Ageing and health care expenditures: Exploring the role of individual health status

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Abstract

In 1999, Zweifel, Felder and Meiers questioned conventional wisdom on ageing and healthcare expenditure. According to these authors, the positive association between age and health care expenditure is due to an increasing age-specific mortality and the high cost of dying. After a weighty academic debate, a new consensus was reached on the importance of proximity to death when analyzing health care expenditure (HCE). Nevertheless, the influence of individual health status remains unknown.

The objective of our study is to analyze the influence individual health status has on HCE, when compared to proximity to death and demographic effects and considering a comprehensive view of health care services and costs.

We examined data concerning different HCE components of N=61,473 persons aged 30 to 95 years old. Using two-part models, we analyzed the probability of use and positive HCE.

Regardless of the specific group of health care services, HCE at the end of life depends mainly on the individual health status. Proximity to death approximates individual morbidity when it is excluded from the model. The inclusion of morbidity generally improves the goodness-of-fit. These results provide implications for the analysis of ageing population and its impact on HCE that should be taken into account.

1. The "red herring" backdrop

In 1999, Zweifel, Felder and Meiers (hereafter ZFM) questioned conventional wisdom on the association between age and healthcare expenditure. Moreover, they generated doubts about the preconceived idea that an ageing population will result in unbearable pressure on the health care sector (Zweifel et al., 1999). According to the authors, this so-called well-known relationship between age and health care expenditure (HCE) is simply a red herring; a notion that actually distracts attention from the relevant issue at hand. In summary, when ZFM were considering previous evidence of the high amount of HCE spent on the last years of life, (e.g. Lubiz & Riley, 1993), they stated that the positive association between age and health care expenditure is because of increasing

age-specific mortality and the high cost of dying, and consequently, population ageing may contribute much less to the future growth of the healthcare sector than previously believed.

Using the Heckman model (Heckman, 1976; 1979), ZFM tested their hypothesis: *HCE during the terminal years increase as a function of proximity to death*. The authors first examined the probability of utilisation, then examined the positive log-HCE and, finally, demonstrated that, provided individuals were 65 years or older, the effect of age was negligible compared to closeness to death (Zweifel et al., 1999).

ZFM's highly cited paper produced a stimulating debate around HCE and the influence of closeness to death compared to age. The endogeneity of the variable closeness to death and the presence of multicollinearity - produced by adopting the Heckman model to control sample selectivity - were the main methodological criticisms they received (Salas & Raftery, 2001). To mitigate endogeneity, subsequent authors proposed a different approach to measure closeness to death, and eliminated the set of quarter dummies included in the original ZFM paper (Stearns & Norton, 2004; Zweifel et al., 2004; Werblow et al., 2007). Moreover, the utilisation of two-part models instead of the original Heckman model became the standard solution for multicollinearity issues (Dow & Norton, 2002; Seshamani & Gray, 2004). Further research provided a comprehensive view of HCE components, including different health care services and costs (Werblow et al., 2007). Other noteworthy papers went into detail on the analysis of disease-specific hospital expenditure (Wong et al., 2011; Howdon & Rice, 2018).

The importance of closeness to death in the analysis of HCE at the end of life was demonstrated within the "red herring" literature. However, as some authors have stated, the influence health status exerts is an issue that still needs addressing (Zweifel et al., 1999; Seshamani & Gray, 2004; Wong et al., 2011). The literature does recognise a strong association between concepts such as morbidity burden, disability, chronic conditions or health status and HCE. In general, the message is that poorer health states are associated with higher levels of the HCE and vice versa (e.g. Dormont et al., 2006; Michaud et al., 2009; Carreras et al., 2013). Thus, a natural hypothesis emerged: At the end of life, besides age and closeness to death, individual health status must exercise a

decisive influence on HCE. In accordance with this idea, the main objective of this study is to analyse the influence individual health status has on HCE when compared to the influence proximity to death and demographic effects have and by considering a comprehensive view of health care services and costs.

2. Methods

2.1 Data

Given that a wide view of healthcare components - beyond acute hospitalisation – fell within the aims of this study, we used data from an integrated health care service. Serveis de Salut Integrats Baix Empordà (SSIBE) is an integrated health care organisation responsible for the provision of public health care services in the Baix Empordà county in Catalonia. The information analysed in our study was supplied by the SSIBE and included acute inpatient care, acute outpatient care, primary care, pharmacy prescriptions, diagnostic tests, emergencies and long-term residential care. Mental health was not included. The study focused on HCE incurred during 2012 for the N=61,473 persons aged 30 to 95 and who were still alive on 31/12/2012. We followed the cohort for 40 months, beginning on 31/12/2012 and finishing on 30/04/2016, when data for the study were collected. Within this period we checked on whether individuals had died or not. For those individuals who did die within those 40 months, we measured proximity to death as a continuous variable: time to death in months (TTD). For those individuals who survived, TTD was censored at 40 months. Individual costs were added up from care episodes, which included the range of services previously described, and pharmacy prescriptions the individuals had received in 2012. Average HCE and basic sample characteristics for the deceased and the survivors are provided in both Figure 1 and Table I. A detailed description of healthcare services is included in the Table I

