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'More than one red herring'? Heterogeneous effects of ageing on health care utilisation

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Abstract

We study the effect of ageing, defined as an extra year of life, on health care utilisation. We disentangle the direct effect of ageing, from other alternative explanations such as the presence of comorbidities and endogenous time to death (TTD) that are argued to absorb the effect of ageing (so-called 'red herring' hypothesis). We exploit individual level end of life data from several European countries that record the use of medicine, outpatient and inpatient care and long-term care. Consistently with the 'red herring hypothesis', we find that corrected TTD estimates are significantly different from uncorrected ones, and their effect size exceeds that of an extra year of life, which in turn is moderated by individual comorbidities. Corrected estimates suggest an overall attenuated 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.

KEYWORDS

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

JEL CLASSIFICATION

I18

1 | INTRODUCTION

Population ageing is commonly portrayed as a central determinant of health care (HC) spending (Marino, Morgan, Lorenzoni, & James, 2017; WHO, 2015).[1] 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 & Balestat, 2007), it is important to understand how ageing affects HC use. However, there are good reasons to argue that the effect of ageing on health expenditure is overestimated. One of the main explanations is that a significant share of expenditures take place around the time of death. Some studies even go as far as to argue that the effect of ageing on

[1]In 2012 and 2013, the percentage of health care expenditure concentrated in the cohort aged 65 and older ranged between 38.8% in the Czech Republic and 46.7% in Germany (European Union, 2016).

HC reflects a 'red herring', given that when time to death (TTD) is accounted for, the effect of ageing disappears (Zweifel, Felder, & Meiers, 1999; Zweifel, Felder, & Werblow, 2004; Hall & Jones, 2007; Shang & Goldman, 2007).[2]

In addition to the consideration of TTD, which is potentially endogenous, another source of overestimation (of ageing effects on health expenditure) results from the correlation between morbidity and an individual's age,[3] as it is subject to omitted variable bias. The effect of such omitted variable bias can be analysed using individual longitudinal data which 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.

Finally, another potential red herring, results from the fact that ageing can change the composition of HC towards a more intense use of end of life care, hospital care and long-term care (LTC).[4] Hence, the effect of ageing is likely to be heterogeneous across different types of HC, which especially differ in their reliance on technology (Breyer, Costa-Font, & Felder, 2010). Finally, ageing can incentivise the utilisation of new technologies that specifically cater to the HC needs of an ageing population.[5] Hence, it is important to understand how it impacts on different types of HC (e.g., medicines, hospital care and home care).

This paper examines the effect of ageing on different types of HC use and disentangles the effect of other confounding effects, namely, (a) proximity to death, (b) comorbidities and lifestyles and (c) differences in the composition of HC. 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 included in the Survey for Health, Ageing and Retirement in Europe (SHARE). The advantage of using a multi-country individual level panel is, that it allows for the inclusion of both individual and country fixed effects that net out both institutional and individual specific explanantions for differences in the effect of ageing on HC use, and by extension on health care expenditures (HCE). SHARE contains an end of life module that identifies the cause of death of the individual which allows identifying deceased (and survivor) individuals, namely, those that have died between two consecutive waves. We report both parametric and non-parametric estimates, and address the problem of endogeneity of TTD by correcting the estimations with rich instruments for parental survival, available in the dataset.

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 the 'red herring hypothesis'. Second, the effect size of TTD exceeds that of ageing, which in turn is attenuated by the presence of comorbidities. Finally, we find that ageing does not explain (both the internal and external margins of) outpatient visits with doctors and nurses once TTD and comorbidities are controlled for.

The structure of the paper is as follows. Section 2 reviews the most relevant literature. Next, we describe the data and empirical exercise. Sections 5 and 6 contain the results, and Section 7 concludes.

2 | RELATED LITERATURE

2.1 | 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 HC expenditure disappears once the effect of TTD is netted out (Zweifel et al., 1999)[6]. 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.

[2]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 15 years before death, and decline once an individual's turns 80, hence casting doubts about the effects of age on health care expenditures.
[3]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.
[4]This puts the coordination of health and long-term care services at the centre stage (Costa-Font, Jimenez-Martin, & Vilaplana, 2018).
[5]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.
[6]That said, given that Zweifel et al. analyze only decedents, one would expect the effect of age on HCE to be negative. Hence, Breyer and Lorenz (2020) suggest that a null effect does not prove the point they want to make. This requires examining evidence for survivors. Which is a point we come back later.

2.2 | 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 TTD estimates (Salas & Raftery, 2001; Seshamani & Gray, 2004). The logic is that if HC investments (e.g., such as new drugs) improve patient's health status, they could extend life. Therefore, estimates that fail to account for the dynamic influence of current and previous health expenditures on life expectancy would overestimate the effect of ageing on HC use. In a later study, Zweifel et al. (2004) confirmed his previous results after restricting the sample to a single year to ensure that HCEs only affect the probability of survival in cases in which individuals are close to death, and considered both survivors and deceased individuals in the sample. The results confirmed that age is not a significant variable in explaining the HCEs of the deceased and, in the case of survivors, the effect of age is much lower when the TTD variable is controlled for. For their part, Seshamani and Gray (2004) conclude that the omission of TTD from the analysis was found to overestimate the effect of ageing, and the number of trimesters before death is a significant explanatory variable, and its impact on cost is found to be higher at the end of life.

Other more recent estimates suggest that TTD accounts for 16.7% and 24.5% of lifetime HC and LTC expenditures (French et al., 2017). Similarly, Breyer, Ihle, and Lorenz (2017) estimate that HCEs in the last 4 years of life, account for20% of total expenditures over a lifetime when accounting for changes in life expectancy (Breyer, Lorenz, & Niebel, 2012). Hence, it seems TTD is not the only red herring underpinning the effects of ageing on HCEs.

2.3 | 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, and corrects the effect of unobserved time-invariant characteristics. However, such strategy does not deal with reverse causality. An alternative strategy lies in employing instrumental variables analysis, namely, exploiting the effect of a variable influencing health expenditure only via TTD, but not the age at which the individual is interviewed (Steinmann, Telser, & Zweifel, 2007). This is important, given that OLS estimates are biased if HCE and medical innovations prolong life (Lichtenberg, 2012).[7] Felder, Werblow, and Zweifel (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 themselves recognise, they are not able to fully purge TTD of its endogeneity, given that when errors are AR(1) distributed, the parameter is not estimated consistently from a lagged instrument.[8]

2.4 | Heterogeneity

Although most of the literture focuses on the effect of ageing on inpatient care[9], there are reasons for ageing to exhibit heterogeneous effects across different types of HC, especially among health care services that differs in its reliance on technology. Werblow, Felder, and Zweifel (2007) eluded the problem of endogeneity and focused on relating individual HCE in a given year with the remaining TTD. They document evidence of heterogeneous effects as the majority of the HCE components (drugs, hospital outpatient and hospital inpatient) are found not be influenced by age, but by TTD. The most significant exception is acute care provided to patients who also receive LTC regardless of their survival chance. They explain these results through the fact that patients with limited survival prospects attract a large share of medical technology. Finally, Kelley et al. (2013) estimates that the increase in out-of-pocket expenditure in the last years of life shows 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.

