The effect of shocks in health on wealth.
*Preliminary draft**

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Abstract

The effect of adverse shocks in health on individuals' saving decisions is important for the design of insurance and pension products and the non-medical consumption costs of medical interventions. We investigate the effect of being admitted to the hospital for six different conditions on wealth in the subsequent years using Dutch administrative data. We apply a "difference in timing" design where we compare individuals admitted in one year to similar individuals admitted three years later. We do this for the Dutch older population, for whom the protection against income risks and medical out-of-pocket spending is high. Consequently, we can identify changes in saving behavior driven by the effect of health one the value of consumption, savings, and bequest rather than by changes in income or out-of-pocket spending. Although the six conditions differ in mortality and disability, we hardly find an effect of any of the conditions on wealth. We do, however, find some evidence of heterogeneity in the effect on wealth.

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1 Introduction

How adverse shocks in health affect an individual's saving and (non-medical) consumption is an important empirical issue from many different perspectives. First, it can say something about how well individuals are insured against income loss and out-of-pocket payments related to health loss (e.g. Dobkin et al., 2018). Second, the trade-offs between consumption and savings individuals make in different health states tells something about the value (utility) they gain from consumption, and for instance leaving a bequest, when in poor or in good health (Finkelstein et al., 2009). This, in turn, is relevant for the optimal design of pensions and (social or private) insurance for health- and long-term-care. Third, studies that want to include non-medical costs ("survivor consumption") in economic evaluations (De Vries et al., 2019; Meltzer, 1997), ideally need disease-specific estimates of consumption (or changes in wealth).

In this paper, we investigate the effect of changes in health on wealth. We use administrative data covering the entire Dutch population from 2006 to 2017 containing annual information on individuals income and wealth, and detailed, diagnose-specific, information on all hospital admissions. We aim to make three contributions. First, we study the older population (65 and older), as they have a secure income position and are almost fully insured against health care and long term care costs. Thus, we can directly estimate the effect of an adverse health shock on the decision between consumption and saving, as confounding by other outcomes (such as income and out-of-pocket expenditures) is less of a concern for this group. Second, we control for possible endogeneity by exploiting differences in the timing of similar health shocks across individuals. Third, our extensive administrative data allows us to estimate the effects of specific diseases, with varying effects on mortality, quality of life, and dependence on informal and formal care. All of which would be expected to affect saving decisions.

It is (ex-ante) ambiguous how an adverse health shock affects consumption and saving. Some individuals might reduce total spending as they are no longer able to enjoy consumption. Other individuals might shift consumption of particular goods to other goods, leaving total expenditures unaffected. Another group might want to cross off their bucket list, thereby even increasing total spending. Crucial here is how utility derived from consumption is affected by health. As noted by Finkelstein et al. (2009), empirically identifying this is hard and different identifying restrictions can be made. As a result, different approaches (based on stated preferences, demand for insurance products, changes in the consumption profile, or differences in utility across individuals with a similar income but different health) tend to produce different outcomes (see Viscusi (2019) for an overview). For instance, health state dependence of the marginal utility of consumption has been found to be negative (Levy and Nir, 2012; Finkelstein et al., 2013), not to exist (De Nardi et al., 2010), or to be positive (Lillard and Weiss, 1997; Kools and Knoef, 2019). Three possible explanations for the differences in findings are the correlation of health with other relevant economic outcomes, endogeneity, and heterogeneity in the effects across severity of the health shocks or diseases.

First, adverse health shocks are found to be correlated with many other economic outcomes (Smith, 2005; Case and Deaton, 2005) such as assets holdings (Poterba et al., 2017; Gilligan et al., 2018), income (García-Gómez, 2011; García-Gómez et al., 2013; Dobkin et al., 2018), bankruptcy (Himmelstein et al., 2009) and out-of-pocket medical expenditures (Dobkin et al., 2018). The majority of these studies rely on data from the United States in which healthcare is characterized by large out-of-pocket medical expenditures. This requires additional assumptions or specific sub-populations to study the effect in isolation (e.g. Finkelstein et al., 2013).

