		0.127***		0.106***		1.417***		1.384***
		(0.002)		(0.001)		(0.004)		(0.003)
Constant	-1.362***	-1.378***	-0.867***	-0.964***	0.490***	0.385***	0.398***	0.187***
	(0.072)	(0.069)	(0.049)	(0.047)	(0.088)	(0.069)	(0.050)	(0.023)
N	68,647	68,647	88,332	88,332	50,048	50,048	68,088	68,088
Log-likelihood	-36,578.437	-33,027.169	-43,412.597	-39,846.821	-81,436.507	-77,291.402	-118,716.483	-112,954.505
AIC	73,182.874	66,082.337	86,851.193	79,721.641	162,883.014	154,594.803	237,442.965	225,921.011
BIC	73,301.544	66,210.136	86,973.331	79.853.175	162,927.076	154,647.678	237,488.640	225,975.821
Chi2	6,388.081	13,490.617	8,880.347	16,011.899	2,044.261	10,334.472	5,479.226	17,003.181
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Polypharmacy	**Probability of consuming 5 or more prescribed drugs**							
Age	0.026***	0.003*	0.037***	0.005***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Age^2	-0.000***	-0.000	-0.000***	-0.000**				
	(0.000)	(0.000)	(0.000)	(0.000)				
TTD	-0.189***	-0.001	-0.300***	-0.029***				
	(0.006)	(0.006)	(0.007)	(0.007)				
Resid 1st stage	0.051***	-0.003*	0.092***	0.010***				
	(0.002)	(0.002)	(0.002)	(0.002)				
CCI		0.113***		0.129***				
		(0.001)		(0.001)				
Constant	-0.115**	-0.129***	-0.014	-0.132***				
	(0.048)	(0.045)	(0.039)	(0.036)				
N	50,048	50,048	68,088	68,088				
Log-likelihood	-19,364.792	-16,366.664	-30,111.391	-26,623.368				
AIC	38,755.585	32,761.327	60,248.782	53,274.736				
BIC	38,874.254	32,889.126	60,370.920	53,406.269				
Chi2	2,268.562	8,264.819	6,092.015	13,068.061				
p	0.000	0.000	0.000	0.000				

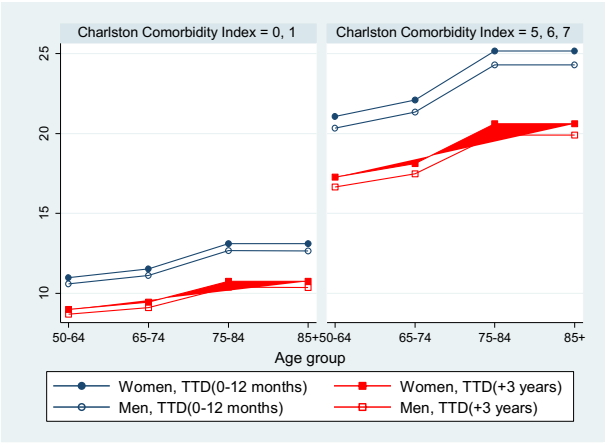
Note: This table reports different specifications of age, TTD and morbidity effect on health care use on both the intensive and extensive margin. M4 includes as explanatory variables age, age squared, TTD, marital status, income and wealth adjusted by the number of household members, municipality size, healthcare resources by NUTS and year fixed effects. IV is used for TTD (CF for logit with fixed effects and a GMM truncated Poisson). M5 uses the same explanatory variables and estimation procedure as M4, and also includes CCI index. Marginal effects are offered for the logit models, and the incidence risk ratio are shown for the truncated Poisson models. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Figure E2. Predicted outcomes conditioned on age, time to death and Charlston Comorbidity Index (CCI). Men and women.