2.2 Health status and individual morbidity burden

The fundamental contribution of the study was the inclusion of morbidity in the analysis of HCE at the end of life. For individuals included in the sample, we assessed the morbidity burden using the Clinical Risk Groups patient classification system (3M™CRG), software version 1.9.1 (Hughes et al., 2004; Clinical Risk Grouping Software. Definitions

Manual, 2004). The CRG model was initially designed to predict future use of healthcare resources. However, the underlying clinical perspective makes it a useful tool for managing patient-centred chronic strategies (Inoriza et al., 2009). Within the CRG model, individuals were classified into single, mutually exclusive and exhaustive categories according to their clinical records and prescription codes. The CRG health status classification contains nine categories: (1) Healthy, (2) History of significant acute disease, (3) Single minor chronic disease, (4) Minor chronic disease in multiple organ systems, (5) Single dominant or moderate chronic disease, (6) Significant chronic disease in multiple organ systems, (7) Dominant chronic disease in three or more organ systems, (8) Dominant and metastatic malignancies and (9) Catastrophic conditions. The CRG system creates patient morbidity categories using all the information on diagnostics, procedures and prescriptions related to the population during a specific period. The system processed all ICD9 and ATC codes collected between 1 January 2012 and 31 December 2012 related to the individuals included in the study. Although the CRG has different levels of aggregation we only show CRG health status, the most aggregated level. A summary of the sample, morbidity and costs for deceased and survivors is presented in the Figures 2 and 3.

Unfortunately, information related to long-term residential care users presented several problems and so was removed from the data set. Specifically, the reduced number of ICD codes registered for residential care users resulted in an underestimation of the individual health status.

2.3 Measuring the influence of health status

In general, since 2004, the adoption of two-part models and the measure of closeness to death as a single continuous variable, became the standard solutions for endogeneity and multicollinearity issues. We followed the same approach. We used a logit model for the probability of having positive costs (part one) and a generalised linear model (GLM) with a log link and Gamma distribution for positive HCE (part two).

The two parts of the models were estimated for each group of integrated services described in the introduction; albeit with the exception of long-term residential care. The specification of the models included: age, age squared, sex (female), time to death

in months, death within 40 months after 31/12/2012 (dummy), CRG health status (set of dummies) and interactions. The set of variables differed slightly from the original ZFM specification, as well as from later studies. The most relevant difference was the inclusion of individual morbidity burden through the CRG health status indicator. We sequentially estimated two models, a first model including demographic and proximity to death variables and a second - extended - model adding health status indicators:

Model 1 - Demographic and proximity to death

Part one (Logit):

$$P(HCE>0) = \beta_0 + \beta_1.Age + \beta_2.Age^2 + \beta_3.SexF + \beta_4.TTD + \beta_5.Death + \beta_6.(Age*SexF) + \beta_7.(Age*Death) + \varepsilon$$

Part two (GLM – log Gamma):

$$HCE = \beta_0 + \beta_1.Age + \beta_2.Age^2 + \beta_3.SexF + \beta_4.TTD + \beta_5.Death + \beta_6.(Age*SexF) + \beta_7.(Age*Death) + \varphi$$

Model 2 - Demographic, proximity to death and health status

Part one (Logit):

$$P(HCE>0) = \beta_0 + \beta_1.Age + \beta_2.Age^2 + \beta_3.SexF + \beta_4.TTD + \beta_5.Death + \beta_6.(Age*SexF) + \beta_7.(Age*Death) + \sum_{j=1}^{9} \delta_j.Status_j + \sum_{q=1}^{9} \gamma_q.(Status_q*Death) + \varepsilon$$

Part two (GLM – log Gamma):

$$HCE = \beta_0 + \beta_1.Age + \beta_2.Age^2 + \beta_3.SexF + \beta_4.TTD + \beta_5.Death + \beta_6.(Age*SexF) + \beta_7.(Age*Death) + \sum_{j=1}^{9} \delta_j.Status_j + \sum_{q=1}^{9} \gamma_q.(Status_q*Death) + \varphi$$

Model selection and specification were supported by precision and systematic bias statistics. The choice of the GLM - log Gamma model, instead of the log OLS alternative - was supported by standard selection procedures, (e.g. Manning & Mullahy, 2001), as well as GLM-link tests. Using the Huber-White estimate of the variance covariance

matrix, we obtained a robust estimation of the standard error for the regression coefficients.

The estimation procedures and the statistical tests described throughout this section were obtained using the R 3.1.2 software version (R Core Team, 2015).