We will focus on the Dutch older population. All Dutch citizens receive a state pension (which is sufficient to cover basic living costs) and most also have a (compulsory) second-pillar pension. As a result, income protection after the official retirement age (65 in our sample) is high, and labor participation above 65 is almost zero. As each Dutch citizen is covered by compulsory health insurance and very comprehensive long term care insurance for home care and nursing home care, out-of-pocket healthcare expenditures are low. Thus, confounding with other outcomes is less of a concern and we can estimate the direct effect of health on saving.

Second, endogeneity is a big concern: individuals who experience a health shock might already have health problems or knowledge about future problems, prior to the shock, and they might exhibit a different lifestyle than the general population. These factors might also affect the individual's saving and consumption prior to the shock. Different authors have come up with different strategies to address this problem. Mohanan (2013), for example, uses a quasi-experimental design by exploiting bus accident injuries as an exogenous shock. He finds that individuals in India after a health shock are able to smooth consumption on food and housing, at the cost of larger levels of indebtedness. Dobkin et al. (2018), use an event-study approach, based on hospital admissions in the U.S. They find that hospital admission in the United States leads to increased out of pocket medical spending, unpaid medical bills, and reduced earnings and income. For a causal interpretation, they have to assume that, conditional on having a hospital admission during their observation window, the timing of the admission is uncorrelated with the outcome. Cheng et al. (2019) use a similar event-study approach and find, using data from the Singapore Life Panel, that a large health shock (e.g. cancer or stroke) leads to a decrease in the households' non-health expenditures, mainly because of a reduction in leisure spending.

The alternative approach, that we will use in this paper, combines a timing of event design with a difference-in-difference design. That is, we compare individuals who are admitted to the hospital for a particular condition at time t, to similar (matched) individuals who are also admitted for the same condition, but in the future (at time $t+k$). Similar "difference in timing" designs have recently been employed to study a broad number of topics (Duggan et al., 2016; Fadlon and Nielsen, 2017; Miller, 2017; Lafortune et al., 2018; Bessen et al., 2019).

Third, health has many dimension that cannot all be reflected in one overall measure, such as self-perceived health. Different diseases can have, for instance, very different effects on survival, wellbeing, and functioning. All of these aspects could be relevant for the effect on consumption and saving. The variety of results regarding the effect of health on the marginal utility of consumption, could for instance partially be due to differences in the type of health shocks across studies. Using a stated preference design, Gyrd-Hansen (2017), for example, only finds evidence of state-dependence for intermediate health states, while Viscusi (2019) concludes in an overview study that moderate health shocks do not affect the shape of the utility function, while severe shocks do. Diseases might also differ in the extent to which people have to rely on informal care. Van der Burg et al. (2018), for instance, find that having children has a much larger negative effect on using formal care after a hospital admission for a femoral fracture than after a stroke. This difference in reliance on informal care is important for the effect on wealth, as health shocks might not only alter the utility derived from consumption but might also induce people to leave a bequest to motivate relatives to provide informal care (Zweifel and Strüwe, 1996).

Most studies use relatively small survey data sets. Consequently, they cannot capture all the possibly important heterogeneity across diseases, as they have to rely on broad measures of health or proxies of health shocks (such as *any* hospital admission). In our study, we will use nationwide administrative data. This allows us to estimate disease-specific effects, including diseases with different effects on survival, disability and reliance on care. Also, our data allows us to identify subgroups (individuals with or without a partner, with or without children) for which we can expect the disease-specific effect on savings to differ.

There are two related studies looking into the effect of an adverse health shocks on wealth or consumption in the Netherlands. First, Suari-Andreu et al. (2019) study the bequest motive for saving, using administrative data on all deaths and hospital admissions in the Netherlands between 2006 and 2013. They compare the net worth of individuals whose cause of death can be classified as sudden (e.g. cardiac arrest, stroke and transport accidents) to those who experienced a non-sudden death and find that individuals who die a non-sudden death, leave less net wealth than those who die a sudden death. The authors argue that this lower level of wealth is due to inter-vivos transfers of those in the first group, which then would provide evidence for a strategic bequest motive. Second, Van Ooijen et al. (2018) use a small panel survey data (LISS) to estimate the effect of health on different types of consumption. They find that non-medical expenditures decline by 3% for respondents in poor health and 7% for households where one of the members reports more than two chronic conditions. Households in poor health, compared to those in good health, spend more on housekeeping and less on leisure. Compared to the existing Dutch studies, our contribution lies in the richness of our data that allows us to identify effects for very specific diseases and the identification strategy, where we compare individuals who are similar and, eventually receive the exact same health shock, but differ in the timing of this shock. Suari-Andreu et al. (2019) looks at differences in wealth across diseases at the end of life. Those differences are the results of a lot of changes in health and savings over a long time period. Instead, we are interested in how individuals adjust their savings right after the occurrence of a (severe) health shock.

