Effects of long-term care benefits on healthcare utilization in Catalonia [1]

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Abstract

This paper estimates effects of long-term care (LTC) benefits on utilization of primary and secondary healthcare in Catalonia (Spain). Identification comes from plausibly exogenous variation in the leniency of LTC needs assessment. We estimate that receiving LTC benefits worth 365 euros per month, on average, reduces the probability of avoidable hospital admissions by 66%, and has no significant effect on planned hospitalisations nor on hospitalisation for any reason. Receiving LTC benefits is estimated to reduce unscheduled primary care visits by 44% and has no significant effect on scheduled visits. These findings have important policy implications suggesting that allocating resources to LTC may not only increase the welfare of LTC beneficiaries but also reduce avoidable and unscheduled utilisation of healthcare.

Keywords:

Long-term care, healthcare use, avoidable hospital admissions, non-scheduled healthcare

JEL codes: I10, I13, J14

Declaration of interests: none

1. Introduction

Population ageing and related increases in disability contribute to rising healthcare costs (Howdon and Rice, 2018; Lorenz et al., 2020). Long-term care (LTC) can potentially relieve this pressure on healthcare systems by improving disease management, treatment adherence, and prevention of falls, infections, and ulcers that result in avoidable healthcare utilization (Costa-Font et al., 2018; Spector et al., 2013). On the other hand, LTC may raise demand for planned healthcare due to closer monitoring of needs (Gonçalves and Weaver, 2017). There is a lack of evidence on which of these two potential effects of LTC on healthcare costs dominates.

This paper estimates effects of receiving LTC benefits on healthcare utilization in Catalonia (Spain). We distinguish between effects on hospital and primary care. For the former, we estimate effects on planned, emergency and avoidable hospitalizations. For primary care, we estimate effects on scheduled and unscheduled visits. We also distinguish by the main diagnosis group of both hospital admissions and primary care visits. Using a representative sample of LTC claimants between 2009 and 2014, we identify the effect of LTC benefits from plausibly exogenous variation in the leniency of LTC needs assessment. Quasi-random assignment of claimants to assessors who differ in leniency provides an instrument for the award of LTC benefits.

Our results show that LTC benefits have different effects across the different types of hospital admissions and primary care visits. The receipt of an LTC benefit of 365 euros per month on average reduces a set of avoidable hospital admissions by 66%. This reduction is especially driven by a drop in emergency hospital admissions caused by injuries, which is the fourth most common cause of admission in our sample[1]. Regarding primary care, LTC benefits decrease unscheduled "walk-in" patient visits by half, and this effect is sustained for up to 36 months. A back-of-the-envelope calculation, based on our estimates, suggests cost savings of 9.58 euros in these avoidable healthcare services for every 100 euros spent on LTC benefits.

1 In the whole Catalan population aged 50 or older, the admissions in the “Injuries and poisoning” diagnosis group account for 9.97% of the hospital admissions during the period 2009-2014. (Source: authors´ calculation based on the Hospital morbidity survey, National Statistics Institute Spain, INE)

These results are in line with existing evidence. Costa-Font et al (2018) find that the introduction of the Spanish LTC system reduced hospital admissions for beneficiaries of homecare and caregiving allowances. Without patient-level administrative data, this study could not identify the most affected types of healthcare. Examining the same setting and using a similar identification strategy as the present paper, Hernández-Pizarro (2018) finds that access to more generous LTC benefits reduces mortality by 13 percentage points but does not estimate effects on healthcare use.

Outside of Spain, Kim and Lim (2015) look at the short-term impact of LTC on medical expenses in South Korea. They find heterogeneous effects depending on the type of care and levels of need. In their most similar estimation to ours, they find that eligibility for subsidised home care does not affect total medical costs nor hospital costs. Feng et al (2020) estimate that the introduction of a pilot LTC insurance in Shanghai reduced total healthcare costs by 8.6 yuan for every yuan spent on LTC. Moura (2021) finds that the introduction of an LTC system based on subsidised nursing home care and home care teams reduced hospital bed-blocking in Portugal. In the UK, Gaughan et al (2015) find that increasing the supply of nursing home beds reduced the number of delayed hospital discharges, while Crawford et al (2021) show that lower public LTC spending increased hospital emergency department visits by older people. However, Liu et al (2021) do not find any evidence that the supply of social care affected hospitalisation rates in the UK. Overall, most previous evidence shows a substitution of LTC for healthcare/hospital care and this is in line with our results.

Our paper expands this literature in several dimensions and provides important contributions. First, as compared to previous evidence in Spain (Costa-Font et al., 2018) we use patient-level administrative data, instead of survey data, which allows us to examine the effect of LTC on healthcare use in a more comprehensive way. In particular, we analyse the effect of LTC on healthcare use by type of admission/PC visit and for the main diagnosis groups. Second, as compared to the international literature, we are the first one to take into account the main diagnosis groups of the affected healthcare use by LTC. By doing so, we can identify avoidable admissions and primary care visits related to LTC provision, issues that have remained unexplored in the previous literature. This may help policymakers to design more efficient integrated health and social care systems by identifying in detail the interdependencies between the two systems. Lastly, we estimate the effect of LTC benefits by directly comparing those who receive LTC benefits vs those who do not receive any benefit providing a clear and policy-relevant estimate of the extensive margin effect of LTC benefits. This is in contrast with the identification strategies of previous literature mentioned above, which rely on differences in the intensity of LTC to estimate the effect of LTC on healthcare use.

2. Institutional setting: Spanish Long-term care system

2.1. Spanish LTC System: main characteristics and implementation

In December 2006, Spain approved the so-called "Dependency Act", Act 39/2006, which provided a universal LTC benefits system. Under this law, eligibility for LTC allowances is determined by the applicant's level of needs. In particular, LTC needs are assessed with a Scale (*Baremo de Valoración de la Dependencia,* BVD) which ranges from 0 to 100. This scale determines three grade of LTC benefits: Grade I (BVD = [25, 49]), Grade II (BVD = [50, 74]), Grade III (BVD= [75, 100]). Claimants with a BVD score lower than 25 were not eligible for LTC allowances.

The LTC allowances can be either services (provided in-kind or via voucher, including tele-assistance, nursing home, day-care centres and home care) or cash transfers for informal caregiving. These allowances are provided for all grades, although the intensity of the care (hours or amount of subsidy) increases with the grades. In addition, the provision of benefits is means-tested such that claimants' level of benefits (voucher amount or co-payment of in-kind services) also depends on their financial capability.

The provision and management of LTC benefits is decentralised at the regional level. To be entitled to LTC benefits, claimants have to apply to the Regional Social Service Department where they are resident. Their LTC needs are then assessed by an independent local team of health and social care professionals. After the assessment, the Regional Social Service Department informs the claimant about the Grade assigned. Those claimants deemed eligible (i.e. a score greater than 24) can then choose from the bundle of LTC services available in the Grade to which they have been allocated[2].

Importantly for our identification strategy, during the first years of the implementation, the law gave preference to the most dependent claimants (Grades II and III), and later in 2012, the Spanish government postponed access to Grade I benefits until 2015 (Peña-Longobardo et al., 2016). This made that most individuals entitled to LTC benefits of Grade I during the period 2009-2014 did not receive LTC benefits at least until 2015. In particular, amongst those entitled to Grade I benefits during the period 2009-2014 in our main sample, only 11% received any allowance by 2015. In contrast, among those who were entitled to Grade II benefits, 87% had received some allowance by 2015. (Figure B1 in Appendix). Therefore, being entitled to Grade II strongly determines the probability of receiving LTC benefits, as compared to being entitled to Grade I. To exploit this variation in the probability of receiving LTC benefits we focus our main analysis on the sample of claimants who were entitled to Grade II or Grade I.