[7]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.

[8]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.

[9]With some exceptions such as Atella and Conti (2014).

2.5 | Technology and ageing

One interpretation of the effects of ageing on HCE is that technological progress is geared more intensively towards older age cohorts (Breyer et al., 2010). Consistently, Goldman et al. (2005) from the United States as well as Wong, Wouterse, Slobbe, and Boshuizen (2012) from the Netherlands concluded that most medical innovations have shifted health expenditures to older age groups. Similarly, Dormont and Huber (2006) used microsimulation techniques to retrospectively evaluate the components of a drift in the age profile of HCE during 1992–2000. They observed that the impact of a change in clinical practice (12.9%) was 3.8 times higher than the increase in HCE. 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 expenditure in the last year of life tends to decrease and they interpret there effect as revelaing a preference of physicians to treat more aggressively patients as their life expectancy increases (controling for age and the relevant diagnoses).

2.6 | Morbidity and health spending

The effect of morbidity on health expenditure and utilisation is well established**.** Geue, Lorgelly, Lewsey, Hart, and Briggs (2015) examined hospital spending data from individuals in the last 3 years of life using data from Scotland for a period of 35 years. They document that costs of younger cohorts (less than 65 and 65–69 years) exceed those of their last 11 quarters of life. Atella and Conti (2014) using primary care data from Italy, report higher costs among those groups aged 70–79 than the eldest cohort. TTD coefficients suggest that 14 quarters remaining before death positively affect primary care costs although the variation between the 14th and the 10th quarter of age, is not significant. In contrast, primary care costs at 8 quarters before death steadily increase by 50% between the age of 45 and age 75. Similarly, Dormont, Grignon, and Huber (2006) estimates suggest that changes in spending for a given morbidity were almost four times higher than the equivalent changes in the structure of the population (+3.4%).[10] Importantly, Ishizaki, Shimmei, Fukuda, et al. (2016) document a negative effect of age on the probability of hospitalisation and no significant effect of age on length of stay at hospital exists 3 months prior to death. Consistently, Howdon and Rice (2018) found that when morbidity is controlled for, it absorbs 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.[11]

2.7 | Ageing and LTC substitution

Finally, a set of studies examine the relationship between age and LTC controlling for TTD. De Meijer, Koopmanschap, d'Uva, and van Doorslaer (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 hospitalisation. Both predict the use of nursing home care.[12] A final set of studies includes Karlsson and Klohn (2011) addressing the problem of the endogeneity of TTD using instrumental variables, and Karlsson and Klohn (2014) which show that TTD dives the use of institutional care whilst age was more important for home care use.

[10]Other similar studies are Payne, Abel, Guthrie, and Mercer (2013) who 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 hospitalisation, especially related to diagnosed mental health conditions. Palladino, Lee, Ashworth, Triassi, and Millet (2016) found a positive and significant relationship between the number of chronic diseases and the use of primary, specialised and hospital care, and Schneider, O'Donnell, and Dean (2009) found a positive relationship between the use of Medicare fee-for-service without institutional claims and the number of chronic diseases.

[11]Carreras, Ibern, and Inoriza (2018) using Spanish data document that the inclusion of morbidity controls reduced the effect of TTD up to 92%.

[12]More specific drawing on two instruments: (a) 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 (b) 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

3.1 | Longitudinal dataset

We use data from Survey of Health, Ageing, and Retirement in Europe (SHARE) corresponding to waves 1, 2, 4, 5, 6, and 7.[13] Our variation originates from representative samples of individuals aged 50 years or above and observed during 13 years (2004–2017). We exploit a cross-country variation of 17 countries, a potential sample of 288,555 individual observations. The following steps were taken to retrieve our sample (see Table 1). First, only individuals who were observed for at least two consecutive waves were selected. This requirement allows us to determine accurately if the individual living status in the subsequent wave is either survivor or deceased. Individuals who are only interviewed once are discarded because we cannot be sure of their living status in the subsequent wave. In the robustness checks section, we study the effect of attrition in detail, and document it has no effect on our estimates. The final sample contains 156,979 observations corresponding to 54,549 individuals (51,789 survivors and 2,760 deceased).

3.2 | Sample description

Table 2 reports the descriptive statistics for the different dependent variables examined both in the extensive and intensive margins. Although a high percentage of zeros is observed for some HC types (hospitalisal stays, stays in other HC facilities, nursing homes, and formal personal care), we observe a high the duration or intensity in the provision of these services suggesting evidence ofoverdispersion. The destribution of outpatient visits (with a doctor or nurse), and the consumption of prescription drugs, reveals a high probability of an outpatient visit (89% and 75% respectively) in the last year (or the probability of consuming at least one medication), but such variables exhibit evidence of overdispersion too.

The Table SA1 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 subsample than in the survivor subsample. The deceased sample exhibits lower income and wealth (even adjusted for household size). However, due to the differences between survivors and deceased being largely time invariant, they will be absorbed by our fixed-effects model.

Our estimations control for comorbidity by using the Charlston Comorbidity Index (CCI) calculated as the sum of the scores that are obtained for seven items, (Charlson, Pompei, Ales, & MacKenzie, 1987) adapted for SHARE by Kusumastuti, Gerds, Lund, Mortensen, and Westendorp (2017). The share of individuals without any comorbidity is 20% higher among the deceased.[14] Compared with survivors, the percentage of deceased respondents that report any of these comorbidities is significantly higher for all items with the exception of arthritis and stomach/duodenal ulcers.[15]

4 | EMPIRICAL STRATEGY

4.1 | Empirical specification

The sample description analysis has indicated that a significant number of respondents report to never have used HC services, which is known to give rise to a *zero-mass problem*. Furthermore, the variance of HC use is higher than the mean variance (overdispersion), resulting in highly skewed (to the right) distributions of the variables because there are a few individuals with high consumption levels. Modelling a variable with excessive zeros and overdispersion with fixed

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

[14]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).

[15]Tables SA2 to SA6 report the descriptive statistics of the dependent variables. Comments are reported on Appendix SA.