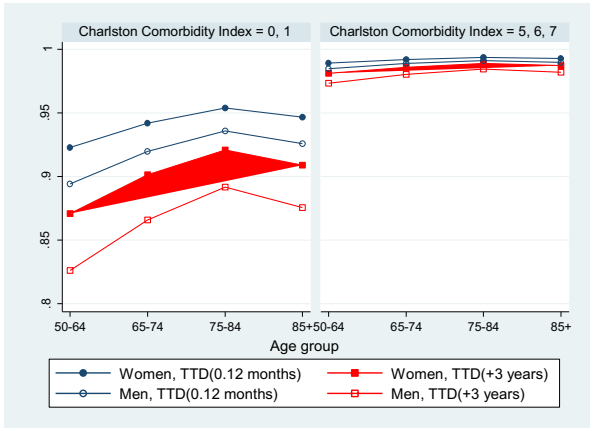
a) Probability of hospitalization



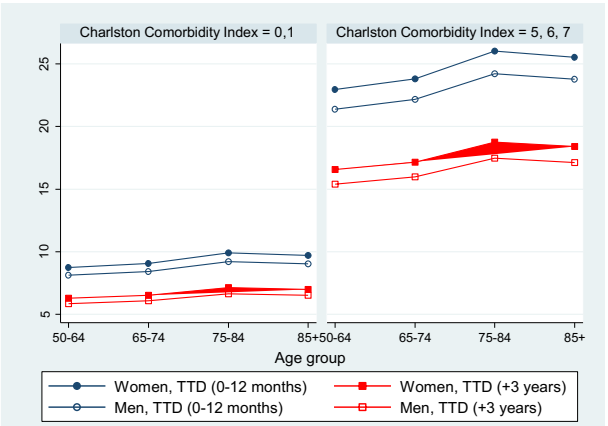
b) Length of stay at hospital (days per year)



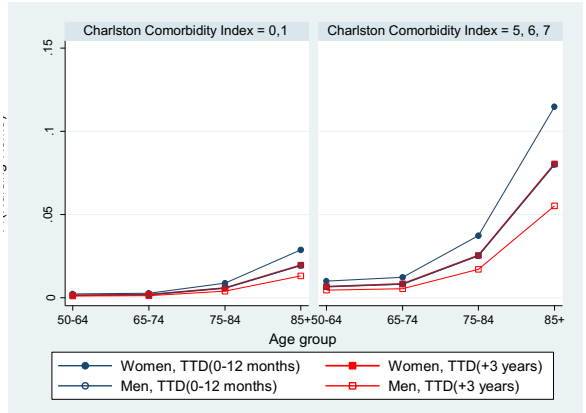
c) Probability of Outpatient visits with doctor/nurse



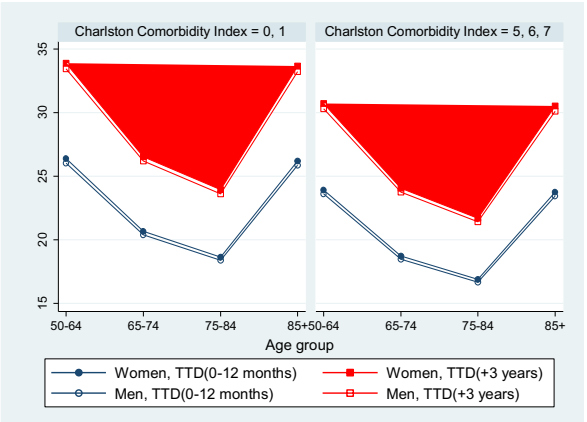
d) Number of Outpatient visits with (per year)



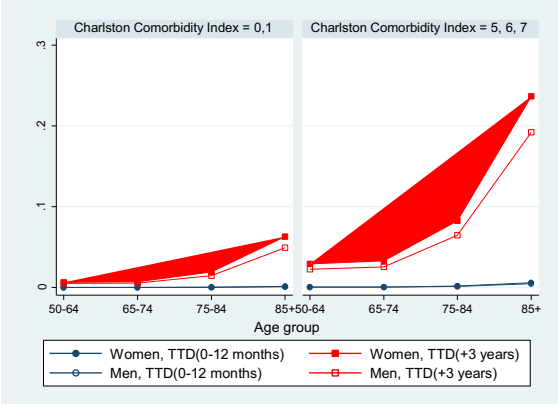
e) Probability of staying at nursing home



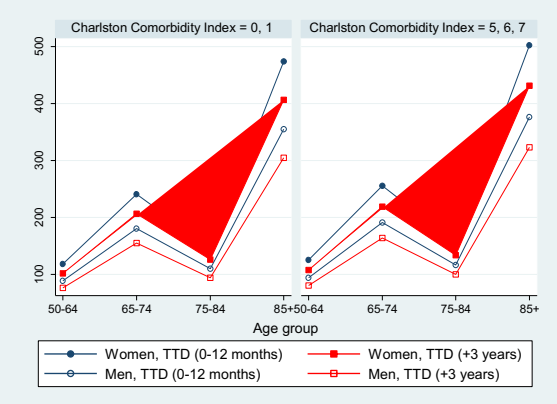
f) Length of stay at nursing home (weeks per year)