2.4 Ethics

The study protocol was approved by the Clinical Research Committee of SSIBE. Given the methodology of the study, based on a retrospective review of clinical and administrative records, no informed consent was requested. Data management was conducted anonymously by members of the SSIBE staff.

3. Results

The results of the simple and extended models are presented in Tables II and III, respectively. Both tables show (in columns) the different groups of integrated services. A final column, 'Integrated services', was included for the aggregation of health care services.

Model results are sorted according to four categories: demographic, proximity to death, morbidity burden and interactions. We presented odds ratios obtained from logit models (Part one) and coefficients of the GLM-log Gamma models (Part two: multiplicative impact in costs).

3.1 Model 1

Demographic variables, in particular, Age and Age squared, showed a reduced influence in both parts of the model. Being a female was associated with a high chance of utilisation.

Compared to demographic, proximity to death variables produced large changes in both probability of utilisation and HCE. However, there was a significant variability across service lines. Within several groups of services, the coefficients from the first part of the model were not found to be significant. Dying before 30/04/2016 had a clear impact on the chance of utilisation.

3.2 Model 2 - Extended

Morbidity coefficients representative of individual health status showed a substantial impact on both probability of utilisation and costs. 'Healthy' was stated as the benchmark category. Odds ratios and coefficients tend to increase progressively according to the burden of morbidity. This tendency was clearly observed across service lines and for the two parts of the models, although with the exception of the logit coefficients for integrated services.

Regarding interactions, age*sex and age*death showed a negative effect on both the probability of utilisation and HCE. In general, the set of interactions death*morbidity were not found to be significant, albeit with the exception of acute inpatient care for the second part of the model. In this case, the interaction explained a surge of acute inpatient costs for individuals who died within the 40 month period or a reduction caused by death censoring, depending on the case. The lack of significance of interactions for the remaining healthcare components means that dying before 30/04/2016 does not imply larger costs in respect to the individuals with the same health status, reinforcing the idea of morbidity as the main HCE driver in the last period of life.

Comparing both versions of the models, the inclusion of morbidity rebalanced the relationship between predictors and response variables. In particular, proximity to death coefficients were reduced up to 92% (Acute inpatient; part two; variable: Death before 30/04/2016). In general, the inclusion of morbidity considerably improves the goodness-of-fit.

4. Discussion

As it was previously stated, the two-part model we used in the analysis differed from the original ZFM approach. However, it is comparable to the majority of studies undertaken since 2004. In particular, our results on the different HCE components are comparable to Werblow et al., (2007), given that the latter provided an equivalent analysis for Acute outpatient, Acute inpatient, Primary care and Pharmacy prescriptions. In general, the magnitude and the sign of the coefficients on the demographic and

proximity to death variables, as well as Age*Sex and Age*Death interactions, are consistent with previous studies. However, in our analysis, morbidity variables accounted for the largest impact in both probability of utilisation and HCE. In this sense, our results are analogous to those obtained by Dormont et al. (2006).

Howdon and Rice (2018) introduced an approximation of morbidity based on ICD10 codes related to hospital episodes. The authors reported that the impact of TTD notably diminishes when morbidity was included in the model, considering TTD itself as a proxy of morbidity. The remaining TTD effects were interpreted as a proxy for unobserved morbidity (not captured from hospital episodes). Our results confirm their main findings for healthcare components beyond hospital care. However, since we obtained morbidity from ICD and ATC codes related to multiple health care components, this study substantially avoids the missing morbidity limitation described by Howdon and Rice. The remaining effects can be interpreted as net proximity to death effects (separated from morbidity) related to each particular health care component.

Recalling the origins of the "red herring" debate, in 1999 ZFM refuted budgetary constraints as macro determinants of HCE, as was also defended by Getzen (1992, 2001), among others. Furthermore, there is some consensus on the importance of change in practice and technology (e.g. Dormont et al, 2006; Newhouse, 1992; Stearns & Norton, 2004). The analysis of morbidity is important because can be directly related to particular chronic conditions, medical practices and technologies, introducing a link between micro (person related) and macro level variables.

Considering the importance of residential care services for older persons, an important limitation was its exclusion. A second limitation concerned the size of the sample. In spite of larger datasets of acute hospitalisation episodes being frequently available, comprehensive datasets including episodes from varied HCE components are rare and difficult to obtain. However, the size of our sample on integrated services is comparable to the sample size previously analysed in similar studies (Zweifel et al., 2004; Werblow et al., 2007).

5. Conclusions

Regardless of the specific group of health care services, HCE at the end of life depends mainly on the individual health status. Proximity to death, sex and marginally age approximate individual morbidity when it is excluded from the model. The inclusion of morbidity generally improves the goodness-of-fit. These results provide implications for the analysis of ageing population and its impact on HCE that should be taken into account.