TABLE 1 Description of the sample

		After merging consecutive waves			Registered in at least three waves					
		Number of observations			Number of observations			Number of individuals		
	Initial sample	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

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

TABLE 2 Dependent variables

	N	Mean	Std. Dev	Min	Max
Hospitalisation 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	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	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	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	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).

effects typically boils down to either running a negative Poisson or binomial model[16] (Allison & Waterman, 2002; Hausman, Hall, & Griliches, 1984). Recently, Winkelmann (2008) developed a double-hurdle model, and an alternative specification used in Majo and van Soest (2011) is 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. Initially our empirical specification can be expressed as:

$$Y_{it} = X_{it}\beta + \eta_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the outcome variable, X_{it} is a vector of explanatory variables, η_i represents an individual fixed effect, δ_t represents a time-fixed effect, and ε_{it} absorbs the effect of other unobservable shocks that are common to all individuals. To account for the effect of unobservables, we consider intraregional unobservable heterogeneity (at the Nomenclature of Territorial Units for Statistics [NUTS] level), and especially, an instrumental variable approach that corrects for the potential endogeneity of TTD. The main downside of our approach is that a linear models don't always fit a count data-generating process well (Wooldridge, 2002). Hence, an appropriate alternative strategy is the use of a 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:

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

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

Individual fixed effects (η_i) pose another problem as they cannot be purged as in linear models (i.e., first differences or mean deviations). Hence, if we proceed to estimate the Poisson model with fixed effects, it will produce inconsistent estimates of η_i (Neyman & 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 for retrieving consistent β and δ_t estimates (Blundell, Griffith, & Windmeijer, 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

[16]The Poisson model is preferred to the negative binomial because the latter does not eliminate the influence of unmeasured characteristics (Allison & 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).

regressors and the proposed instruments to obtain the residuals. Next, a Poisson model is estimated using all explanatory variables and residuals.[17]

Our panel data specification separates the 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 can be modelled using a truncated distribution (Cameron & Trivedi, 2013).[18]

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

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

where Y_{it} is the outcome variable, X_{it} is the explanatory variable, and η_i is the unobservable heterogeneity of the individual i (i.e., the propensity of a person to use a HC service or LTC 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).[19]

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:

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

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 use of HC services. This model is more flexible than the Poisson model because it can model both overdispersion and underdispersion:

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

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 hospitalisations, use of nursing home care and home care. 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. However, Majo and van Soest (2011) use 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

[17]Guo and Small (2016) show that the control function (CF) estimator applied to nonlinear 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.

[18]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 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 nonnested 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.

[19]The percentage of respondents who do not change behaviour is 59.02% for hospitalisation, 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.

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 merely depends on explanatory variables (and time-fixed effects). In addition, Gillingham and Tsvetanov (2019) demonstrate that when the explanatory variables are strictly exogenous, the resulting estimator is consistent.

4.2 | Endogeneity of TTD

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

4.3 | 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 (Gjonca & Zaninotto, 2008; Goldberg, Larson, & Levy, 1996). However, other studies, such as Ikeda et al. (2006), have found that the time of death of both the father and the mother is important, and parents' longer lifespan decreases the probability that their children will die between the ages of 40 and 79.

The SHARE data only report maternal and paternal age at death for the deceased sample. Therefore, parental age at death is imputed for those respondents whose parents were alive when the survey was conducted. Because age is a continuous variable, we use a multiple imputation (MI) procedure proposed by Rubin (1987) to predict the time of death of living parents.[20]

4.4 | Instrument validity

To verify the validity of our instruments, we report in the Supporting information the results of a linear regression for the TTD using these instruments, the other explanatory variables and the year fixed effects (Table SB2). The four proposed instruments are significant with the effect of a mother's age at death being larger for both men and women. Each father's additional year of life 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[21] in the EU in 2017, offspring's TTD would be between 17.43 and 22.86(7.92 and 14.02) days later for men (women). We also show that TTD decreases for men alongside lower educational levels, however, it increases with wealth, in smaller municipalities.[22]

[20]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 SB for a detailed explanation of these variables and the result of the MI).

[21]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.

[22]Table SB3 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. We are concerned with respect to idiosyncratic heterogeneity, 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 distributional misspecification and serial dependence. First, we estimate a fixed effects model and retrieve the fixed effects residuals. Second, we 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)

One potential threat to the identification, is the presence of intergenerational transmission of lifestyles, namely, that behaviours that shorten parent's life expectancy are more likely to be adopted by their children, who would also experience a reduction of TTD. To address this specific concern, we have regressed the effect of parents' age at death, as well as other explanatory variables, over the probability of having sedentary lifestyles, being overweight, having ever smoked daily, being a smoker at present time, and having consumed at least one alcoholic beverage during the last 7 days (-Table SB4). Overall, our results suggest that the effect of parent's age at time of death over TTD is not channelled through potential inherited habits from parents. Finally, although genetics are still important, we do not expect a significant estimate change in later life overall, and they woud be absorved by a FE estimator.[23]

5 | RESULTS

5.1 | Baseline results

Table 3 reports the results of the logit model with fixed effects for the probability of using HC (extensive margin) and the truncated Poisson model for the duration of HC or the number of visits (intensive margin). Both margins were estimated using five different specifications. The first set of estimates (M1–M3 specifications) are not estimated using instrumental variables (IV) and consider a different set of controls as follows:.specification M1 includes individual specific controls (age, age squared, marital status, income, and wealth adjusted by the number of household members) alongside spatial controls such as the size of the municipality of residence, the availability of health care resources by NUTS, and year fixed effects.[24] Next, we add TTD (proximity to death) in the M2, and CCI in the M3 specification. M4 and M5 specifications report the effect of the same explanatory variables as before but correcting TTD with an instrumental variable (IV) strategy (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. Our estimates come from clustered robust standard errors (at the NUTS level) with 100 bootstrap replications.

5.2 | Extensive margin

Estimates reported in the M5 specification suggest that TTD and CCI have opposite effects (negative for the former and positive for the latter) for the extensive margin (probability) of hospitalisation, as well as the probability of nursing home stays, home care, and prescription drug consumption. Comparing the M2 and M4 estimates for the probability of hospitalisation, we identify an increase in the effect of age (from 0.005 to 0.117) and TTD (from −0.016 to −0.376). Hence, we conclude that IV estimates correct for the underestimation of the two-reference variable. Yet, even more importantly, the magnitude of the TTD coefficient declines to one-seventh (−0.054) of its previous value when we control for comorbidities in M5. We find that a closer TTD reduces the likelihood of hospitalisation, but an increase in CCI increases the likelihood of hospitalisation. It is important to note that, as expected, controlling for comorbidities using CCI (in M5) significantly reduces the effect of ageing. Without CCI, an additional year of life increased the probability of hospitalisation by 11.7 percentage points, whereas after controlling for CCI, an additional year of life only increased this probability by 1.4 percentage points.