2.2. Assignment of claimants to examiners

On average the local teams of examiners consist of eight examiners who can be nurses, physiotherapists, psychologists or social workers. Within each local team, the claimant is assessed by an examiner on a rolling basis (i.e.: based on the date of application) using a common waiting list. No other factors are considered when allotting applicants to assessors or vice versa. Examiners do not rotate daily and they work during the same hours. Therefore, the assignment to a particular examiner is effectively random within each local team of examiners.

To determine the claimant's LTC needs, the examiner uses the BVD scale, a tool that includes more than 100 items to assess the claimant's ability to perform tasks related to activities of daily living. For each task where the claimant demonstrates a weakness, the examiner must indicate: (i) the medical diagnosis that could explain this limitation (drawn from NHS (National Health System) diagnosis records), (ii) the type of care required and (iii) the frequency of care required. Then, the final score is

2 After the claimant is assigned to a benefit, there is a delay until she actually receives any allowance (cash or in-kind). The average delay is 5 months (Hernández-Pizarro, 2018).). However, outstanding benefits may be paid back to the date she acquired the right to the benefit.

automatically generated by the assessment tool. Lastly, before issuing the score to the Regional Social Service Department, all of the examiners within the team review and validate each assessment.

Despite the complexity and double checks of the assessment procedure, there is some room for examiners to adjust the score by a few points. More lenient examiners can overrate the type of care needed and its frequency. This will allow claimants to access a higher Grade and therefore more benefits (Hernández-Pizarro et al., 2020). This is particularly true for claimants whose score is close to the threshold between two Grades. Thus, the assessment process creates a quasi-random variation in the assignment of LTC Grade, conditional on the residence of the claimant (which determines the local team that evaluates the claimant). More concretely, in our main analysis of the sample of claimants entitled to Grade I or Grade II, being assigned to a more lenient examiner will increase the probability of being entitled to Grade II. Then, it will also increase the probability of receiving LTC benefits since the implementation of Grade I benefits was delayed up to 2015, as explained above in section 2.1.

3. Data

We use data from the Spanish region of Catalonia, which accounts for 16% of the Spanish population, and 17% of the public LTC beneficiaries, making it the region with the second largest number of beneficiaries in Spain (IMSERSO, 2015). Our dataset consists of all individuals older than 50 who were evaluated for LTC benefits from 2009 to 2014 – 347,197 individuals[3]. This data has been granted by the Social Affairs and Family department of the Catalan Government. We are able to link 108,391 of this group with their healthcare data. Of those, 20,483 claimants were not entitled to any LTC benefit (BVD< 25); 33,600 were entitled to Grade I; 32,211 to Grade II; and 22,097 to Grade III.

We base our main analysis on comparing those claimants who have received a LTC benefit versus those who have not yet received any allowances, as we can interpret the treatment effect as the change in the healthcare utilization due to the receipt of LTC benefits. As explained in section 2.1, our empirical strategy relies on the delayed implementation of Grade I benefits with respect to Grade II. Given this, our main sample is formed by 65,811 individuals who were entitled to either Grade II or I, of whom 31,650 received a LTC benefit ("treatment" group) and 34,161 did not receive any benefit ("control" group). Grade III is then not included in our main analysis. Still, in subsection 5.6, we also carry out the analysis for the other two cut-offs of LTC Grade benefits (Grade III vs Grade II and Grade I vs non-entitled to benefits)

The institution that provided us the healthcare data did not randomly select this subsample of applicants.[4] However, we carry out a bivariate comparison of means of observable characteristics of our final sample vs the excluded sample (Table B1 in Appendix B) and although there are significant differences, they are very small in magnitude. More concretely, those taking part in our final sample are 0.23 years older, 0.8 pp more likely to have a partner, 0.4 pp less likely to be single and 0.6 pp more likely to be a disability (earnings) insurance

3 Those aged 50 or older represent 90% of the applicants during this period.

4 The linkage with healthcare data was done by the Catalan Agency for Quality and Health Evaluation ("AQuAS"). They could only provide us a subsample in order to satisfy Data Protection Guarantees.

as compared to the excluded sample. They also have small differences in the probability of having pre-LTC assessment health conditions, with a maximum difference of 7 pp in the Neurological diagnosis group, but the difference being mostly lower than 2 pp for the rest of the diagnosis groups. This suggests that our final subsample of 65,811 claimants is fairly representative of the population of LTC applicants at the Grades of interest. In addition, to explore more the potential selection issue of this subsample, in section 6.3 we provide a robustness check using inverse probability weights to account for sample selection and our results remain unchanged.

Most of the claimants in our final sample who receive any LTC benefit receive cash transfers for informal caregiving (70.3%). The rest receive some type of formal care benefit: 11.9% nursing home, 10.9% home care, 3.7% daily care centres, and 3.3% tele-assistance. The average monetary value of the LTC benefits is 365 euros[5] (Appendix C reports how we calculated the monetary value of LTC benefits), being 88.2% of them receiving Grade II benefits and 11.8% Grade I benefits.

To measure the health care services used by applicants we use secondary care and primary care data. For secondary care, we use hospital admissions data from 2007 until 2017 and include information on the type of admission (emergency vs planned) and the main diagnosis of admission. For primary care (PC) data, we use a subsample of our dataset, as data on PC visits was only available from 2013 to 2017. These data include the type of visit (scheduled vs non-scheduled) and the main diagnosis. Our main PC subsample consists of 18,624 individuals entitled to either Grade II or I, of whom 5,575 received LTC benefit ("treatment" group) and 13,049 did not receive any benefit ("control" group). In Table B2 of Appendix B, we explain how we constructed these outcome variables.

Our first outcome of interest is whether the individual has one or more hospital admissions. We also explore the type of admissions, either emergency or

5 Note that this value corresponds to the average monetary value in our dataset during the period 2009-2014. This value was not exactly constant across the whole period. In July 2012, the Government introduced LTC spending cuts, that among others, reduced the informal cash transfers of Grade II by 15% (Costa-Font et al., 2018). For comparative means, 365 euros amount accounts to 60% with respect to the average widowhood pension of the same period (607 euros), the most common source of income of the LTC claimants (Source: Spanish Ministry of Labour).

scheduled. Additionally, we group admissions by main diagnoses into two indicators: i) Ambulatory Care-Sensitive Conditions (ACSCs) which include conditions, such as pneumonia, congestive heart failure, hypertension, asthma or diabetes, for which hospital admissions are potentially avoidable with effective primary and outpatient care and ii) Nursing Home Avoidable Conditions (ANHACs) which includes conditions that can be managed effectively in nursing homes through infection control, skin and wound care, medication management and an appropriate diet. This comprises, amongst others, injuries and poisoning, skin ulcers, anaemia or nutritional deficiencies. Both indicators have been used in the medical literature to study potentially avoidable hospital admissions (Spector et al., 2013).

The second outcome that we study is the number of PC visits, scheduled and non-scheduled. Finally, we also explore the effects of LTC on both hospital admissions and PC visits by the main diagnoses group based on the International Classification of Diseases (ICD9) chapters.