6. Acknowledgements

7. References

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Table I. Descriptive statistics

	Deceased (n = 2,394)		Survivors (n = 59,079)	
	Mean	SE	Mean	SE
Age	78.45	12.79	53.49	15.59
Time to death in months	19.77	11.67	>40	0.00
HCE in 2012				
Integrated services (Total)	3,207.72	4,665.58	930.99	2,059.74
Probability of utilisation	0.97	-	0.81	-
A. Acute inpatient care	504.84	2,178.92	290.72	732.53
B. Acute outpatient care	3,280.16	4,401.27	1,851.01	3,218.01
C. Primary care	429.82	469.82	177.24	188.22
D. Pharmacy prescriptions	1,313.70	1,928.73	399.97	1,102.34
E. Diagnostic tests	161.31	250.42	87.29	142.22
F. Accident and emergencies	539.37	644.69	192.57	290.37
G. Long-term residential care	18,735.46	15,331.79	13,736.77	13,863.87

€; N= 61,473; % sex female = 50.28%

A. Acute hospitalization, blood transfusions, convalescence, day hospital, inpatient medication, palliative care, surgical areas.

B. Haemodialysis, hyperbaric oxigen therapy, rehabilitation, specialist consultation.

C. General practitioner consultation.

D. General practitioner and specialist prescription. Antiviral drugs, biopharmaceutical products chemotherapy and other high cost chronic acute outpatient prescription.

E. Anatomical Pathology, Laboratory, Radiology, electrodiagnostic medicine, nuclear medicine, respiratory tests and other test.

F. A&E episodes.

G. Day-care centres, long-term residential, nursing home care.

Table II. Model 1 - Demographic & proximity to death

Variable	Acute outpatient Part one OR	SE	sig	Part two Beta	SE	sig	Acute inpatient Part one OR	SE	sig	Part two Beta	SE	sig	Primary care Part one OR	SE	sig	Part two Beta	SE	sig	Pharmacy Part one OR	SE	sig	Part two Beta	SE	sig
Constant	0.029	0.005	***	4.847	0.458	***	0.023	0.006	***	8.458	0.390	***	1.092	0.326		4.463	0.101	***	0.634	0.200		3.488	0.247	***
Demographic																								
Age	1.061	0.004	***	0.018	0.009	.	1.037	0.007	***	-0.033	0.011	**	0.972	0.006	***	0.007	0.002	***	0.969	0.005	***	0.072	0.008	***
Age^2	1.000	0.000	**	0.000	0.000		1.000	0.000		0.000	0.000	***	1.001	0.000	***	0.000	0.000	***	1.001	0.000	***	0.000	0.000	***
Sex Female	4.184	0.261	***	0.247	0.172		6.043	0.636	***	0.120	0.170		3.613	0.280	***	0.491	0.032	***	3.671	0.273	***	-0.622	0.136	***
Proximty to death																								
TTD (in months)	1.006	0.004		-0.011	0.009		0.977	0.004	***	-0.010	0.005	*	1.010	0.007		-0.008	0.002	***	1.010	0.007		-0.008	0.003	**
Death (before 30/04/2016)	15.362	4.304	***	3.431	0.615	***	19.139	6.092	***	1.652	0.452	***	19.733	8.793	***	1.281	0.143	***	7.151	2.998	***	2.874	0.536	***
Interactions																								
Age*Sex Female	0.980	0.001	***	-0.005	0.003	.	0.974	0.002	***	-0.001	0.003		0.983	0.002	***	-0.006	0.001	***	0.984	0.001	***	0.008	0.002	***
Age*Death	0.969	0.003	***	-0.040	0.008	***	0.963	0.004	***	-0.020	0.006	***	0.961	0.006	***	-0.014	0.002	***	0.979	0.006	***	-0.031	0.006	***
R^2 or Pseudo R^2	0.06			0.01			0.05			0.03			0.07			0.15			0.1			0.06		

Variable	Diagnostic tests Part one OR	SE	sig	Part two Beta	SE	sig	A&E Part one OR	SE	sig	Part two Beta	SE	sig	Integrated Services Part one OR	SE	sig	Part two Beta	SE	sig
Constant	0.085	0.020	***	3.266	0.154	***	1.865	0.365	**	5.285	0.214	***	2.226	0.973	.	5.636	0.168	***
Demographic																		
Age	1.047	0.005	***	0.048	0.004	***	0.933	0.004	***	-0.003	0.006		0.956	0.006	***	0.025	0.004	***
Age^2	1.000	0.000	.	0.000	0.000	***	1.001	0.000	***	0.000	0.000	***	1.001	0.000	***	0.000	0.000	*
Sex Female	5.660	0.365	***	1.038	0.059	***	2.124	0.147	***	0.326	0.084	***	3.342	0.292	***	0.678	0.074	***
Proximty to death																		
TTD (in months)	1.001	0.005		-0.017	0.003	***	0.982	0.004	***	-0.013	0.003	***	1.007	0.010		-0.014	0.003	***
Death (before 30/04/2016)	5.866	1.955	***	2.095	0.216	***	5.838	1.644	***	1.827	0.277	***	1.840	1.003		3.172	0.216	***
Interactions																		
Age*Sex Female	0.978	0.001	***	-0.016	0.001	***	0.989	0.001	***	-0.007	0.001	***	0.986	0.002	***	-0.011	0.001	***
Age*Death	0.981	0.004	***	-0.025	0.003	***	0.981	0.003	***	-0.020	0.003	***	1.002	0.008		-0.037	0.003	***
R^2 or Pseudo R^2	0.09			0.03			0.02			0.1			0.07			0.08		