When examining the extensive margin of outpatient care with a doctor and nurse, we find that IV estimates result in a series of changes in the relevant estimates. First, age is no longer a significant variable, indicating that ageing does not increase outpatient visits to a doctor or nurse. Second, the positive effect of the TTD increases (from 0.001 to 0.042). Therefore, visiting a doctor or nurse is primarily driven by TTD and the presence of comorbidities, especially the latter.

[23]We have reestimated 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.(results are available upon request).

[24]Descriptive statistics are shown on Table SA7. Specifically, the number of hospital beds per 100,000 inhabitants is included in the probability of hospitalisation 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.

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

	Logit (marginal effects)				
	Exogenous TTD			TTD (IV)	
	M1	M2	M3	M4	M5
Hospitalisation	**Hospitalisation (extensive margin)**				
Age	0.001(0.001)	0.005***(0.001)	0.0001(0.001)	0.117***(0.002)	0.014***(0.005)
Age^2	0.000***(0.000)	−0.000**(0.000)	0.0001*(0.0005)	−0.001***(0.000)	−0.000** (0.000)
TTD		−0.016***(0.000)	−0.013***(0.000)	−0.376***(0.004)	−0.054***(0.015)
CCI			0.074***(0.001)		0.066***(0.003)
Resid first stage				0.363***(0.004)	0.042***(0.015)
Constant	−0.013(0.030)	0.019(0.030)	0.159***(0.029)	0.704***(0.031)	0.223***(0.037)
N	156,979	156,979	156,979	156,979	156,979
Log-likelihood	−62,829.0	−61,333.0	−59,872.7	−58,447.2	−57,055.6
AIC	125,737.9	122,744.1	119,821.7	116,968.8	114,183.8
BIC	126,136.5	123,133.3	120,201.5	117,339.6	114,545.8
Chi^2	259.069	376.764	981.128	935.454	906.317
Outpatient visit	**Doctor/nurse outpatient visit (extensive margin)**				
Age	0.014***(0.001)	0.014***(0.001)	0.010***(0.001)	0.089***(0.001)	−0.003 (0.004)
Age^2	−0.000***(0.000)	−0.000***(0.000)	−0.000***(0.000)	−0.001***(0.000)	0.000 (0.000)
TTD		−0.001**(0.000)	0.001***(0.000)	−0.241***(0.004)	0.042***(0.013)
CCI			0.051***(0.001)		0.058***(0.003)
Resid first stage				0.242***(0.004)	−0.041***(0.013)
Constant	0.292***(0.026)	0.293***(0.026)	0.389***(0.026)	0.750***(0.027)	0.327***(0.033)
N	156,979	156,979	156,979	156,979	156,979
Log-likelihood	−48,406.3	−47,253.8	−46,128.7	−45,030.4	−43,958.3
AIC	96,892.7	94,585.7	92,333.7	90,135.2	87,989.2
BIC	97,291.2	94,974.8	92,713.5	90,506.0	88,351.1
Chi^2	267.389	243.466	599.165	555.220	553.854
Stays nursing home	**Nursing home stays (extensive margin)**				
Age	−0.004***(0.000)	−0.003***(0.000)	−0.003***(0.000)	−0.001***(0.000)	−0.002*(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		−0.002***(0.000)	−0.002***(0.000)	−0.008***(0.001)	−0.006** (0.003)
CCI			0.001***(0.000)		0.0003**(0.001)
Resid first stage				0.006***(0.001)	0.004 (0.003)
Constant	0.111***(0.006)	0.115***(0.006)	0.117***(0.006)	0.126***(0.006)	0.124***(0.007)
N	156,979	156,979	156,979	156,979	156,979
Log-likelihood	−3,734.2	−3,645.3	−3,558.5	−3,473.8	−3,391.1
AIC	7,548.5	7,368.8	7,193.3	7,022.0	6,854.9
BIC	7,947.0	7,757.8	7,573.1	7,392.8	7,216.8
Chi^2	189.305	236.533	220.782	220.925	203.962
Personal care	**Home care (extensive margin)**				
Age	0.022***(0.000)	0.020***(0.000)	0.021***(0.000)	0.026***(0.001)	0.028***(0.002)
Age^2	0.000***(0.000)	0.000***(0.000)	0.000***(0.000)	0.000***(0.000)	0.000***(0.000)
TTD		−0.010***(0.000)	−0.009***(0.000)	−0.095***(0.002)	−0.049***(0.008)
CCI			0.017***(0.000)		0.009***(0.001)
Resid first stage				0.086***(0.002)	0.040***(0.008)
Constant	0.670***(0.016)	0.706***(0.016)	0.734***(0.016)	0.864***(0.016)	0.794***(0.020)
N	156,979	156,979	156,979	156,979	156,979
Log-likelihood	−7,964.6	−7,774.9	−7,589.8	−7,409.1	−7,232.7
AIC	16,001.1	15,620.2	15,248.3	14,885.2	14,530.8
BIC	16,334.1	15,945.1	15,565.5	15,194.9	14,833.1
Chi^2	1,007.573	1,078.357	1,114.884	1,113.728	1,031.372
Any prescribed drug	**Prescription drug consumption (extensive margin)**				
Age	0.048***(0.001)	0.049***(0.001)	0.041***(0.001)	0.236***(0.002)	0.185***(0.005)
Age^2	−0.000***(0.000)	−0.000***(0.000)	−0.000***(0.000)	−0.002***(0.000)	−0.001***(0.000)
TTD		−0.005***(0.000)	0.000(0.000)	−0.007***(0.005)	−0.009***(0.017)
CCI			0.117***(0.001)		0.032***(0.003)
Resid first stage				0.607***(0.005)	0.449***(0.017)
Constant	−1.273***(0.035)	−1.264***(0.035)	−1.043***(0.034)	−0.118***(0.035)	−0.355***(0.042)
N	156,979	156,979	156,979	156,979	156,979
Log-likelihood	−72,245.1	−70,525.0	−68,845.8	−67,206.6	−65,606.5
AIC	144,570.2	141,128.1	137,767.9	134,487.7	131,285.6
BIC	144,968.7	141,517.1	138,147.6	134,858.4	131,647.5
Chi^2	1,783.305	1,631.050	2,793.264	2,854.246	2,643.527

TABLE 3 (Continued)

	Logit (marginal effects)				
	Exogenous TTD			TTD (IV)	
	M1	M2	M3	M4	M5
Polypharmacy	**Probability of consuming 5 or more prescribed drugs**				
Age	0.011***(0.001)	0.012***(0.001)	0.004***(0.001)	0.024***(0.001)	0.004***(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)	0.001(0.001)	−0.147***(0.004)	−0.002 (0.004)
CCI			0.126***(0.001)		0.126***(0.001)
Resid 1st stage				0.042***(0.001)	0.001 (0.001)
Constant	−0.406***(0.037)	−0.390***(0.037)	−0.216***(0.034)	−0.208***(0.037)	−0.213***(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
Chi^2	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, health care 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 is 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%.