3.1. Descriptive statistics

Table 1 shows the descriptive statistics of claimants in Grades I or II who received LTC benefits vs those who did not receive LTC benefits. We can observe differences between the two groups. Claimants who received LTC benefits are 0.7 years older and 2 pp less likely to receive disability (earnings) insurance (24% vs 26%). Regarding health status, they show different probabilities of having at least one health condition in all but one diagnosis group, although the sign of those differences depends on the diagnosis group. Looking at the probability of hospitalisation 12 months before LTC Grade entitlement, those who receive a LTC benefit have a 1.6 pp higher probability of emergency hospitalization and 1.7 pp lower probability of planned hospitalisation. Finally, those who received a LTC benefit report 0.7 more non-scheduled PC visits and 0.5 fewer scheduled PC visits in the 12 months after LTC entitlement than those who did not receive any LTC benefit (In Table B3 of Appendix B we report the descriptive statistics for the PC sample).[6]

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6 Note that we could not report data on PC use before LTC Grade entitlement because we only have PC data from 2013.

Table 1 - Descriptive statistics by LTC benefit receipt.

	(1) LTC benefit		(2) No LTC benefit		Difference in means[a] (1) – (2)
	Mean	SE	Mean	SE	
Sociodemographic characteristics prior to LTC Grade entitlement					
Female	0.693	0.461	0.696	0.46	-0.003
Age	78.781	9.481	78.114	9.554	0.667***
With partner	0.498	0.5	0.495	0.5	0.003
Widow	0.416	0.493	0.414	0.493	0.002
Single	0.086				

0.28

0.091
0.287

-0.005*
Disability (earnings) insurance
0.245
0.43

0.265
0.441

-0.020***
Pre-LTC assesement diagnosis groups[b]
Circulatory
0.489
0.5

0.509
0.5

-0.020***
Digestive
0.031
0.172

0.038
0.191

-0.007***
Osteoarticular
0.475
0.499

0.56
0.496

-0.084***
Ear
0.018
0.131

0.042
0.201

-0.025***
Eye
0.104
0.305

		0.132
		0.339
	-0.028***	
Respiratory		
		0.196
		0.397
		0.199
		0.399
	-0.003	
Nephro-Urology		
		0.301
		0.459
		0.259
		0.438
	0.041***	
Mental Disorder		
		0.301
		0.459
		0.293
		0.455
	0.009*	
Neurological		
		0.419
		0.493
		0.337
		0.473
	0.081***	
Endo-metabolic		
		0.396
		0.489
		0.375
		0.484
	0.021***	
Cancer		
		0.134
		0.341
		0.123

0.328

0.011***

Hematologic

0.007
0.082

0.017
0.129

-0.010***

Dermatological

0.001
0.032

0.002
0.044

-0.001**

Probability of hospitalization 12 months prior to LTC Grade entitlement

Any hospitalisation

0.348
0.476

0.346
0.476

0.003

Any emergency hospitalisation

0.27
0.444

0.253
0.435

0.016***

Any planned hospitalisation

0.131
0.338

0.148
0.355

-0.017***

Any ACSC hospitalisation[c]

0.077
0.267

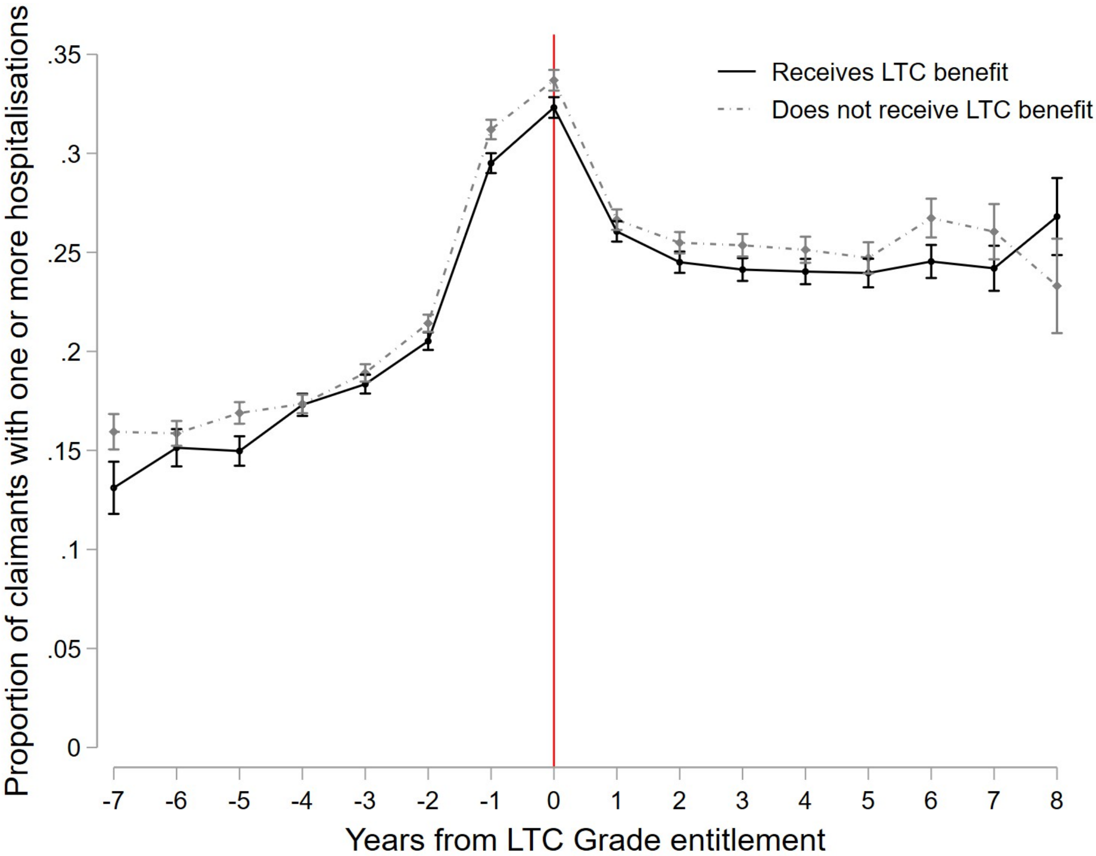
0.076
0.265

			0.001
Any ANHAC hospitalisation[d]	0.087	0.076	0.010***
	0.281	0.266	
Number of observations	25,830	26,107	51,937

NOTES: This table reports descriptive statistics prior to LTC Grade entitlement for our sample of LTC claimants entitled to Grade I or II who survive up to 24 months after entitlement. Column (1) sample is formed by those who received any LTC benefit by 2015 (our "treatment" group). Column (2) sample is formed by those who did not receive any LTC benefit by 2015, despite being entitled to one (our "control" group) [a] p-values of the independent sample t-test for the difference in means: *** p<0.01, ** p<0.05, * p<0.1. [b] Proportion of respondents with at least one health condition registered prior to LTC assessment in each of the diagnosis groups, based on the International Classification of Diseases (ICD-10). [c] Ambulatory care-sensitive conditions (ACSC) admissions are those whose main diagnosis is classified as an ACSC. These are diagnoses for which admissions are potentially avoidable by effective outpatient care. This includes principal diagnoses such as pneumonia, congestive heart failure, hypertension, asthma or diabetes (Spector et al., 2013). [d] Nursing Home Avoidable Conditions (ANHACs) admissions are those whose main diagnoses are additional conditions that can be managed effectively in Nursing Homes through infection control, skin and wound care, medication management and an appropriate diet and are not included in ACSC (Spector et al., 2013). In Table B4 Appendix B we report both average cumulative probability of hospitalisation and PC visits for every 6 months after LTC entitlement.

In Figure 1, we report the evolution of hospital use before and after LTC Grade entitlement for claimants who received a LTC benefit vs those who did not. We can see that the probability of hospital admission increases sharply for the two groups from two years before LTC Grade entitlement, a sign of deterioration in health status that could push individuals to apply for LTC benefits. However, this increase is significantly higher for those who received a LTC benefit. This means that analysing claimants who received a LTC benefit versus those who did not receive one in OLS or difference-in-difference models would give biased estimates of the effect of LTC benefits given the differences in their pre-LTC assessment hospitalisation trends.