Part one: Logit; Part two: GLM log Gamma; Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table III. Model 2 - Demographic, proximity to death & morbidity burden

	Acute outpatient						Acute inpatient						Primary care						Pharmacy					
	Part one			Part two			Part one			Part two			Part one			Part two			Part one			Part two		
Variable	OR	SE	sig	Beta	SE	sig	OR	SE	sig	Beta	SE	sig	OR	SE	sig	Beta	SE	sig	OR	SE	sig	Beta	SE	sig
Constant	0.058	0.012	***	4.902	0.193	***	0.051	0.014	***	8.758	0.401	***	0.912	0.332		4.974	0.095	***	0.473	0.219		4.135	0.344	***
Demographic																								
Age	1.006	0.005		-0.002	0.004		0.970	0.007	***	-0.049	0.011	***	0.973	0.006	***	-0.029	0.002	***	0.957	0.006	***	-0.013	0.010	
Age^2	1.000	0.000		0.000	0.000		1.000	0.000	***	0.000	0.000	***	1.000	0.000	**	0.000	0.000	***	1.000	0.000	***	0.000	0.000	.
Sex Female	2.953	0.203	***	0.327	0.064	***	4.025	0.441	***	0.189	0.183		2.552	0.234	***	0.393	0.028	***	2.608	0.243	***	-0.187	0.168	
Proximty to death																								
TTD (in months)	1.011	0.004	**	-0.010	0.004	**	0.981	0.004	***	-0.009	0.005	.	1.018	0.008	*	-0.004	0.002	*	1.026	0.011	*	-0.006	0.003	.
Death (before 30/04/2016)	4.944	1.806	***	1.361	0.510	**	2.944	2.272		0.130	0.442		3.022	1.546	*	0.406	0.160	*	1.266	0.728		1.072	0.398	**
Morbidity burden																								
Healthy	-	-		-	-		-	-					-	-		-	-					-	-	
Acute disease	7.637	0.308	***	0.609	0.035	***	10.625	0.760	***	0.148	0.077	.	26.244	2.468	***	0.701	0.016	***	11.759	0.630	***	0.546	0.094	***
Minor chronic disease	6.503	0.212	***	0.387	0.044	***	5.439	0.384	***	-0.001	0.144		23.608	1.545	***	0.600	0.013	***	17.867	0.832	***	1.053	0.091	***
Minor chronic >=2	13.086	0.643	***	0.574	0.037	***	10.267	0.831	***	-0.066	0.114		118.786	25.564	***	1.006	0.017	***	106.241	16.872	***	1.721	0.081	***
Dominant chronic disease	7.472	0.224	***	0.526	0.034	***	7.055	0.457	***	0.020	0.092		36.348	2.208	***	0.911	0.013	***	46.354	2.501	***	2.160	0.091	***
Dominant chronic = 2	18.302	0.607	***	0.949	0.036	***	16.638	1.054	***	0.574	0.100	***	169.162	18.246	***	1.396	0.013	***	454.755	62.545	***	2.959	0.085	***
Dominant chronic >= 3	42.859	4.517	***	1.336	0.073	***	36.751	3.589	***	0.981	0.144	***	196.379	80.986	***	1.845	0.031	***	1.7E+03	1.7E+03	***	3.704	0.091	***
Metastatic malignancies	46.777	8.236	***	1.321	0.112	***	45.060	6.022	***	0.758	0.143	***	403.403	404.386	***	1.611	0.051	***	60.887	19.714	***	3.692	0.171	***
Catastrophic conditions	94.105	25.314	***	3.537	0.164	***	32.748	5.288	***	0.918	0.179	***	23.873	7.757	***	1.423	0.069	***	88.987	40.339	***	5.076	0.105	***
Interactions																								
Age*Sex Female	0.985	0.001	***	-0.004	0.001	***	0.980	0.002	***	-0.001	0.003		0.988	0.002	***	-0.005	0.000	***	0.989	0.002	***	0.003	0.002	
Age*Death	0.979	0.004	***	-0.017	0.004	***	0.973	0.005	***	-0.012	0.007	.	0.986	0.007	.	-0.006	0.002	***	0.999	0.008		-0.009	0.004	*
Death*Acute disease	0.673	0.345		-0.260	0.615		1.116	1.070		1.604	0.371	***	0.629	0.491		-0.188	0.210		2.445	1.890		0.208	0.550	
Death*Minor chronic disease	0.711	0.282		-0.615	0.547		0.774	0.790		-0.753	0.528		0.671	0.375		-0.198	0.213		2.097	1.317		0.060	0.712	
Death*Minor chronic >=2	0.772	0.379		0.358	0.681		1.345	1.283		0.034	0.436		3.2E+04	5.8E+06		-0.098	0.245		2.1E+04	2.3E+06		-0.480	0.488	
Death*Dominant chronic	1.305	0.355		0.070	0.574		2.159	1.604		0.612	0.322	.	0.675	0.203		0.051	0.145		0.729	0.220		-0.102	0.483	
Death*Dominant chronic = 2	1.244	0.318		-0.130	0.525		2.386	1.725		0.764	0.239	**	0.386	0.106	***	0.188	0.121		1.399	0.670		-0.151	0.461	
Death*Dominant chronic >= 3	1.246	0.376		-0.143	0.537		2.714	1.988		0.736	0.256	**	1.006	0.649		0.159	0.130		0.235	0.277		-0.388	0.464	
Death*Metastatic malignancies	1.048	0.397		-0.185	0.538		2.026	1.512		0.959	0.259	***	1.2E+04	8.6E+05		0.259	0.185		8.119	8.728	.	-0.055	0.496	
Death*Catastrophic conditions	1.556	1.254		0.814	0.568		4.055	3.252	.	0.711	0.319	*	2.980	3.216		0.385	0.221	.	3.1E+04	2.7E+06		-1.205	0.458	**
R^2 or Pseudo R^2	0.22			0.17			0.14			0.05			0.35			0.27			0.42			0.23		