When we turn to nursing home use, we observe a positive and linear effect of age, but TTD (proximity to death) reduces (increases) the probability of nursing home care use. That is, nursing home care is more commonly used by individuals closer to death. 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 the negative effect of age in absolute value.

Next, the extensive margin of home care use is examined using the same strategy, our IV strategy produces a TTD coefficient that is almost 10 times larger than before (from −0.010 in M2 to −0.095 in M3), which reinforces the idea that TTD is underestimated when omitted variable bias and reverse causality are adjusted for. However, the effect decreases by half when CCI is included (−0.049). This supports the idea that the need for home care decreases with proximity to death and the existence of comorbidities. Notice that TTD refers to proximity to death, hence a negative coefficient means that HC utilisation increses with time to death.

Lastly, when comparing the medication consumption in the M2 and M4 estimates, we find that the IV estimation amplifies the positive effect of age (from 0.049 to 0.236) and amplifies the negative effect of TTD (from −0.005 to −0.607). Both effects decrease when CCI is introduced in M5, and the effect of age on the probability of consuming medicine decreases by 5%.

The extensive margin of the probability of five or more medicines (polypharmacy) is then estimated using a sample that is limited to individuals who consume at least one form of medication. When comparing M2 and M4, we find that the effect size of TTD increases considerably. In M2, an additional year closer to death produces a barely perceptible decrease in the probability of consuming five or more medications. In contrast, in M4, each year closer to death decreases this probability by 14.7%. Finally, the inclusion of CCI in M5 suggests that an additional comorbidity increases the probability of polypharmacy by 12.6%, but the TTD variable is no longer significant and the effect of age declines by 2%.

5.3 | Intensive margin

M5 model specification, reveals that TTD and CCI exhibit opposite effects on length of hospital stay, on the number of doctor or nurse outpatient visits, and on the number of prescription drugs consumed. An additional comorbidity increases the probability that a hospital stay will extend by an additional day by 15.3%. Likewise, it increases the

TABLE 3 Continued

	Truncated Poisson (IRR)				
	Exogenous TTD			TTD (IV)	
	M1	M2	M3	M4	M5
Hospitalisation	**Length of stay at hospital (days per year)**				
Age	1.031**(0.013)	1.054***(0.013)	1.034***(0.013)	1.053***(0.013)	1.023*(0.013)
Age^2	1.000(0.000)	1.000***(0.000)	1.000**(0.000)	1.000***(0.000)	1.000(0.000)
TTD		0.828***(0.008)	0.847***(0.009)	0.840***(0.035)	0.951***(0.034)
CCI			1.146***(0.013)		1.153***(0.013)
Resid first stage					
Constant	2.674**(1.213)	2.962**(1.347)	4.619***(2.119)	2.911**(1.361)	4.055***(1.893)
N	24,020	24,020	24,020	24,020	24,020
Log-likelihood	−218,658.6	−213,452.4	−208,370.2	−203,409.0	−198,566.0
AIC	437,397.2	426,983.0	416,816.7	406,892.5	397,204.6
BIC	437,720.7	427,298.8	417,125.0	407,193.5	397,498.4
Chi^2	111.811	483.975	773.145	487.113	757.891
Outpatient visit	**Doctor/nurse outpatient visit (intensive margin)**				
Age	1.015**(0.007)	1.030***(0.007)	1.004(0.006)	1.057***(0.008)	0.999 (0.006)
Age^2	1.000(0.000)	1.000***(0.000)	1.000(0.000)	1.000***(0.000)	1.000(0.000)
TTD		0.876***(0.006)	0.911***(0.006)	0.658***(0.026)	0.953** (0.018)
CCI			1.307***(0.011)		1.310***(0.011)
Resid first stage					
Constant	3.078***(0.688)	3.375***(0.767)	6.559***(1.349)	4.992***(1.164)	6.189***(1.270)
N	140,139	140,139	140,139	140,139	140,139
Log-likelihood	−664,679.6	−648,853.9	−633,405.0	−618,323.9	−603,601.9
AIC	1,329,439.0	1,297,785.7	1,266,886.0	1,236,722.1	1,207,276.3
BIC	1,329,833.0	1,298,170.3	1,267,261.5	1,237,088.6	1,207,634.1
Chi^2	305.588	498.450	1.048.862	700.224	1.075.492
Stays nursing home	**Nursing home stays (weeks per year)**				
Age	0.865***(0.005)	0.867***(0.005)	0.884***(0.005)	0.859***(0.005)	0.877***(0.005)
Age^2	1.001***(0.000)	1.001***(0.000)	1.001***(0.000)	1.001***(0.000)	1.001***(0.000)
TTD		0.967***(0.004)	0.963***(0.004)	1.073***(0.014)	1.034** (0.014)
CCI			0.910***(0.005)		0.914***(0.005)
Resid first stage					
Constant	5,740***(1,222.08)	6,133***(1,307.23)	3,323***(717.62)	5,542***(1,182.57)	3,193***(690.08)
N	668	668	668	668	668
Log-likelihood	−7,647.2	−7,465.1	−7,287.3	−7,113.8	−6,944.5
AIC	15,374.3	15,008.3	14,650.9	14,302.1	13,961.6
BIC	15,553.5	15,183.1	14,821.6	14,468.7	14,124.2
Chi^2	572.234	623.327	917.038	690.499	947.197
Personal care	**Home care (hours per year)**				
Age	1.092***(0.001)	1.072***(0.001)	1.072***(0.001)	1.132***(0.001)	1.136***(0.001)
Age^2	1.000***(0.000)	1.000***(0.000)	1.000***(0.000)	0.999***(0.000)	0.999***(0.000)
TTD		1.237***(0.001)	1.237***(0.001)	0.706***(0.002)	0.696***(0.002)
CCI			1.003***(0.001)		1.080***(0.001)
Resid first stage					
Constant	2.888***(0.112)	2.347***(0.091)	2.363***(0.092)	4.407***(0.172)	4.234***(0.165)
N	2,095	2,095	2,095	2,095	2,095
Log-likelihood	−232,886.3	−227,341.4	−221,928.5	−216,644.5	−211,486.3
AIC	465,832.7	454,741.4	443,914.3	433,344.9	423,027.1
BIC	465,984.6	454,889.7	444,059.0	433,486.2	423,165.1
Chi^2	330,768.242	385,346.242	385,358.220	439,649.931	440,320.107
Any prescribed drug	**Prescription drug consumed (drugs per week)**				
Age	1.066***(0.003)	1.072***(0.003)	1.039***(0.003)	1.125***(0.003)	1.039***(0.003)
Age^2	1.000***(0.000)	1.000***(0.000)	1.000***(0.000)	0.999***(0.000)	1.000***(0.000)
TTD		0.951***(0.003)	0.998(0.003)	0.562***(0.006)	0.990 (0.009)
CCI			1.395***(0.002)		1.394***(0.002)
Resid first stage					
Constant	0.122***(0.011)	0.124***(0.011)	0.253***(0.023)	0.248***(0.022)	0.256***(0.023)
N	118,159	118,159	118,159	118,159	118,159
Log-likelihood	−170,029.2	−165,980.9	−162,029.0	−158,171.1	−154,405.1
AIC	340,138.3	332,039.8	324,134.1	316,416.6	308,882.9
BIC	340,525.5	332,417.8	324,503.0	316,776.8	309,234.5
Chi^2	12,103.814	12,449.715	48,742.386	15,111.931	48,743.353