Figure 1 - Probability of having one or more hospital admissions by year, with respect to the year of LTC Grade entitlement



NOTES: The sample is not constantly formed by the same number of individuals over time. As we go from year -2 backwards the sample gets smaller due to the normalization of the year of LTC Grade entitlement to year zero. For instance, a claimant with year of entitlement in 2009 will only be observed backwards until 2007 since our first year of observation for admissions was 2007. The same occurs if we go forward after LTC Grade entitlement (year zero). Additionally, the number of observations also goes down after year zero due to mortality. See Table B5 in Appendix B for more detailed information about the sample forming each year.

4. Empirical strategy

We model the probability of hospital admission as follows:

= + (1)

where is equal to 1 if the individual has one or more admissions and zero if none. We estimate this model for different hospital outcomes and time periods (up to 6, 12, 18, 24, 30 and 36 months) since LTC Grade entitlement. equals 1 if individual received a LTC benefit, and zero if the individual did not receive any benefit, despite being entitled to it. is a vector of control variables including gender, 5-year age group fixed effects, marital status, receipt of disability (earnings) insurance and fixed effects for each diagnosis group in which the claimant has at least one health condition, prior to LTC assessment (hereinafter "diagnosis groups fixed effects")[7]**.** is a dummy indicating any hospitalisation in the 12 months before LTC Grade entitlement. We also include territory fixed effects, (based on the local team of examiners) and year fixed effects, , and interaction between the two (. Then, our coefficient of interest measures the impact of receiving LTC benefits on the probability of hospitalization.[8]

As suggested Hernández-Pizarro (2018)**,** receiving LTC benefits may also affect the mortality of claimants. In order to control for any potential selection bias caused by this, we perform a set of robustness checks in section 6.1.

4.1. Dealing with endogeneity of LTC benefits. IV construction

As reported in the data section, the use of the healthcare system between claimants who received a LTC benefit and those who did not differ even before LTC benefits entitlement and therefore an OLS estimation of Equation 1 will

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7 The diagnosis groups correspond to the following chapters of the International Classification of Diseases (ICD -10): circulatory, digestive, osteoarticular, ear, eye, respiratory, nephro-urology, mental disorder, neurological, endo-metabolic, cancer, hematologic and dermatologic

8 Note that our baseline date is the date of entitlement to LTC benefits (i.e.: acknowledgement), since by definition we do not have the date of receipt for the control group. It is possible that there is a gap between the date when the claimant is entitled to a Grade II benefit and the date when she effectively receives it, though usually this gap is not very large (around 5 months in our data).

most likely provide a biased estimator of . To control for this endogeneity of LTC benefits we instrument the LTC benefit dummy variable with the leniency of the examiners (i.e. their propensity to grant higher LTC Grades). This instrumental variable exploits the fact that individuals quasi-randomly assigned to more lenient examiners will be more likely to be classified in Grade II, and as result also more likely to receive LTC benefits since the implementation of Grade I benefits was delayed until at least 2015.

We construct the IV using a residualised examiner leniency measure following Dahl et al (2014). First, we calculate the examiner leniency,

= (2)

where A_{ij} represents the leave-out mean for individual examined by examiner ; represents the number of assessments carried out by examiner indexes the assessment of examiner ; and Grade II equals 1 if the individual is classified above the cutoff for Grade II (i.e: BVD =[50 – 74]), and zero if the individual is assigned to Grade I (i.e: BVD =[25 – 49]).

Then, we define the instrument as the residuals from an OLS equation in which the examiner leniency leave-out mean () is regressed on year-by-territory fixed effects[9]. We do this to take into account that random allocation of claimants takes place at a territorial level and also that the implementation of the LTC system was gradual over the years.[10] Thus, the instrument can be interpreted as the variation in examiner leniency that cannot be explained by the year-by-territory fixed effects[11]. This provides exogenous variation in examiner leniency after controlling for differences by territory (teams) over time.[12]

9 Each territory fixed effect represents a local team of examiners. There are 14 local teams.

10 In section 2.1 we explain in detail the assignment of claimant to examiners.

11 As robustness check we also used as an IV the simple leave-out mean (i.e.: without residualising), and our main results hold. These results are available upon request.

12 One might have first thought to use a Regression Discontinuity design exploiting the thresholds in the BVD score that grant higher LTC benefits. However, such design cannot be used since there are strong discontinuities around the thresholds in the density function of claimants by BVD score (See Figure B2 in Appendix B). It is actually these discontinuities around the threshold that show how examiners have room to adjust the BVD around the thresholds and grant higher LTC benefits as further discussed in Hernández-Pizarro et al (2020).

We then use an instrumental variable two-stage least square model (IV-2SLS), where the second stage is Equation 1 above, and the first stage is this equation:

$$= + + \qquad (3)$$

Where the variables and subscripts are the same as those defined in Equation 1.

In section 5.1, we discuss in detail the validity of the instrument. The same instrument has been previously used by Hernández-Pizarro (2018) to estimate the causal effect of LTC benefits on mortality in Spain, and in the Netherlands by Bakx et al (2020) to study the effectiveness of nursing home admissions versus home care. It has also been used to estimate the causal effects of disability benefits (Dahl et al., 2014) or incarceration (Dobbie et al., 2018).

4.2. Estimation model for primary care use

In order to estimate the causal effect of LTC benefits on the number of PC visits, IV methods may be problematic since the dependent variable is a count variable (Windmeijer and Santos Silva, 1997). Classic linear two-stage least squares (2SLS), or two-stage predictor substitution (2SPS) for non-linear models can provide inconsistent estimators in such settings (Terza et al 2008). To address this issue, we use the Two-stage Residual Inclusion (2SRI) method as proposed by Terza (2018). 2SRI provides unbiased parameter estimates for nonlinear models. This method has been widely used in settings similar to ours (Bruni et al., 2016; Grabowski et al., 2013; Nguyen and Connelly, 2014). However, in a robustness check of section 6.3, we also estimate a 2SLS to compare the results and our main results hold.

Under this methodology, the predicted error of the first stage is included as a regressor in the second stage in order to account for the endogeneity of the explanatory endogenous variable, as follows[13]:

(4)

13 We calculated the raw residuals of the first-stage following Terza (2018). However, other authors have suggested the use of generalized residuals instead (Wooldridge, 2014). Our results (available upon request) do not change when we use generalized residuals following Gourieroux et al (1987). Actually, the raw residuals and generalized residuals have a very strong correlation in our setting ($\rho = 0.999$).

(5)

= (6)

The dependent variable measures the number of PC visits (scheduled, non-scheduled and by main diagnosis group). We estimate this model for different time periods (up to 6, 12, 18, 24, 30 and 36 months) since LTC Grade entitlement. The rest of the variables, including the examiner leniency IV (), are similar to those in Equations 1 and 3. The first stage parameters (Equation 4) are estimated using a Probit model. Then we get the predicted residuals in Equation 5 and include them in the second stage (Equation 6). Second stage parameters are estimated using a Negative Binomial model[14] assuming a variance function quadratic in the mean (negbin2 model). Results are presented as average marginal effects. Standard errors are clustered at the examiner level and bootstrapped (200 replications) in order to approximate the asymptotically correct standard errors (Terza, 2016).