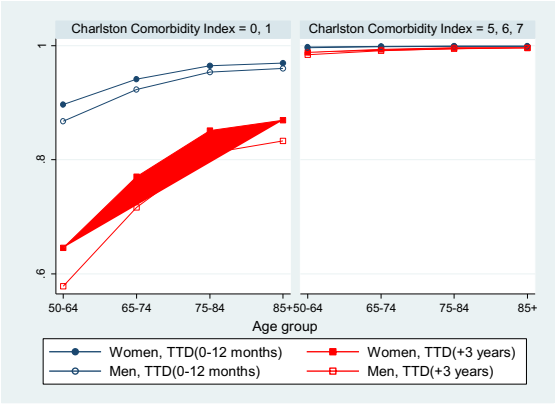
g) Probability of receiving formal care for personal care



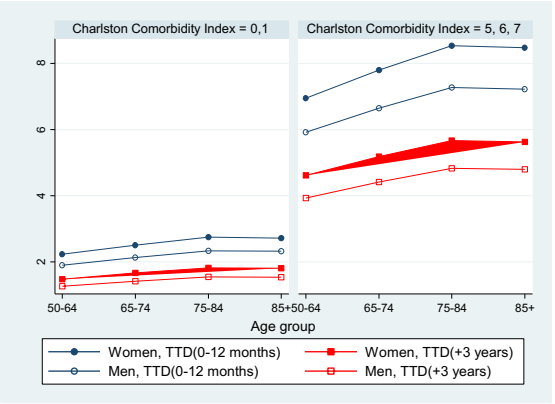
h) Hours receiving help for personal care (per year)



i) Probability of consuming any prescribed drug



j) Number of prescribed drugs consumed



k) Probability of polypharmacy (5 or more prescribed drugs)

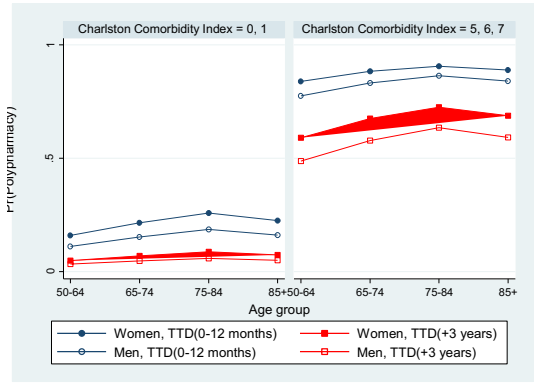


Table E2. North vs. South Heterogeneity. Marginal effects reported for logit part; incidence rate ratios reported for truncated Poisson. Northern countries: Denmark, Estonia, Poland and Sweden. Southern countries: Greece, Italy and Spain.