TABLE 3 (Continued)

	Truncated Poisson (IRR)				
	Exogenous TTD			TTD (IV)	
	M1	M2	M3	M4	M5
Polypharmacy					
Age					
Age^2					
TTD					
CCI					
Resid 1st stage					
Constant					
N					
Log-likelihood					
AIC					
BIC					
Chi^2					

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, health care 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 is 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%.

probability that an outpatient visit will increase by 31% and increases the probability of consuming additional medication by 39.4%. In contrast, a one-year increase in the TTD decreases the probability that a hospital stay will be extended for another day by 4.9%. Similarly, TTD also decreases the probability of an additional outpatient visit by 4.7% and the probability of consuming an additional medication by 1%. When we turn to examine the effect of age, we find that including CCI in M5 attenuates the effect of age. We find that each additional year of life only increases the probability of an additional day of hospitalisation by 2.3% compared to 5.3% as reported in M4 (without CCI).

We find that TTD produces the largest effect on home care use. A one-year increase in TTD decreases the probability of receiving an additional hour of personal care by 30.4%. Moreover, increasing CCI increases the probability of personal care by 8%. In some cases, the inclusion of the Charlson comorbidity index (CCI) significantly decreases the effect of TTD. For example, TTD effect decreases (from −16% to −4.9%) the length of hospital stay, and (from −34.2% to −4.7%) the number of doctor/nurse consultations. When we examine the effect of length of stay in t nursing home, and the hours of home care, we find a decrease of a smaller magnitude. Finally, when we examine the the number of prescribed drugs, we find that TTD ceases to be significant when controlling for CCI (in estimates with and without IV). M5 estimates suggest that each year of additional life only increases the probability of large medication consumption by 3.9% which compares to 12.5% estimate in M4 (without including CCI).

[25]So the effect we are interested is the effect of age above the effect of CCI. Co-morbidities might change over time with behavioral change irrespective of ageing.

5.4 | Ageing effects

We find that each additional year of life has a positive effect on the length of hospital stay (+2.3%) and on the number of medications consumed (+3.9%). This effect is six and ten times lower respectively, than the effect of an additional comorbidity. The significance of CCI emerges when examining the number of outpatient care use, because age ceases

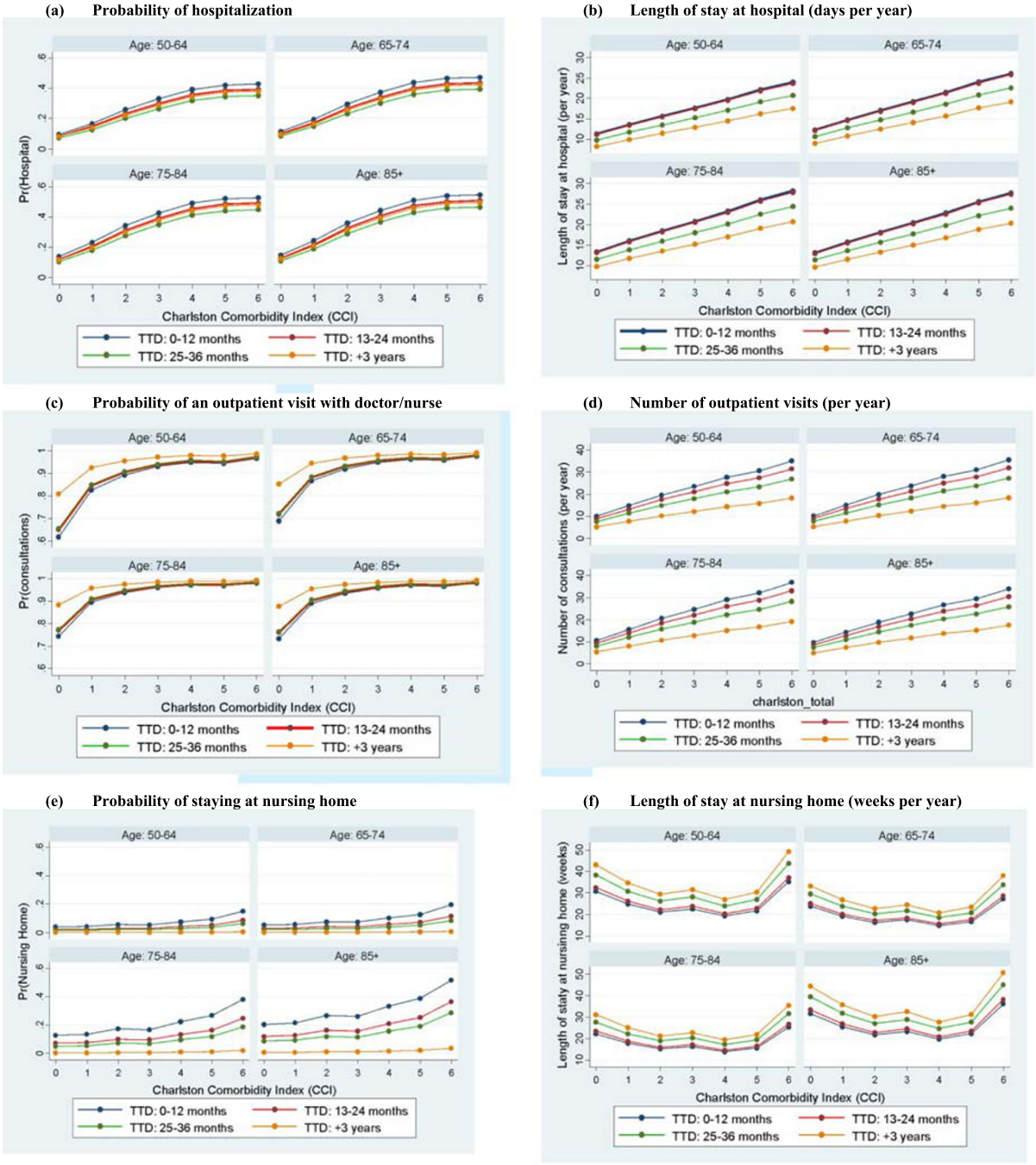
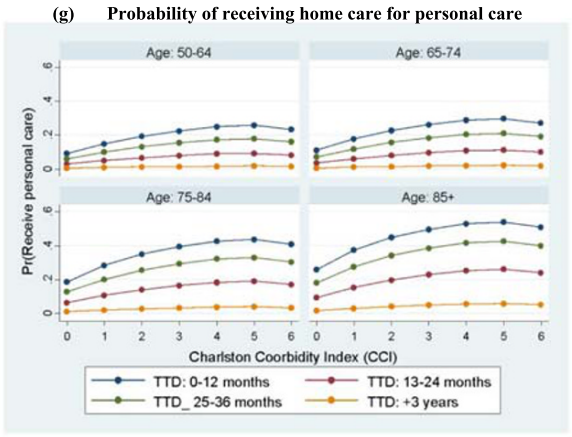
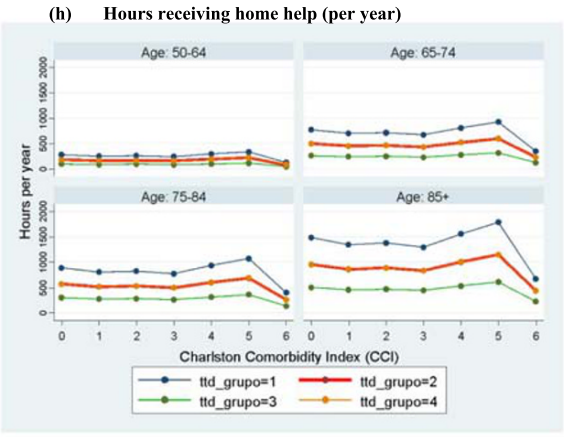
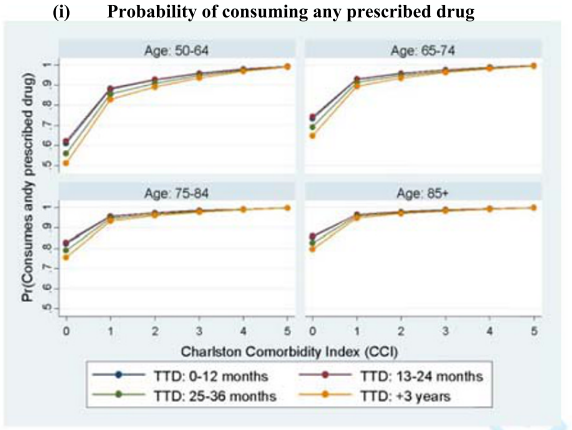
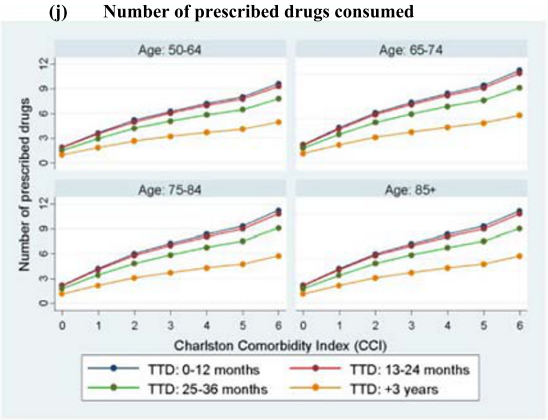