5. Results

5.1. First stage and validity of the instrumental variable

Error: Reference source not found shows the results of the first-stage regressions from equation 3. The instrument is strongly significant (F-test=237.59) in the model with all covariates. In Table B6 of Appendix B, we also show the results of the first-stage regressions adding control variables in a stepwise manner. Furthermore, we consider the time since the LTC Grade entitlement (baseline, 12, 24 and 36 months, Columns 1 to 4, Table 2). The sample gets smaller as we move further from the date of LTC Grade entitlement due to mortality. The coefficient only slightly changes up to 36 months after the Grade entitlement (Column 4). This might be a consequence of differential mortality rates across Grades[15]. Still, the effect of the instrument on the

14 We tested for over-dispersion and the null hypothesis of no over-dispersion was rejected, leading us to use a Negative Binomial model, instead of a Poisson model. Results of these tests are available upon request.

15 In the robustness check section 6.1. we discuss in detail how attrition due to mortality might affect our results.

probability of receiving LTC benefits remains very strong and relatively constant over time. There is also a strong first stage for the PC subsample (Table B7 in Appendix B).

Taking into account the distribution of the instrumental variable[16], a one-standard deviation increase in leniency increases the probability of receiving LTC benefits by 4.7 percentage points. Or, being assigned to an examiner in the 75th percentile of the leniency distribution increases your probability of receiving LTC benefits by 6.2 pp compared to being assigned to an examiner in the 25th percentile of the leniency distribution. Indeed, the probability of receiving LTC benefits monotonically increases with the leniency values (Figure B3, Appendix B). Thus, the instrument strongly predicts the endogenous variable (i.e.: LTC benefits receipt), and the effects are sizeable.

Aside from the first stage, the validity of our empirical strategy requires the instrument to not be correlated with the error term of the second stage (Equation 1). This implies two conditions. First, the instrument is as good as randomly assigned conditional on the control variables and time and territory fixed effects. In Appendix A.1, we show that, in general, our control variables do not predict examiner leniency.[17] Also, the first-stage coefficients remain stable as we add control variables in a stepwise manner (Table B6 Panel A to C). Both observations support that, conditional on our controls, our instrumental variable is as good as randomly assigned. The second condition is the exclusion restriction. Since the examiners only meet the applicants during the one-hour assessment and they do not have any continuing responsibility for the claimants, we find very unlikely that an examiner could affect future healthcare use through any other channel. In Appendix A.1, we discuss both conditions more in-depth.

Lastly, with heterogeneous effects of the LTC benefits, and in order to interpret our 2SLS estimates as the Local Average Treatment Effect (LATE), the

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16 The leniency IV has a zero mean as it is constructed as a residualised measure, and a standard deviation of 0.072. Figure B3 in Appendix B shows the full distribution of our instrumental variable.

17 Only the first year lag of hospitalisation and 2 out of 13 pre-LTC assessment diagnosis groups are significantly associated with the leniency instrument, although the coefficients are close to zero.

monotonicity assumption must also hold (Angrist and Pischke, 2008). In Appendix A.2 we test for two implications that support this assumption: i) the first stages in different subsamples (based on our control variables) are positive and significant, ii) the first stage for the same subsamples but using the so-called reverse sample (Bhuller et al., 2020) are positive and significant.

Table 2 - First stage regressions. Coefficients of examiner leniency on the probability of receiving LTC benefits

	Time after LTC entitlement			
	Baseline	12 months	24 months	36 months
	(1)	(2)	(3)	(4)
Examiner Leniency	0.6511***	0.6714***	0.6804***	0.6733***
	(0.0422)	(0.0451)	(0.0481)	(0.0478)
F-test (on IV)	237.59	221.59	199.99	198.78
Dependent var. mean (LTC benefit)	0.4841	0.5005	0.4973	0.4904
Covariates	Yes	Yes	Yes	Yes
Any hospitalisation in the prior 12 months	Yes	Yes	Yes	Yes
Territory FE, Year FE, Territory FE x Year FE	Yes	Yes	Yes	Yes
Observations	64,550	58,054	51,937	45,959

NOTES: All estimates come from OLS regressions. Column (1) corresponds to the sample of individuals observed at the time of Grade entitlement (i.e.: baseline) for whom we have information in all the control variables. We have excluded 1,261 individuals with missing values. Columns (2) (3) and (4) correspond to the sample of individuals for whom we have information in all the control variables, and who are observed up to 12, 24 and 36 months after LTC Grade entitlement, respectively. Robust standard errors clustered at examiner level in parenthesis. There are 114 examiners. *** p<0.01, ** p<0.05, * p<0.1.

5.2. Effect of the LTC benefits on hospital admissions

Table 3 shows the results of estimating Equation 1 by both OLS and IV-2SLS for the probability of any hospital admission within 24 months after LTC Grade entitlement. OLS coefficients show that those who received LTC benefits have a lower probability of a planned admission, but a higher probability of an emergency admission. However, both coefficients change to the opposite sign when we account for endogeneity in the IV – 2SLS estimates. OLS coefficients may be affected by self-selection. Claimants entitled to Grade II benefits (and therefore more likely to receive LTC benefits) have a worse functional status, and they seem to substitute planned care with emergency admissions as their functional status deteriorates (Figure B4 in Appendix B) shows how hospital care use evolves by functional status, as measured by the BVD score). However, the sign of the coefficients changes when we account for endogeneity in the IV-2SLS. Receiving LTC benefits seems to increase planned admissions and decrease emergency admissions (although they do not reach significant levels).

When we focus on potentially avoidable admissions (ANHACs), coefficients turn negative in the IV-2SLS specifications. The entitlement to an LTC benefit significantly decreases the probability of avoidable admissions by 6.6 pp. These are sizeable effects since they represent a 66% reduction with respect to the mean probability (Table B4 in Appendix B). ANHACs include conditions that may be managed effectively through LTC such as injuries and poisoning, skin ulcers, anaemia or nutritional deficiencies. In particular, our results by main diagnosis group show that this reduction is driven by a significant drop of 6.7 pp in the probability of emergency admission due to “Injuries and Poisoning”(Table B8, Appendix B), which are the fourth leading cause of hospitalisation in our sample (Table B9, Appendix B).[18] There is also a significant reduction by 3.8 pp in emergency admissions of the genitourinary system. Note that up to 51% of

18 85% of admissions in the “Injuries and Poisoning” diagnosis group are emergency ones and only 15% are planned. The most prevalent diagnoses in this group are fractures (53%), followed by “Complications peculiar to certain specified procedures” mainly related with prostheses (20%) and intracranial injuries (9%). Only 1% were due to poisoning.

admissions in this category are due to Urinary tract infections[19]. On the other hand, the apparent increase in the probability of planned hospital admissions seems to be driven by Nervous System conditions (+3.8 pp), although the significance of this coefficient vanishes after adjusting for multiple hypothesis testing. 79% of admissions in this category are due to Cataract surgery, a very common procedure at old ages.[20]

In Figure 2, we plot the IV estimates with the full sets of controls by 6, 12, 18, 24, 30 and 36 months to see if the results by type of hospital admission hold over time. The positive effect on the probability of any planned admission seems to increase over time, but never reaches significance over the 36 months after LTC Grade entitlement. Similarly, the negative coefficient on emergency admissions remains not significant over the period. Lastly, the reduction in the probability of potentially LTC avoidable admissions (ANHACs) starts from 18 months after LTC Grade entitlement and remains significant up to 36 months.

19 Looking solely at hospital admissions due to Urinary tract infection (ICD-9: 599.0), we find a significant decrease in the probability of hospitalisation by 2.5 pp (p-value < 0.05), 24 months after LTC benefit entitlement

20 Looking solely at hospital admissions due to Cataracts (ICD-9: 366), we find a significant increase in the probability of hospitalisation by 4.2 pp (p-value < 0.05), 24 months after LTC Grade II entitlement.