Part one: Logit; Part two: GLM log Gamma; Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

**Table III. Model 2 - Demographic, proximity to death & morbidity burden (continued)**

	Diagnostic tests						A&E						Integrated Services					
	Part one			Part two			Part one			Part two			Part one			Part two		
Variable	OR	SE	sig	Beta	SE	sig	OR	SE	sig	Beta	SE	sig	OR	SE	sig	Beta	SE	sig
Constant	0.117	0.031	***	3.402	0.147	***	3.352	0.689	***	5.579	0.204	***	0.117	0.031		6.490	0.177	***
Demographic																		
Age	1.017	0.005	**	0.023	0.004	***	0.900	0.005	***	-0.030	0.006	***	1.017	0.005	**	-0.044	0.005	***
Age^2	1.000	0.000	*	0.000	0.000	***	1.001	0.000	***	0.000	0.000	***	1.000	0.000		0.000	0.000	***
Sex Female	4.688	0.347	***	1.124	0.053	***	1.511	0.109	***	0.239	0.074	**	4.688	0.347	***	0.782	0.079	***
Proximty to death																		
TTD (in months)	1.005	0.006		-0.012	0.003	***	0.985	0.004	***	-0.010	0.003	**	1.005	0.006		-0.010	0.003	***
Death (before 30/04/2016)	1.526	0.597		0.913	0.280	**	1.865	0.712		1.111	0.593	.	1.526	0.597	.	1.122	0.247	***
Morbidity burden																		
Healthy	-	-		-	-		-	-		-	-		-	-		-	-	
Acute disease	11.057	0.512	***	0.500	0.028	***	5.995	0.258	***	0.560	0.038	***	11.057	0.512	***	1.209	0.036	***
Minor chronic disease	7.870	0.263	***	0.445	0.025	***	2.565	0.104	***	0.386	0.044	***	7.870	0.263	***	0.977	0.042	***
Minor chronic >=2	18.282	1.175	***	0.696	0.030	***	4.047	0.223	***	0.561	0.058	***	18.282	1.175		1.513	0.036	***
Dominant chronic disease	12.787	0.409	***	0.625	0.027	***	3.050	0.112	***	0.706	0.047	***	12.787	0.409	***	1.537	0.033	***
Dominant chronic = 2	37.360	1.584	***	1.133	0.026	***	5.623	0.211	***	1.148	0.043	***	37.360	1.584	***	2.394	0.033	***
Dominant chronic >= 3	132.313	29.595	***	1.596	0.053	***	13.390	1.070	***	1.591	0.074	***	132.313	29.595		3.144	0.053	***
Metastatic malignancies	66.912	18.438	***	2.135	0.073	***	9.797	1.217	***	1.437	0.111	***	66.912	18.438		3.092	0.087	***
Catastrophic conditions	177.076	89.517	***	2.216	0.067	***	8.988	1.308	***	1.767	0.145	***	177.076	89.517		4.194	0.064	***
Interactions																		
Age*Sex Female	0.981	0.001	***	-0.017	0.001	***	0.995	0.001	***	-0.004	0.001	***	0.981	0.001	***	-0.011	0.001	***
Age*Death	1.003	0.005		-0.010	0.003	***	0.989	0.004	**	-0.006	0.004	.	1.003	0.005	**	-0.017	0.003	***
Death*Acute disease	0.463	0.239		0.534	0.431		1.187	0.626		-0.528	0.655		0.463	0.239		0.429	0.455	
Death*Minor chronic disease	0.415	0.150	*	-0.363	0.273		1.028	0.499		-0.279	0.703		0.415	0.150		-0.137	0.335	
Death*Minor chronic >=2	0.683	0.441		-0.511	0.247	*	0.622	0.386		-0.561	0.723		0.683	0.441		-0.047	0.269	
Death*Dominant chronic	0.529	0.119	**	-0.070	0.215		1.315	0.415		-0.501	0.634		0.529	0.119		0.254	0.236	
Death*Dominant chronic = 2	0.601	0.125	*	-0.122	0.184		1.645	0.477	.	-0.466	0.620		0.601	0.125		0.305	0.213	
Death*Dominant chronic >= 3	0.416	0.162	*	-0.069	0.194		1.446	0.449		-0.361	0.625		0.416	0.162		0.218	0.219	
Death*Metastatic malignancies	0.597	0.301		-0.087	0.208		1.547	0.538		-0.238	0.623		0.597	0.301		0.370	0.240	
Death*Catastrophic conditions	0.148	0.119	*	-0.110	0.238		2.606	1.206	*	-0.436	0.637		0.148	0.119		0.239	0.244	
R^2 or Pseudo R^2	0.31			0.11			0.08			0.16			0.41			0.26		