Our findings suggest that adverse health shocks generally do not affect the wealth holding of individuals, regardless of the effect of the shock on survival, disability or household type. We find some evidence that individuals who experience a "heart failure", a condition with a severe effect on mortality and disability, tend to increase their savings. We also find some evidence that individuals who experience a very lethal health shock with only a moderate effect on disability ("colon, rectal, anal cancer") spend down their wealth.

The remainder of this paper is structured as follows. In Section 2 we explain the econometric models that we will use, namely a difference-in-timing model. We compare individuals with the same disease, but who are admitted at different points in time. In Section 3, we describe our data and elaborate on the selection of the diseases and their impact on mortality and disability. In Section 4, we present our estimation results. The final section provides discussion and some preliminary conclusions.

2 Methodology

To analyse how wealth develops in the years after a hospital admission for a particular condition, we use an adaption of a standard difference-in-difference design. The regression specification is similar to that of a standard difference-in difference design, but we will use a different control group. Formally, we have that

$$y_{i,t} = \alpha + \beta treat_i + \sum_{p \neq 0; p=-5}^{5} \gamma_p \times I_p + \sum_{p \neq 0; p=-5}^{5} \delta_p \times I_p \times treat_i + \lambda X_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $y_{i,t}$ is the wealth of individual i in year t. The variable indicating whether the individual belongs to the treatment group is denoted by $treat_i$. We use I_p as indicators for the time relative to the treatment year: I_p is 1 if year t is p years from the year of hospital admission and 0 otherwise. Note, this is actual admission for the treatment group and placebo admission for the control group. The δ parameters are the main parameters of interest. For the years after treatment, $p > 0$, they capture the treatment effect. That is, the development of wealth, relative to the period of admission, $p = 0$, of the treatment group compared to the control group. For the difference-in-difference analysis to be valid, the development of wealth *before* admission ($p < 0$) should be similar between the treatment and the control group (the common trend assumption), which means that for these periods δ_p should be zero. The vector $X_{i,t}$ contains controls: calendar year dummies, age dummies, gender, household status, having children, gross household income (if applicable), medicine usage and the duration of the hospital admission.

In a standard difference-in-difference design, we would draw a random sample from the Dutch population aged 65 and older and match on observable characteristics to make the control group comparable to the treatment group. However, even after matching on observable characteristics, it might still be the case that individuals who are admitted for a particular condition differ in unobserved ways from the control group. In particular they might already have a poorer health or prior knowledge about their future health state in the years before the actual admission which, in turn, could affect their saving decision. We therefore create a different control group consisting of individuals who receive the same health shock (i.e. are being admitted for a particular condition), but at time $t+k$ instead of t. Here, the identifying assumption is that individuals might have knowledge about their risk of a particular health shock (for instance as a consequence of their lifestyle), but not of the timing of the shock - i.e. whether the shock occurs at time t or $t + k$ is random. Throughout the paper, we refer to this specification as a difference-in-timing design.

For the difference-in-timing design we thus construct a control group by matching individuals who are admitted to the hospital at time t to individuals with similar characteristics who are admitted k years later. To make the control group even more comparable to the treatment group, we match individuals from the control to individuals in the treatment group at $p = 0$ based upon propensity score matching for gross household income (if applicable), medicine usage and duration of hospital stay, and exact matching for year of birth, gender, household status and having children. The choice of k involves a trade-off. On the one hand, the number of years between the treatment and control determines the maximum number of years we can compare post-admission wealth. On the other hand, the assumption that individuals in the treatment and the control group have similar (knowledge of their) health, is more credible when the time between admission is relatively small. We use $k = 3$ in our main specification, so we compare individuals who are admitted now to those who are admitted the years later. We also perform a sensitivity test using $k = 5$.