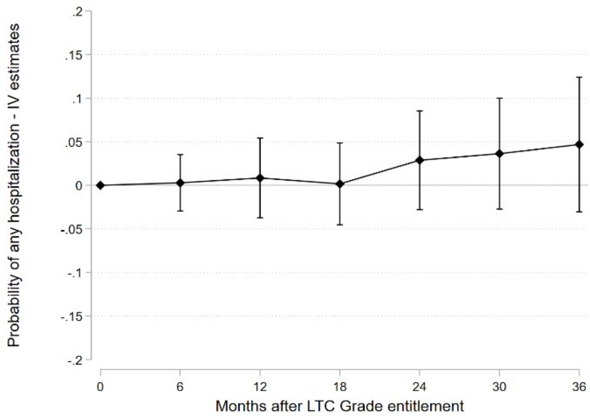
Table 3 - Coefficients of the effect of receiving LTC benefits on the probability of hospitalisation 24 months after LTC Grade entitlement.

VARIABLES	(1) Any	(2) Planned	(3) Emergency	(4) ACSC [a]	(5) ANHAC [b]
OLS	-0.0039	-0.0203***	0.0157***	0.0122***	0.0112***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
IV - 2SLS	-0.0353	0.0288	-0.0457	-0.0250	-0.0660***
	(0.034)	(0.029)	(0.033)	(0.027)	(0.025)
First stage			0.6804***		
			(0.0481)		
F-test (on IV)			199.99		
Covariates	Yes	Yes	Yes	Yes	Yes
Any hospitalization in prior 12 months	Yes	Yes	Yes	Yes	Yes
Territory FE, Year FE, Territory FE x Year FE	Yes	Yes	Yes	Yes	Yes
Dependent var. mean	0.416	0.188	0.305	0.123	0.100
Observations	51,937	51,937	51,937	51,937	51,937

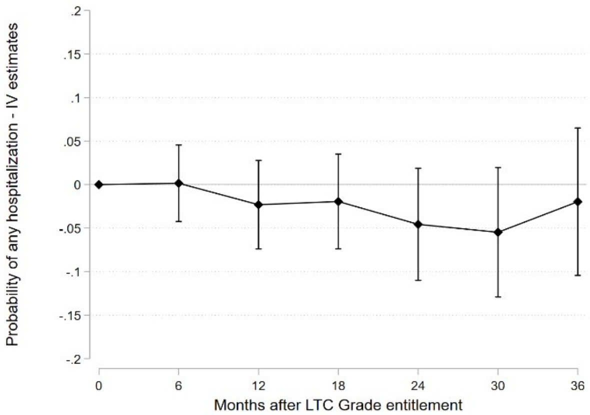
NOTES: Each column and line represents the coefficients of a different regression. Standard errors clustered at examiner level in parenthesis. There are 114 examiners. *** p<0.01, ** p<0.05, * p<0.10. [a] Ambulatory care-sensitive conditions (ACSC) admissions are those diagnoses for which admissions are potentially avoidable by effective outpatient care. This includes principal diagnoses such as pneumonia, congestive heart failure, hypertension, asthma or diabetes. [b] Nursing Home Avoidable Conditions (ANHACs) admissions are those whose main diagnoses are additional conditions that can be managed effectively in Nursing Homes through infection control, skin and wound care, medication management and an appropriate diet and are not included in ACSC. In Table B10 of Appendix B, we also show the results of the OLS and IV – 2SLS models adding control variables stepwise.

Figure 2 - IV-2SLS Coefficients of the effect of receiving LTC benefits on the probability of hospitalisation t months after LTC Grade entitlement, by hospitalisation type.

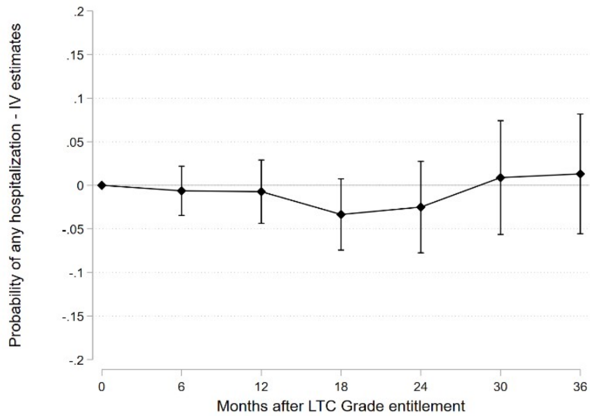
a) Any planned hospitalisation



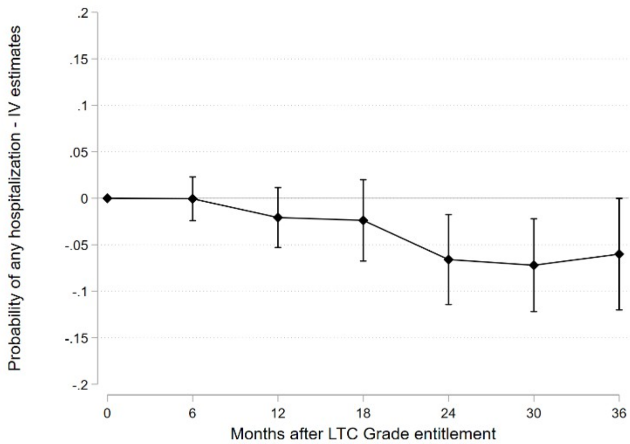
b) Any emergency hospitalisation



c) Any ACSC hospitalisation



d) Any ANHAC hospitalisation



NOTES: IV-2SLS Coefficients (and 95% Confidence Intervals) of receiving LTC benefits on the (cumulative) probability of any hospitalisation after 6, 12, 18, 24, 30 and 36 months. Number of observations at each 6-month period: 6 (n= 61,239), 12 (n= 58,054), 18 (n= 55,030), 24 (n= 51,937), 30 (n= 48,902), 36 (n= 45,959). Results from the model with the full set of demographic and health controls, any hospitalisation 12 months before Grade entitlement and territory and year fixed effects. Standard errors clustered at examiner level. There are 114 examiners.

5.3. Effect of the LTC benefits on primary care visits

In Table 4, we report the effects of LTC benefits on PC use. 2SRI results, which control for endogeneity, show that LTC benefits reduce non-scheduled visits by an average of 7, two years after LTC Grade entitlement. This is a reduction of 42% when compared to the mean (Table B4 in Appendix B). This significant effect is sustained over time up to 36 months after entitlement (Error: Reference source not found). On the other hand, they do not seem to significantly affect planned PC visits.

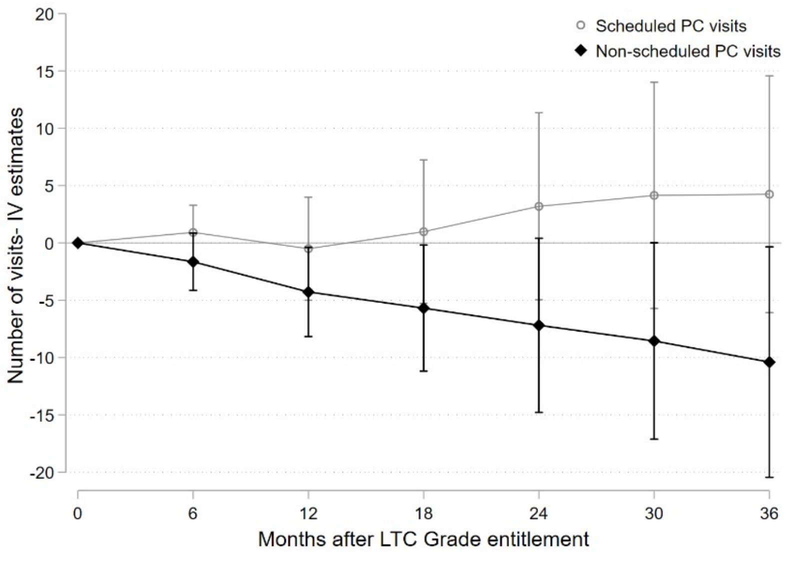
Lastly, we look at the effect on PC visits by the main diagnosis group, based on the International Classification of Diseases (ICD-9) in Table B11 of Appendix B. The reduction in non-scheduled visits seems to be driven by a reduction in the category “Factors influencing Health Status and Contact with Health Services”, although the significance of this group vanishes after correcting for multiple hypothesis testing. This category is the leading cause of PC visits, accounting for 22% of the total PC visits (Table B12, Appendix B), and is mostly formed of visits due to housing, household and economic circumstances on the one hand, and due to the long-term use of anticoagulants on the other hand.