Part one: Logit; Part two: GLM log Gamma; Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Figure 1. Average HCE in 2012 by age group

Source: Serveis de Salut Integrats Baix Empordà

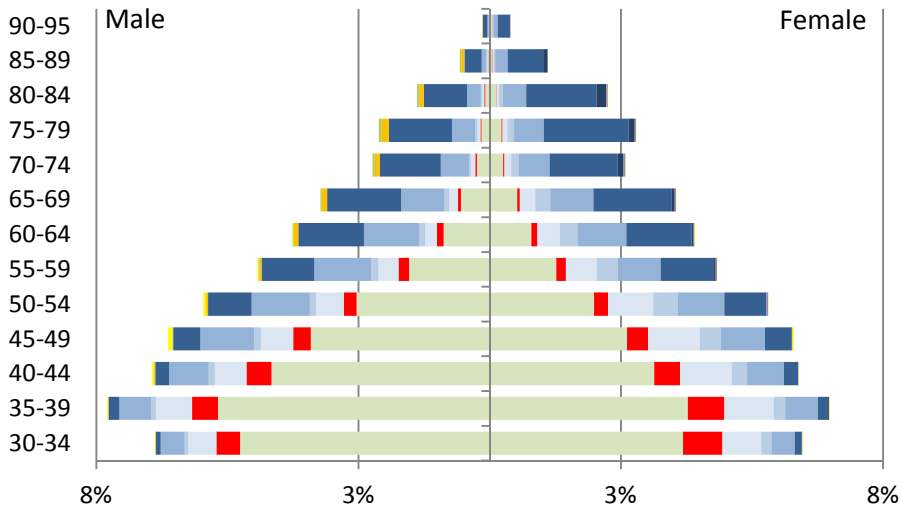□ Survivor after 30/04/2016

▨ Deceased [31/12/2012 to 30/04/2016]
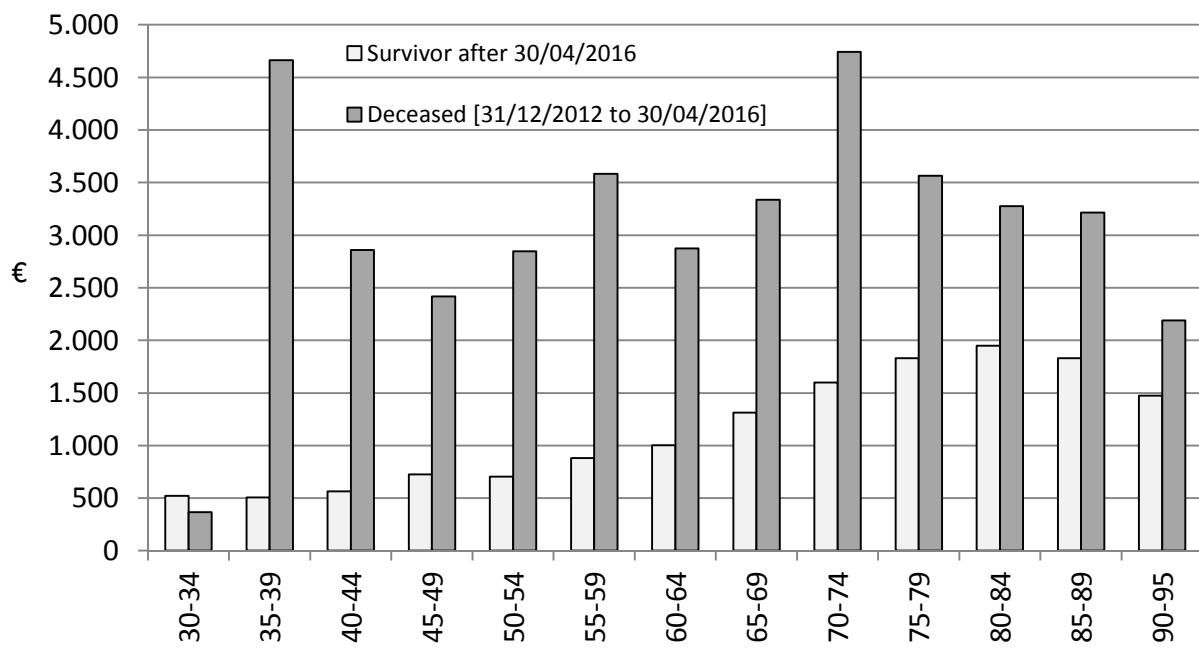
Figure 2. Average HCE in 2012 by health status