FIGURE 1 Predicted outcomes conditioned on age, time to death, and Charlston Comorbidity Index (CCI). Charlston Comorbidity Index: Level 6 also includes Level 7. In the graphs for the probability of hospitalisation: The probability for time to death (TTD; 13–24 months) overlaps with probability for TTD (+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) [Colour figure can be viewed at wileyonlinelibrary.com]









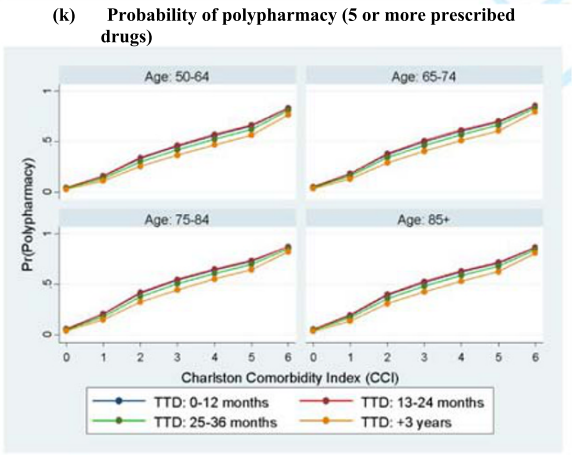


FIGURE 1 (Continued)

to be significant once CCI is introduced[25]. Moreover, we estimate that an additional year of life decreases the length of stay in nursing homes by 13%. The largest impact of age corresponds to the frequency of home-based assistance for personal care because each additional year increases the probability of receiving one more hour by 13.6%.

Figure 1 depicts the predicted probability and duration of HC use as a function of the age cohort, TTD, and the value of the Charlson Comorbidity Index (CCI). We show that the probability of hospitalisation exhibits no change with TTD, but quadruples with a six-fold increase in CCI (when it varies from 0 to 6/7). In contrast, the length of a hospital stay reduces with TTD and increases as CCI rises, but the probability of an outpatient visit with a doctor/nurse consultation in the last year is higher for a TTD of more than 3 years. However, the number of consultations is lower for a TTD of more than 3 years compared to shorter TTD horizons. Figure 1 shows that the probability of a nursing home stay reaches a 40–50% magnitude among the 75–84 and 85+ age cohorts, with the maximum levels of comorbidity and

close to death (TTD within 0–12 months). In contrast, it is almost zero for a TTD of more than 3 years and for all age cohorts and CCI values, and the length of stay exhibits a U-shaped curve for all TTD horizons. The difference in probability for home care use (for personal care) by TTD exhibits the largest effect among the 75–84 and 85+ age cohorts, with large CCI and reaches the maximum when TTD falls in the 0–12 month range. When we turn to examine the number of hours of care received, we find a significant rise in the number of formal caregiving hours for CCI = 5, and then it decreases for CCI = 6. Finally, the probability of medicine consumption is greater than 50% for all age cohorts (80% after the age of 75). As CCI increases, the probability of consuming one medication or of consuming 5 or more medicines (polypharmacy) is close to one for all age cohorts.