3 Data

To address our research question, we need to first link the (administrative) data from various sources to each other. We describe this procedure below. Second, we motivate our decision for the six (out of 84) selected conditions. Third, for each of these conditions we present some descriptive statistics.

3.1 Source data

Our starting point is administrative data on hospital admissions from the Dutch Base Register Hospitals (LBZ) and its predecessor the Dutch Hospital Discharge Register (LMR) for the years 2006-2017. The LBZ is a register of hospital admissions. All university and general hospitals and most specialized hospitals participate in the LBZ. Therefore, the dataset provides a nearly complete coverage of hospital inpatient treatments in the Netherlands. All clinical and day admissions are registered based on a uniform registration system. The data include admission and discharge dates, diagnosis information on ICD-9 or ICD-10 level, and extensive treatment information.

We classify admissions based on the main diagnosis using the International Shortlist for Hospital Morbidity Tabulation (ISHMT). The ISHMT divides the ICD diagnoses in 20 main groups en 128 subgroups[1]. We use the subgroup level. Diagnoses related to pregnancy, accidents and injuries (with the exception of fractures) and diagnostics are excluded. An overview can be found in Appendix A.

We link the hospital admission data to other datasets using a unique personal identification number. The Dutch Municipal Register provides basic information on everyone enlisted in a Dutch municipality. From this register, we obtain date of death, age, sex, household status, and number of children. We use data from the tax services to obtain different wealth components, measured at January 1 in each year, and annual gross household income. In our analyses, we will focus on liquid financial wealth, held at a savings account. We choose this wealth measure, because it is relatively unaffected by year-to-year changes in price (returns). Changes in the savings account are thus more likely to be due to changes in saving behavior (see, for example, Ji et al. (2019), who use the same wealth measures and data, for a detailed exposition). In addition, we consider financial wealth (savings account and stocks and bonds) and net wealth (differences between all assets and debt, including the house and mortgage debt). As income measure we use gross household income. We further link the sample to administrative data on medicine use (ATC4 level) and institutional care use.

Our sample consist of individuals who are newly admitted to the hospital for a particular condition (ISHMT subgroup) within our observation period. We define an admission as new, when an individual has not been admitted in the hospital for the same condition in the year before.[2] To ensure that we have enough power to detect any effects, we drop all conditions with less than 1,000 cases in our dataset. This leaves 84 different disease groups (see Appendix A). As a control group, we add a random sample of 2.5 percent from the older population of individuals not admitted to the hospital during the entire observation period.

Moreover, we restrict the sample to individuals who are older than 65 years of age and younger than 95 during the whole sample period. We drop individuals who live in an institutional household prior to the time of admission, or who live with their children. We also drop outliers in wealth and income: individuals who earn less than 10,000 euros or more than 120,000 euros per year, and individuals with more than 200,000 euros on their savings account (in any observation year).

[1]A mapping from ICD-9 and ICD-10 codes to ISHMT is available at the website from the OECD, see: http://stats.oecd.org/wbos/fileview2.aspx?IDFile=e477970b-3024-4188-8dc6-13f3db20184.

[2]For individuals who are 'newly' admitted to the hospital more than once within the entire observation period, we randomly select one admission.

3.2 Selection of conditions

From the total set of 84 condition, we select six. We construct six samples, based on having a hospital admission for a specific condition, for individuals who are 65 years of age or older. To select the conditions, we apply a number of informal selection criteria. As we hypothesize that the effect of a health shock on wealth depends on how lethal and disabling the disease is, we want to select a set of diseases that differ across both dimensions. Further, we want to select diseases that occur relatively often, as to increase our power. Last, we select diseases for which we expect that a hospital admission indeed indicates a new important negative health shock.