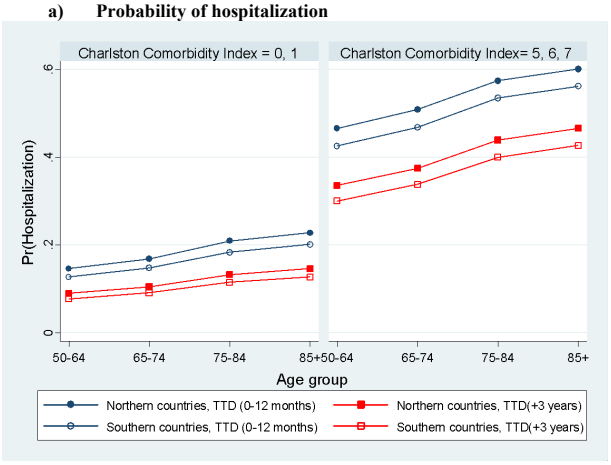
	Logit (marginal effects)				Truncated Poisson (IRR)			
	Northern countries		Southern countries		Northern countries		Southern countries	
	TTD (IV)	TTD(IV) +CCI	TTD (IV)	TTD(IV) +CCI	TTD (IV)	TTD(IV) +CCI	TTD (IV)	TTD(IV) +CCI
Hospital	**Hospitalization (extensive margin)**				**Length of stay at hospital (days per year)**			
Age	0.007***	0.005**	0.009***	0.003*	1.161**	1.135**	1.045**	1.112**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.078)	(0.067)	(0.022)	(0.021)
Age^2	-0.000**	0.000***	-0.000***	0.000**	0.999**	0.999*	1.000**	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.098***	-0.0015***	-0.096***	-0.019**	0.950	1.009	0.933	1.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.171)	(0.155)	(0.101)	(0.092)
Resid 1st stage	0.015***	-0.006***	0.013***	-0.008***				
	(0.002)	(0.002)	(0.002)	(0.002)				
CCI		0.078***		0.058***		1.148***		1.117***
		(0.002)		(0.002)		(0.035)		(0.024)
Constant	0.181***	0.246***	0.124**	0.174***	0.037*	0.055*	2.588	4.155
	(0.062)	(0.060)	(0.056)	(0.054)	(0.064)	(0.089)	(2.541)	(3.955)
N	39,647	39,647	39,009	39,009	5,667	5,667	4,924	4,924
Log-likelihood	-10,837.5	-10,579.5	-22,582.6	-21,771.9	-37,279.8	-36,392.2	-176,258.5	-168,831.6
AIC	21,723.0	21,205.8	68,911.8	66,174.3	74,607.7	72,831.3	631,238.3	603,271.2
BIC	21,923.7	21,401.7	69,988.4	67,204.9	74,757.9	72,978.0	633,632.3	605,556.1
Chi2	103.237	246.112	145.407	339.664	512.708	1.368.773	166.259	270.664
Outpatient visits	**Outpatient visits with doctor/nurse (extensive margin)**				**Number of Outpatient visits with doctor/nurse (intensive margin)**			
Age	0.023***	0.015***	0.022***	0.011***	1.072***	1.016	1.056***	1.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.018)	(0.011)	(0.015)	(0.014)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	0.999***	1.000	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.049***	0.0008***	-0.063***	0.007***	0.662***	0.918***	0.642***	0.872***
	(0.007)	(0.002)	(0.008)	(0.002)	(0.063)	(0.019)	(0.099)	(0.014)
Resid 1st stage	0.013***	-0.001	0.018***	-0.001				
	(0.002)	(0.002)	(0.002)	(0.002)				
CCI		0.051***		0.069***		1.291***		1.343***
		(0.002)		(0.002)		(0.020)		(0.017)
Constant	0.171***	0.204***	0.239***	0.299***	2.847***	3.924***	4.924***	6.246***
	(0.053)	(0.053)	(0.064)	(0.063)	(0.822)	(1.315)	(3.010)	(3.301)
N	39,647	39,647	39,009	39,009	33,550	33,550	30,883	30,883
Log-likelihood	-10,202.1	-9,959.2	-20,610.4	-19,877.8	-14,6970.4	-14,3471.1	-2,307,000.2	-2,201,866.9
AIC	20,452.2	19,965.3	62,281.5	59,826.4	293,988.8	286,989.1	8,936,930.3	8,523,261.5
BIC	20,652.9	20,161.2	63,307.1	60,808.4	294,186.6	287,182.2	8,948,762.2	8,534,541.3
Chi2	113.630	197.039	59.080	173.005	422.966	920.182	486.406	33.696.947
Nursing home	**Nursing home stays (extensive margin)**				**Nursing home stays (weeks per year**			
Age	0.004***	0.004***	0.002***	0.002***	0.892***	0.924***	0.991	1.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.013)	(0.031)	(0.031)
Age^2	0.000***	0.000***	0.000***	0.000***	1.001***	1.001***	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.009***	-0.008***	-0.006***	-0.005***	1.037*	0.985	0.935*	0.908**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.022)	(0.022)	(0.036)	(0.036)
Resid 1st stage	-0.000	-0.001	-0.000	-0.000				
	(0.000)	(0.000)	(0.000)	(0.000)				
CCI		0.001***		0.001***		0.868***		0.890***
		(0.000)		(0.000)		(0.009)		(0.014)
Constant	0.156***	0.157***	0.100***	0.101***	1052.776***	427.898***	34.188***	21.343**
	(0.012)	(0.012)	(0.012)	(0.012)	(580.511)	(235.528)	(43.690)	(26.931)
N	45,238	45,238	43,932	43,932	219	219	215	215
Log-likelihood	-818.9	-799.4	-885.9	-863.3	-1,225.5	-1,196.3	-1,375.7	-1,339.4
AIC	1,681.7	1,641.7	1,964.5	1,911.2	2,495.0	2,435.6	3,117.4	3,028.7
BIC	1,865.3	1,820.9	2,213.3	2,152.5	2,558.5	2,497.6	3,213.2	3,121.4
Chi2	97.472	91.104	65.371	59.545	236.255	439.110	91.117	150.055
Personal home care	**Home care (extensive margin)**				**Home care (hours per year)**			
Age	0.021***	0.023***	0.016***	0.019***	0.943***	0.945***	1.011*	1.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.006)	(0.007)
Age^2	0.000***	0.000***	0.000***	0.000***	1.001***	1.001***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	0.030***	0.012***	0.045***	0.018***	0.833***	0.831***	0.751***	0.739***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Resid 1st stage	-0.002	-0.007***	0.002*	-0.005***				
	(0.001)	(0.001)	(0.001)	(0.001)				
CCI		0.016***		0.017***		0.729***		0.649***
		(0.001)		(0.001)		(0.004)		(0.004)
Constant	0.728***	0.734***	0.645***	0.641***	620.433***	820.435***	119.261***	220.341***
	(0.030)	(0.030)	(0.032)	(0.031)	(116.183)	(157.019)	(26.103)	(50.688)
N	39,647	39,647	39,009	39,009	596	596	329	329
Log-likelihood	-13,096.8	-12,785.0	-30,249.5	-29,130.6	-36,753.7	-35,878.6	-171,837.4	-164,606.3
AIC	26,241.6	25,616.8	95,103.8	91,238.9	73,555.5	71,804.1	614,596.0	587387.6
BIC	26,442.3	25,812.7	96,361.8	92,442.4	73,750.3	71,994.4	617,661.4	590313.3
Chi2	403.101	392.220	221.148	234.417	16,037.877	20,589.783	11,939.625	18,227.823
Medication	**Prescription drug consumption(extensive margin)**				**Prescription drug consumed (drugs per week)**			
Age	0.065***	0.050***	0.058***	0.038***	1.098***	1.036***	1.126***	1.046***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.013)	(0.012)	(0.007)	(0.006)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	0.999***	1.000**	0.999***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TTD	-0.132***	-0.095***	-0.127***	-0.082 ***	0.706***	0.972***	0.633***	0.878***