5.5 | Robustness checks

5.5.1 | Comparison between truncated Poisson and truncated negative binomial

Table SC1 compares the estimated odds ratios obtained from a truncated Poisson specification (the same shown in Table 3) and those obtained when 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 of the effect is always higher when a negative binomial model is used. 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).[26] Nonetheless, the economic explanation underpinning our results is satisfied regardless of the estimator.

5.5.2 | Attrition

Given that our estimates could be biased by potential non-random selection of the final sample, Table SC2 compares the outcome variables of the initial sample and the final sample. Test statistics for equality of means between samples do not reject the null hypothesis of equal means for all variables. We have also conducted a test for attrition suggested by Verbeek and Nijman (1992) which involves the estimation of all the cross-sections introduced as an 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 SC3 (binary outcomes) and SC4 (count data variables). The variable "present in all samples" is only significant for the probability of nursing home use and length of stay. Although the effect on the probability of nursing home stay is small (1.3 pp.), the effect on the length of stay is larger (e.g., being in the final sample increases the probability that duration of stay rises by 1 week with 14.4%). Hence, we conclude that attrition does not diminish the validity of our estimations.

5.6 | Instrument validity

In order to dispel any cloud of doubt surrounding the instrument (parent's age at death) used, and to show that the causal inferences about TTD on health care outcomes are credible, we rely on a two bound method, originally proposed by Conley, Hansen, and Rossi (2012) that allows to obtain inferences even when the instrumental variables do not satisfy the exogeneity restriction (see Appendix SD for explanation of both approaches). Figure SD1 shows the results of 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 death effect estimate for the respective outcome variable. The two dash lines represent the upper and lower limits of the respective test scores. Overall, the results confirm that even with substantial deviation from the exclusion restriction, the instrument still has a considerable effect over the outcome variable.[27]

[26]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).

[27]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

5.7 | Effect of CCI over estimations

To verify the model fit after controlling for CCI, Figure SE1 compares the residuals from the logit and truncated Poisson models (using IV for CCI) conditioned on including CCI or not, 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 are driven by specific groups of people or countries. All the models are re-estimated for men and women and for two groups of countries.

6.1 | Gender differences

Table SA8 displays the descriptive statistics for outcome variables, and Table SE1 reports the model estimation results. A 1-year increase in the TTD decreases both, the probability of hospitalisation 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). Sometimes, the effect is more intense for women: (a) a 1-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 (b) a 1-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.

We estimate that each additional CCI increases the probability of receiving an additional hour of personal care by 3% among men and 10.6% among women, but decreases the probability of extending the duration of stay at a nursing home by 1 week in 12.1% among men and 5.5% among women. When we turn o the effect of age, we find a large effect size for the number of prescribed medicines consumed: an additional year of life increases the probability of consuming one additional prescribed drug by 2.6% among men, and 5.8% among women.

Figure SE2 depicts the predicted probabilities and predicted values of count data variables broken down by gender, TTD, and CCI. It is worth noting that hospital length of stay increases significantly from the age of 75 (for high CCI, irrespectively of TTD). In contrast, the length of stay at a 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 in the oldest cohort. Finally, we find that as an individual ages, the higher TTD is, and the steeper the probability of consuming any prescribed drug (for low CCI).

6.2 | Northern and Southern European countries

Next, we test whether there is a North-South effect by selecting four northern countries (Denmark, Estonia, Poland, and Sweden) and three southern countries (Greece, Italy, and Spain). Table SA9 shows the descriptive statistics for a number of outcome variables, and Table SE3 displays the model estimation results. The most striking result is the different impact of 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. Consistently, the effect of ageing on hospitalisations is smaller in the southern countries. In northern countries, each additional year of life increases the likelihood that hospitalisation will be extended by 1 day by 13.5% compared to an 11.2% estimate in southern countries. Furthermore, in both groups of countries, TTD predicts the probability of hospitalisation, but not for length of stay.

As previously, the probability and the number of an outpatient visits with a doctor or nurse decrease with TTD. A one-year leap towards death increases the number of outpatient visits by 12.8% in southern countries and 8.2% in northern countries. Another significant difference between both country groups is in the effect of CCI, which is larger in southern countries. An increase in CCI by one unit, increases the probability of an outpatient visit in 6.9 percentage points in southern countries and in 5.1 percentage points in northern countries. Consistently, a one unit increase in CCI increases the number of outpatient visits in 34.3% in southern countries and in 29.1% in northern countries. The estimates for home care are interesting as well. The probability of receiving formal care at home increases slightly with TTD for both country groups. However, TTD's effect on the number of formal, in-home care hours is different for each

country group. A 1-year step towards death increases the provision of personal care by 1 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 use. (a) One year of life increases the probability of medicine consumption by five percentage points in northern countries versus an increase of 3.8 percentage points in southern countries. (b) In contrast, an increase by one additional year in the TTD, decreases the amount of medicine consumed by 2.8% (and the probability of polypharmacy with a sample limited to individuals who consume at least one medicine by 7.1 percentage points) in northern countries versus 12.2% (10.8 percentage points) in southern countries. (c) Each unit increase in comorbidity in CCI increases the probability of polypharmacy by 13.6 percentage points in northern countries compared with 11.4 percentage points in southern countries.

Figure SE4 in the Supporting information 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 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 length of hospital stay are higher for northern countries. In contrast, the probability of an outpatient visit with a doctor or nurse is higher for northern countries only when 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, is higher in southern countries, and a high CCI increases the gap 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 3 years, a high CCI, and after the age of 75. Finally, when we examine medication consumption, the picture is drastically different depending on morbidity controls.

7 | CONCLUSION

This paper studies the effect of ageing on HC utilisation to disentangle the effect of ageing from other determinants of HC utilisation. We exploit longitudinal individual end of life data that measures the effect of TTD. We control for and measure a number of comorbidities and consider the endogeneity of TTD.

Our estimates suggest that, as predicted by the 'red herring' hypothesis, proximity to death increases hospitalizations, length of hospital stay, LTC use (home and nursing home care), and outpatient care use. More importantly, we document that the effect size of proximity to death exceeds that of an extra year of life. However, our estimates are heterogeneous across different types of HC. More specifically, we find that ageing 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.[28] Although we cannot directly observe such behaviour 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'[29].

These results taken together indicate that estimates of the effect of ageing on HC utilisation are attenuated, or become insignificant, when alternative explanations of an ageing effect such as endogenous TTD and the influence of comorbidities, as well as omitted variable bias, are accounted for. The effect of ageing on HC use seems to be simultaneously affected by several red-herrings.

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[28]Some studies (Munro, Smith, & Parke, 2002; Norman, Semmens, Lawrence-Brown, Holman, & D'Arcy, 1998; Pilote et al., 1996; Stone, Thompson, & Anderson, 1996) 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.

[29]The effect of age over the hospital length of stay is estimated to be positive (although only significant at 10% level), and it is not predict 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%).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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