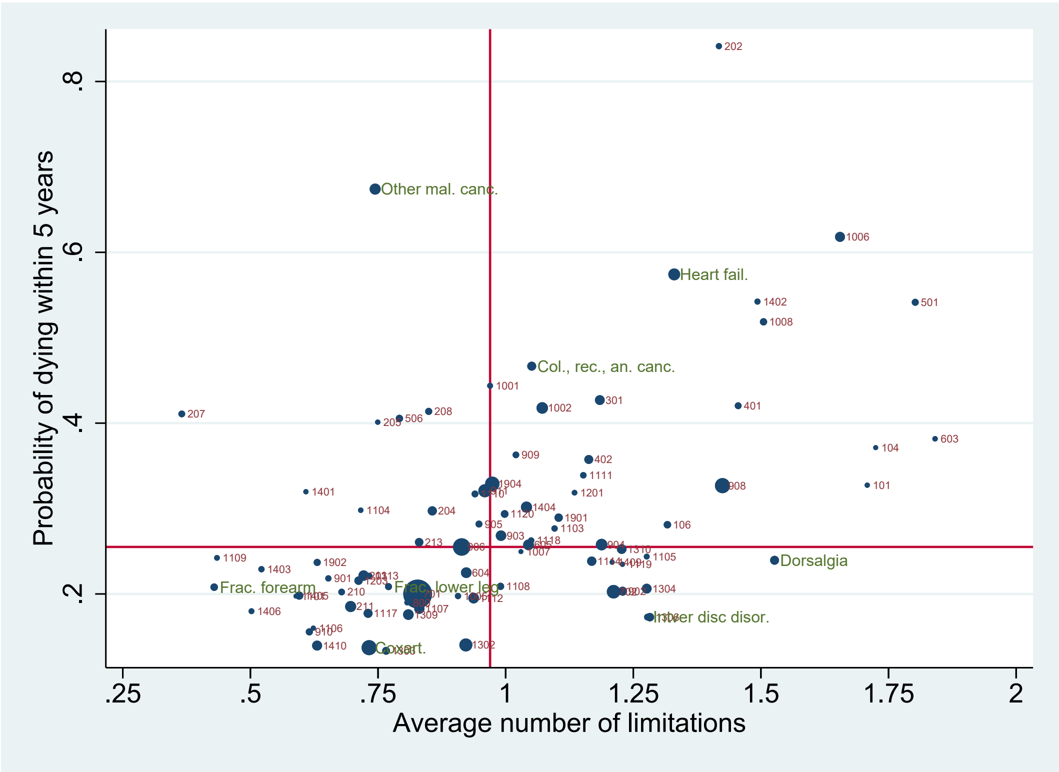
Figure 1 plots mortality against disability for each disease. For each ISHMT group, we estimated the probability to die within five years after admission, and the average number of limitations in the first five years after admission (controlled for sex and age). The figure is divided into quadrants by a vertical line indicating the median disability level and a horizontal one indicating the median mortality. We select one or more diseases from each quadrant. We select "other malignant cancers", because it stands out in terms of high mortality (almost 70 percent of patients dies within five years) and relatively low level of disability among survivors. Because the group "other malignant cancers" is a rest category, consisting of potentially heterogeneous diseases, we also select "colon, rectal, and anal cancer". This group of cancers is more homogeneous and has a relatively high mortality as well, combined with a median level of disability. In the upper right quadrant we select "heart failure", which has a high mortality and relatively strong disabling effect. In the lower right quadrant we combine "dorsalgia" and "intervertebral disc disorders", which are both part of the same ISHMT chapter and have a relatively low mortality combined with a high disabling effect. Last, we combine "fractures of the forearm" and "fractures of the lower legs". Both indicate acute health problems related to accidents or falls, and are associated with a low level of mortality and disability.

The six conditions we selected also differ in terms of the progression of mortality and disability over time. Figure 2 show the survival over the first five years after admission and the percentage of people who are eligible for home care in the years prior to and after admission. There is an interesting difference in survival between individuals with "other malignant cancers" and individuals with either "heart failure" or "colon, anal, and rectal cancers": the probability of dying within a year after admission is much higher for the first group, but the other two groups 'catch up' in the following years. To get an impression of the disabling effect of the diseases for our whole sample[3], Figure 2b shows what percentage of individuals are eligible for home care. The eligibility (need) for *formal* care might also be indicative for the need for *informal* care, as formal and informal care can function as substitutes (Bonsang, 2009). There are again some relevant differences in the time patterns across diseases: heart failure and the cancers lead to a high need for home care after admission, and this need remains high in the consecutive years. Coxarthrosis and fractures also lead to a high need right after admission, but this need decreases substantially in the consecutive years.