	(0.009)	(0.009)	(0.009)	(0.009)	(0.030)	(0.034)	(0.013)	(0.017)
Resid 1st stage	0.037***	0.004	0.034***	-0.002				
	(0.003)	(0.003)	(0.003)	(0.003)				
CCI		0.119***		0.122***		1.393***		1.380***
		(0.002)		(0.002)		(0.011)		(0.005)
Constant	-1.289***	-1.212***	-1.110***	-1.000***	0.185***	0.263***	0.145***	0.196***
	(0.069)	(0.067)	(0.076)	(0.073)	(0.070)	(0.100)	(0.029)	(0.039)
N	39,647	39,647	39,009	39,009	32,448	32,448	28,605	28,605
Log-likelihood	-2,358.4	-2,302.3	-2,914.7	-2,832.3	-111,957.1	-109,291.5	-1,365,396.,3	-1,303,753.7
AIC	4,760.9	4,647.5	7,027.5	6,807.5	223,956.2	218,623.9	5,239,594.2	4,998,265.3
BIC	4,932.3	4,814.9	7,365.0	7,133.1	224,024.9	218,691.0	5,242,740.5	5,001,265.2
Chi2	612.730	898.005	372.093	665.737	898.983	2,409.962	3,045.913	10,744.550
Polypharmacy	**Probability of consuming 5 or more prescribed drugs**							
Age	0.024***	0.005**	0.027***	0.009***				
	(0.002)	(0.002)	(0.002)	(0.002)				
Age^2	-0.000***	-0.000	-0.000***	-0.000***				
	(0.000)	(0.000)	(0.000)	(0.000)				
TTD	-0.139***	-0.071***	-0.159***	-0.108***				
	(0.008)	(0.008)	(0.008)	(0.007)				
Resid 1st stage	0.038***	0.003	0.032***	0.000				
	(0.003)	(0.002)	(0.002)	(0.002)				
CCI		0.136***		0.114***				
		(0.002)		(0.002)				
Constant	-0.274***	-0.222***	-0.442***	-0.361***				
	(0.075)	(0.070)	(0.077)	(0.072)				
N	32,448	32,448	28,605	28,605				
Log-likelihood	-9,438.6	-9,213.9	-18,347.4	-17,703.5				
AIC	18,925.3	18,474.6	54,741.8	52,605.9				
BIC	19,125.9	18,670.6	55,706.1	53,529.5				
Chi2	116.357	616.068	50.654	385.655				