Source: Serveis de Salut Integrats Baix Empordà
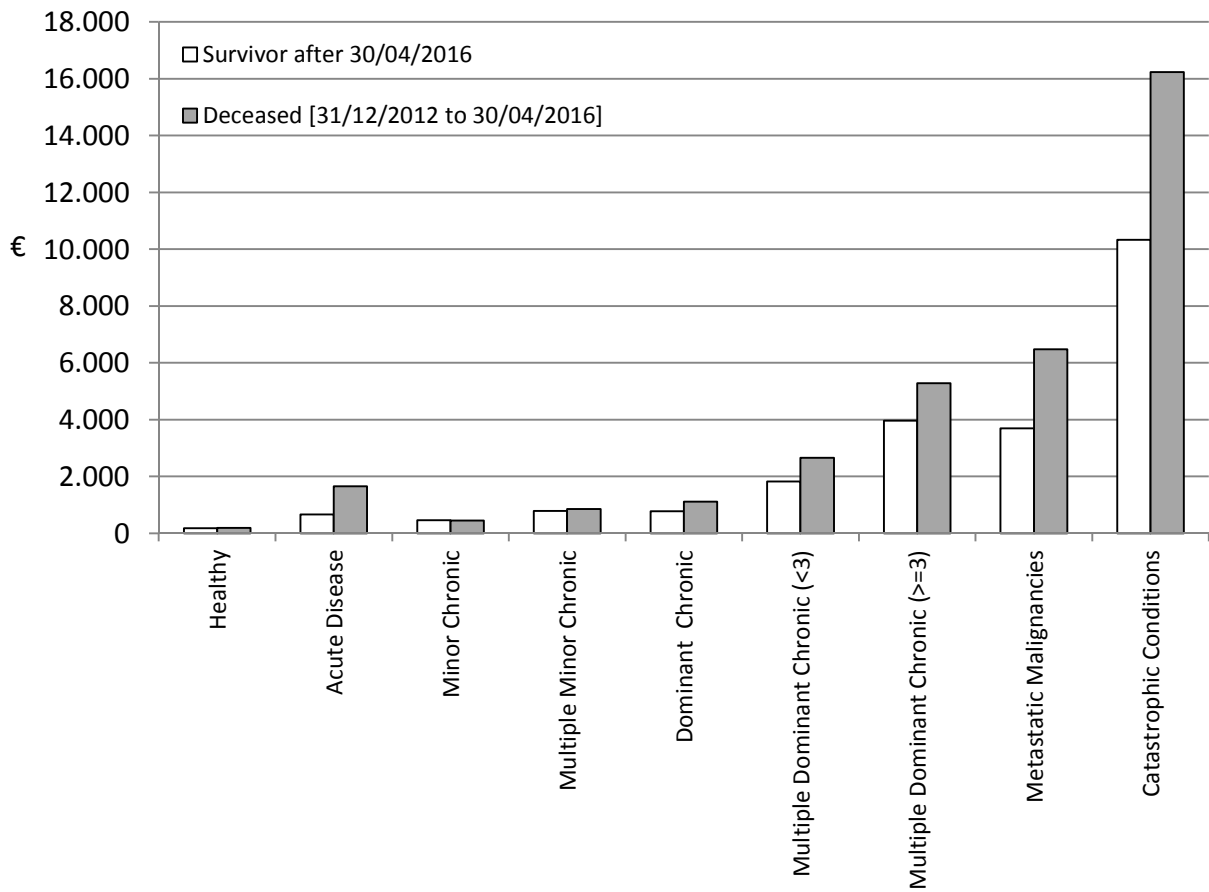
Figure 3. Population pyramids at 31/12/2012

(a) Survivors after 30/04/2016 (n = 59,079)

(b) Deceased [31/12/2012 to 30/04/2016] (n = 2,394)