Table 4- Coefficients effect of receiving LTC benefits on the number of PC visits 24 months after LTC Grade entitlement. Negative Binomial vs 2SRI.

	(1)	(2)	(3)
VARIABLES	Any	Planned	Emergency
Negative binomial	1.262**	-0.472	1.686***
	(0.571)	(0.370)	(0.325)
2SRI	-2.913	3.192	-7.191*
	(6.885)	(4.162)	(3.874)
First stage[a]		0.597***	
		(0.073)	
F-test (on IV)[b]		98.05	
Covariates	Yes	Yes	Yes
Territory FE, Year FE, Territory FE x Year FE	Yes	Yes	Yes
Dependent var. mean	36.49	19.43	17.06
Observations	14,104	14,104	14,104

NOTES: Each column and line represents the coefficients of a different regression. 2SRI coefficients are calculated as marginal effects. [a] First stage coefficient is reported as the marginal effect from the first stage probit regression of equation (4). [b] F-test is derived from the first stage regression estimated by OLS. In Table B13 of Appendix B, we also show the results of the Negative Binomial and 2SRI models adding control variables stepwise. Standard errors clustered at examiner level in parenthesis. 2SRI standard errors were estimated using bootstrapping (200 replications). There are 75 examiners. *** p<0.01, ** p<0.05, * p<0.1.

Figure 3 - 2SRI coefficients of the effect of receiving LTC benefits on the number of PC visits. Marginal Effects



NOTES: 2SRI coefficients (and 95% Confidence Intervals) of receiving LTC benefits on the number of PC visits after 6, 12, 18, 24, 30 and 36 months. Number of observations at each 6-month period: 6 (n=

17,231), 12 (n= 16,161), 18 (n= 15,104), 24 (n= 14,104), 30 (n= 13,120), 36 (n= 12,281). 2SRI coefficients are calculated as marginal effects. Results from the model with the full set of demographic and health controls, and territory and year fixed effects. Standard errors clustered at examiner level, estimated using bootstrapping (200 replications). There are 75 examiners.

5.4. Interpretation of the results: LATE and ATE

Our 2SLS results for hospitalisations report the LATE. That is, the average causal effect of receiving LTC benefits for the claimants whose LTC Grade was affected by the leniency of their examiners (i.e.: compliers). To put it another way, the effect of LTC benefits for claimants at the margin of the cut-off between Grade II and I. This is an estimate of policy relevance. If policymakers consider increasing the generosity of the LTC system, they most likely would do so gradually. This could mean a slight reduction in the thresholds for each Grade cut-off. Then, our 2SLS estimations may identify the effect of lowering the cut-off necessary to receive LTC benefits.

On the other hand, the 2SRI estimates for primary care visits report the Average Treatment Effect (ATE) on our sample of claimants (Terza et al., 2008). Although LATE (average effect on compliers) and ATE (average effect on our sample of claimants) are not directly comparable, results from the first stage by subsample can demonstrate how different compliers are, as compared to the average claimant in our sample. We follow Maestas et al (2013) and divide the first-stage coefficient of each subsample (based on observable characteristics) by the first-stage coefficient of the full sample. By doing this, we get the relative likelihood that compliers have a particular characteristic with respect to the average claimant in our sample (see Panel A of Table A2 in Appendix A). This shows that compliers are not very different from the rest of the claimants in our sample. In particular, compliers are 5% more likely to be female, 3% more likely to be 80 or older, 3% more likely to have a partner and 12% more likely to have 3 or more diagnosis groups with health conditions.

Additionally, we have used an endogenous switching regression model following Hasebe (2020) in order to derive estimates of both ATE and LATE for our main primary care results (Figure B5, Appendix B). Both estimates show a very similar reduction in non-scheduled PC visits. This suggests that ATE and LATE estimates may not be very different in our population under study. If this is the case, our 2SRI and 2SLS should be equally informative for policymakers.

5.5. Cost savings of LTC benefits

Our results show that LTC benefits reduce LTC avoidable hospital admissions (ANHAC hospitalisations) and non-scheduled PC visits. This means that the LTC implementation affects avoidable health care expenditure. Unfortunately, we do not have direct information on costs in our database to calculate the cost-saving of LTC benefits. However, In Appendix C we carry out a “back of the envelope” cost savings calculation based on the reduction of this avoidable healthcare use and unit healthcare costs from Spain. To do this, we first calculate the effect of an increase in €100 in monthly LTC benefits on healthcare use, using as our treatment variable the monthly monetary value of LTC benefits received, instead of the binary treatment variable (receive vs not received). The results of this model show that an increase of €100 in monthly LTC benefits reduces the probability of ANHAC hospitalization by 1.6 percentage points and the number of PC visits by 2.7, 24 months after LTC Grade entitlement (Table C1 in Appendix C). Then, based on these estimates, we estimate that every 100 euros spent on LTC benefits can save 9.58 euros in avoidable healthcare costs (3.76 euros in ANHAC hospital admissions and 5.82 euros in non-scheduled primary care visits). This would imply an elasticity of around -0.1 of avoidable healthcare costs with respect to LTC spending (Table C2 in Appendix C). Importantly, this reduction in avoidable healthcare costs is not outweighed by any significant increase in planned healthcare use. Then, we can assume that the reduction in avoidable healthcare costs would translate into a reduction in total healthcare expenditure.

5.6. Results in other cut-offs

Grade I vs non-entitled to LTC benefit. The “acknowledgement effect”

As explained in the Data section, most of the claimants entitled to Grade I (89%) did not actually receive any benefit during our period of analysis. Hence, comparing those at Grade I (BVD=25-49) with those who were not entitled to LTC benefits (BVD=0-24) means essentially looking at the effect of entitlement and recognition of LTC Grade I level of needs, instead of the receipt of benefits. We may interpret this as a sort of “acknowledgement effect”. After an individual is recognised as requiring a higher level of support, her relatives may acknowledge her real level of health status and LTC needs. Relatives may then provide her more (or better) care on an informal or private basis. This “acknowledgement effect” might have both direct effects on healthcare use but also indirectly through an improvement in health or more generally in quality of life. In Table B14 of Appendix B, we report the results of the effect of being entitled to Grade I ("treatment" group), as compared to not being entitled to any Grade ("control" group). They suggest that being entitled to Grade I does not affect hospital and primary care use.

Grade III vs Grade II benefits

In Table B15 of Appendix B, we also report the comparison between being entitled to Grade III and being entitled to Grade II benefits. Grade III benefits do not seem to reduce avoidable healthcare use. This can be explained by two factors. First, unlike Grade I, most of the claimants entitled to Grade II and Grade III benefits actually received them (87% in Grade II and 81% in Grade III). Therefore, when we compare entitlement to Grade III vs Grade II we are looking at the intensive margin effect of higher value benefits, rather than the extensive margin effect. Both Grade III and Grade II receive similar care, they only differ in the intensity of care or the amount of the cash transfers.[21] Second, Grade III individuals suffer from very severe functional limitations and have a low life expectancy. As a result, it could be that higher benefits do not alter their healthcare use, even though they could improve other dimensions of quality of life.