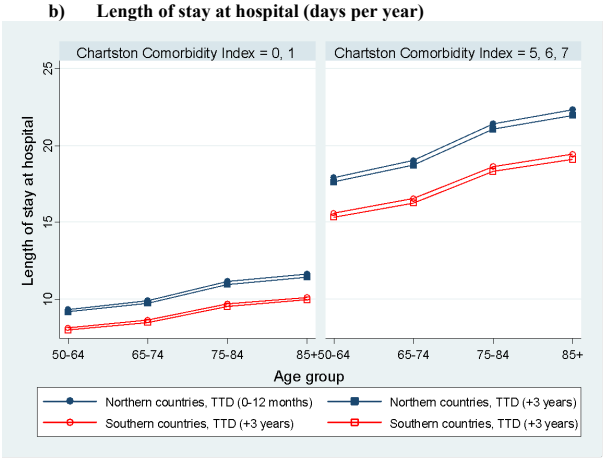
This table reports different specifications of age, TTD and morbidity effect on health care use on both the intensive and extensive margin. All models include the following explanatory variables: age, age squared, marital status, income and wealth adjusted by the number of household members, municipality size, healthcare resources by NUTS, TTD and year fixed effects. Additionally, CCI is included in the model shown in the right column (for each pair of columns). In all models IV is used for TTD (CF for logit with fixed effects and a GMM truncated Poisson). Marginal effects are offered for the logit models, and the incidence risk ratio are shown for the truncated Poisson models. Clustered robust standard errors (at the NUTS level) with 100 bootstrap replications are obtained in all models. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%.

Figure E3. Predicted outcomes conditioned on age, time to death and Charlston Comorbidity Index (CCI). Northern countries: Denmark, Estonia, Poland and Sweden. Southern countries: Greece, Italy and Spain.

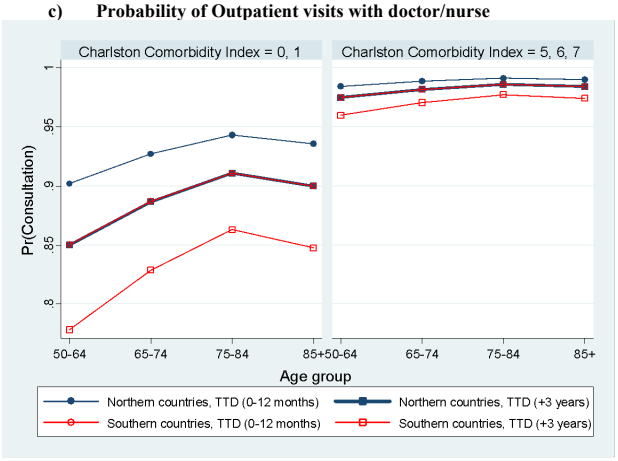
a) Probability of hospitalization



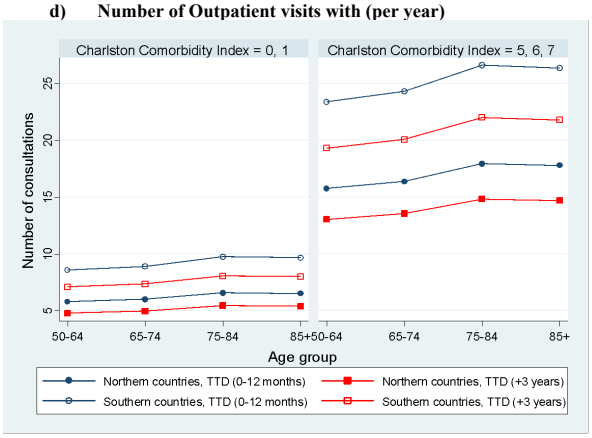
b) Length of stay at hospital (days per year)



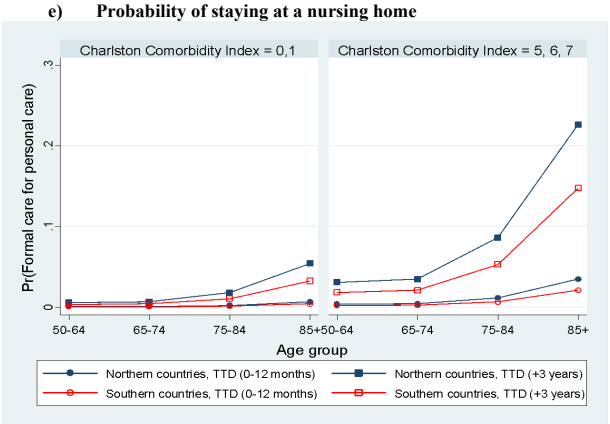
c) Probability of Outpatient visits with doctor/nurse



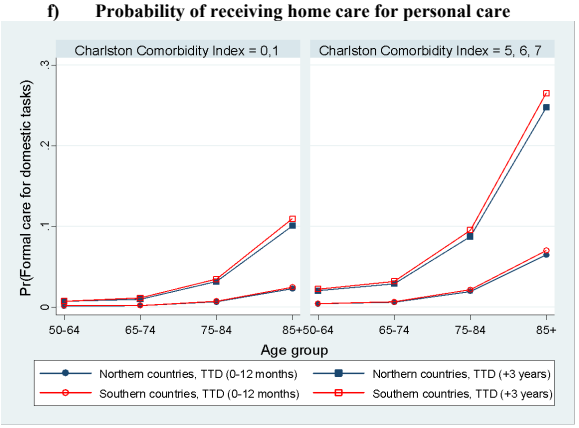
d) Number of Outpatient visits with (per year)



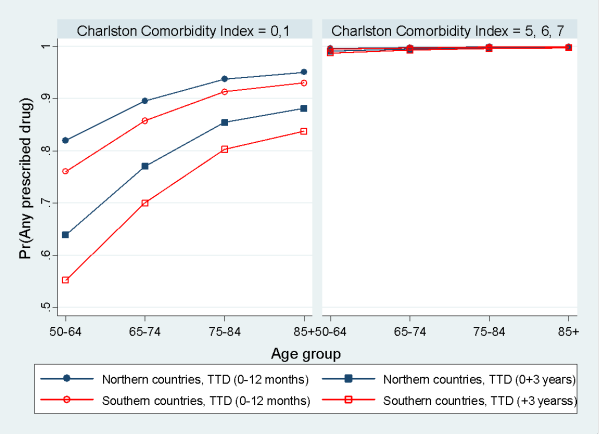
e) Probability of staying at a nursing home



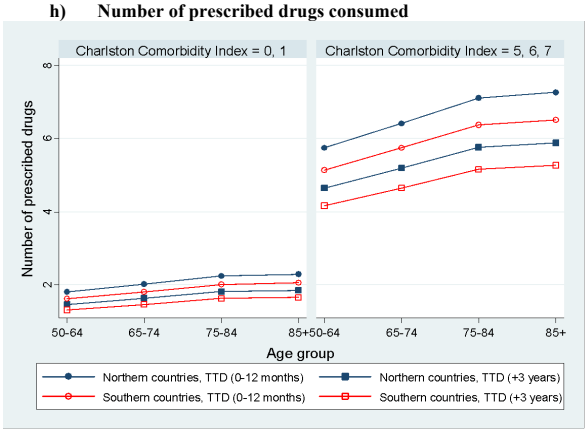
f) Probability of receiving home care for personal care



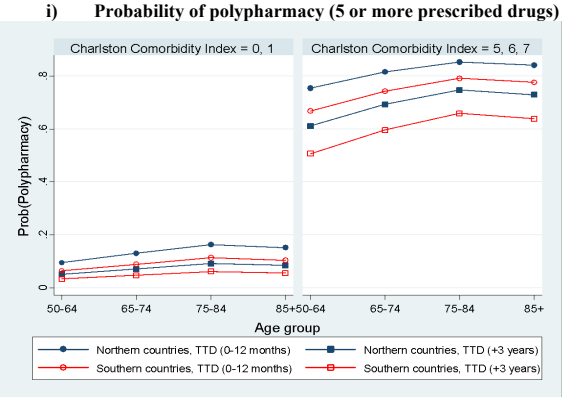
g) Probability of consuming any prescribed drug



h) Number of prescribed drugs consumed



i) Probability of polypharmacy (5 or more prescribed drugs)



In the graphs for the probability of consultation with doctor/nurse and CCI=5, 6 or 7: the probability for Northern countries & TTD (+3 years) overlaps with the probability for Southern countries &TTD (0-12 months).