However, we find a significant increase in scheduled PC visits. This could reflect better access to PC derived from higher intensity of LTC. Still, these results should be interpreted with caution since they could be affected by different mortality rates of Grade III and II recipients.[22]

6. Robustness checks

6.1. Attrition due to mortality

As previously found in Hernández-Pizarro (2018), LTC benefits might also affect the mortality of claimants. In particular, in our main sample receiving LTC benefits reduced mortality by 14 pp by 36 months after LTC Grade entitlement (Table B16 in Appendix B)[23]. We expect that if LTC reduces mortality, those who prolong their life due to the LTC benefits in the Grade II group are those with marginally worse health. Equally, those who die in the Grade I group without benefits should be those in worst

21 The average monetary value of Grade III benefits is 695 euros as compared to 412 euros for Grade II.

22 Only 49% of the PC subsample in Grade III survived up to 24 months after entitlement, as compared to 70% in Grade II.

health amongst the Grade I population. As a consequence, there may be a differential attrition in the Grade I group that makes the average health of those remaining in the Grade I group relatively better than that of the Grade II group over time. Hence, as long as better health is associated with less healthcare use, our estimates of the reduction of healthcare use (i.e. ANHAC admissions and non-scheduled PC visits) might be underestimated. If this is the case, our estimates would identify a lower bound of the reduction in healthcare use caused by LTC benefits, and not necessarily the exact causal effect.

To address this issue we carry out two robustness checks. First, we run the same estimations on the effect of LTC benefits on healthcare use over time (as in Figures 2 and 3) but always using the balanced subsample of those who survived up to 36 months after LTC entitlement was determined when attrition reaches its maximum of 28% (34% in the PC sample). If our results are biased by selective attrition, estimates of the balanced subsample should significantly differ from those of our original sample, where attrition is lower. However, our main estimates hardly change (Figure B6 and Figure B7 in Appendix B).

Second, for the case of hospital admissions, we also use a multinomial model where we incorporate attrition due to death as one of the outcomes, following Grabowski et al (2013). The dependent variable has three categories: i) at least one hospitalisation, ii) death and iii) no hospitalisation nor death. To address endogeneity of LTC Grade entitlement we use a 2SRI model with a first stage Probit model for the probability of receiving LTC benefits, and a second stage multinomial model. We report marginal effects for the probability of hospitalisation and compare it with the original model results (Figure B8 in Appendix B). Our main results for ANHAC admissions lose significance but coefficients remain negative.

6.2. The effect of LTC benefits on the extensive margin of hospital demand

So far, we have only analysed the effect of LTC benefit on the extensive margin of hospitalisation (i.e. hospital admission probability). The main reason to focus on the

23 Mortality within 36 months (i.e. attrition) is also associated with age, being male, not receiving a disability (earnings) insurance and having any hospitalisation 12 months prior to LTC entitlement in both the hospitalisations sample and the PC subsample. In the PC sample, however, we don’t find a significant effect of receiving LTC benefits on mortality (Table B16 in Appendix B)

extensive margin is that even though our sample is formed of elderly and sick people, the number of hospitalisations is still low. For instance, in the 24 months after LTC entitlement was determined, only around 20% of the sample had 2 or more hospital admissions, and 6% and 13% have 2 or more planned and emergency admissions respectively (Figure B9, Appendix B). When performing the same estimations as above but using as the dependent variable the number of admissions, using a 2SRI model (as in the case of PC visits) the results for ANHAC are very similar; although now only marginally significant ($p<0.10$) by 24 months after LTC entitlement. This may suggest that the effect of LTC benefits on avoidable hospitalizations is concentrated on the intensive margin of hospital demand, not on the extensive margin (Figure B10, Appendix B).

6.3. Other robustness checks

Our main results are also robust to the following robustness checks reported in Table B17 of Appendix B: First, we run a specification including one-year age fixed effects rather than 5-year age group fixed effects (Panel A). Second, we cluster standard errors at examiners team-by-year level (Panel B). Third, in Panel C, we use inverse probability weights (IPWs) to control for potential sample selection bias (see Appendix D for a detailed explanation of how we constructed the IPWs). Finally, in Panel D, we use 2SLS instead of 2SRI to study the effect of LTC benefits on both the number of hospital admissions (rather than the probability) and the number of PC visits. Results continue to show a significant reduction in ANHAC hospitalizations and PC visits.

7. Discussion and conclusion

Our results show that providing LTC benefits has significant causal effects on the healthcare use of the beneficiaries. However, such effects are not homogenous across the type of hospital admissions and primary care visits. Our results point to a reduction in avoidable admissions in a more detailed analysis than previous literature, which finds a reduction in overall hospital admissions (Costa-Font et al., 2018). We find a 66% reduction in Nursing Home Avoidable Conditions (ANHACs); which are diagnoses identified by the medical literature as potentially avoidable with appropriate care in nursing homes but indeed potentially avoidable with any kind of appropriate care. This effect seems to be driven by a reduction in emergency hospital admissions due to injuries, which is the fourth highest cause of admissions in our sample. These are admissions particularly sensitive to the presence of a carer, who can prevent falls that might occur due to deteriorating physical and cognitive abilities of the dependent elderly. These results demonstrate the role of LTC as a preventive care tool.

Regarding primary care use, previous research has pointed towards PC being both a complement (Costa-Font et al., 2018; Gonçalves and Weaver, 2017) and a substitute for LTC (Forder et al., 2019). Our results lean towards a substitution relationship. LTC benefits significantly decrease the number of non-scheduled PC visits through the 36-month period after LTC entitlement was granted. This reduction accounts for as much as 42% of the mean number of non-scheduled PC visits. This seems to be driven by a reduction in PC visits associated with “housing, household and economic circumstances”, which could be considered as those mostly related to social exclusion of the patients. These results prove that LTC benefits can lead to better use of this type of care and ultimately to contain the pressure on primary care services.

LTC benefits will not only increase quality of life and life expectancy of the recipient but also provide savings to the healthcare system. Our “back of the envelope” calculations show that every 100 euros spent on LTC benefits can save 9.58 euros in avoidable healthcare costs (5.22 euros in hospital admissions due to injuries and 5.60 euros in non-scheduled primary care visits). This would imply an elasticity of around -0.1 of avoidable healthcare costs with respect to LTC spending. These estimates should be taken as a lower bound for the reduction in healthcare use since LTC benefits may also lower mortality among those with marginally worse health.

We have omitted from our analysis the potential effect by type of LTC benefits due to space and data limitations. However, we believe it is important to research this subject in order to understand which types of LTC services are most able to increase the efficiency of the LTC and healthcare systems.

Our results show that there are significant interdependencies between the LTC and healthcare systems, although the direction and size of these interdependencies depend on the type of diagnoses and whether the healthcare utilization is caused by emergencies or not. This has important policy implications for the organization of the

LTC and healthcare systems, especially as the aim to reduce overall costs is balanced with the aim to guarantee the quality of care. As an example, the fact that LTC largely prevents the use of non-scheduled PC indicates that a re-allocation of resources towards LTC might not only increase the welfare of the LTC recipient but also decrease primary care spending. This is just one of the interdependencies between LTC benefits and healthcare found in this study that should be taken into account when organizing the LTC and healthcare systems in a more integrated manner.

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