Figure 2b also shows that a hospital admission for one of the selected diseases indeed signifies a shock in care need. For some of the diseases, individuals do tend to have a higher care need than the general population already in the years *prior to* admission. This illustrates why a standard difference-in-difference approach, based on a comparison to the not-admitted general population, might not suffice. Although we can and will control for a lot more observable differences between the disease groups and the general population, this prior differences

[3]The disability measure used in Figure 1 is based on survey data based on a random subsample of the population. This leaves too few observations per disease per year to say anything meaningful about the time pattern.

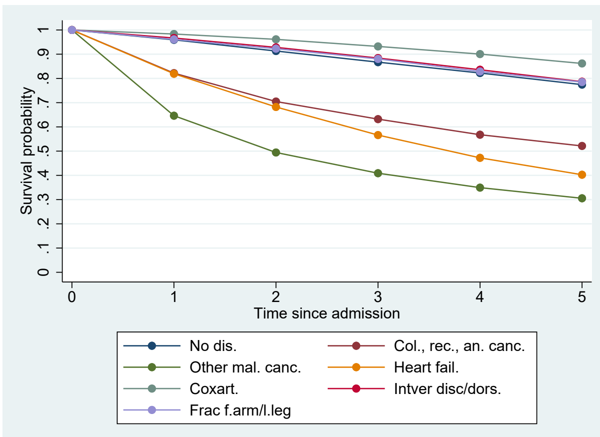
Figure 1: Mortality and disability across disease groups



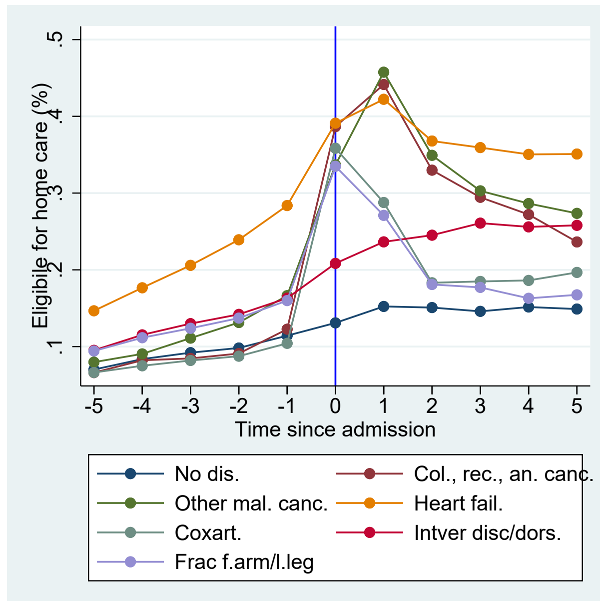
Notes: Data on limitations is based on the Dutch 2012 and 2016 Health Monitor: a large cross-sectional survey (about 200,000 respondents per wave), representative for the Dutch population. We link our sample, with individuals admitted to the hospital between 2006 to 2017, to this survey. We base the estimate on all observations included in the survey within 5 years after admission. The number of limitations is based on a list of seven: following a conversation, carrying a conversation, reading small print, recognizing someone from a distance of 4m, carrying a 5kg object for 10m, picking something up from the ground, and walking 400m without standing still. The probability of dying withing 5 years is based on individuals admitted before 2013 only.

in need makes it questionable whether that is sufficient to capture all relevant (unobserved) factors. In case of heart failures there seems to be an increasing trend in care need in the years before admission. This is relevant for our empirical design, which is based on the assumption that individuals cannot predict the health shock associated with a hospital admission, at least not within k years before admission. This means that we have to pay specific attention to the pre-trends in wealth for heart failure, and that we should choose a relatively small time lag k.

Figure 2: Survival and the eligibility for home care before and after hospital admission.



(a) Survival



(b) Eligible for home care

Notes: In case of the "no disease" group, admission is a placebo admission. The disease groups are all separately matched to the "no disease" group by exact matching on calendar year, age, and sex. The data on eligibility for home care and nursing home care are based on administrative data for the period 2007-2014.

3.3 Descriptive statistics

Table 1 shows the mean values of the most important covariates in the year of admission. Our sample consists of 25 687 cases for "cox arthrosis" (the largest disease group) to 7 103 cases for "colon, rectal, anal cancer' (the smallest sample). "Cox arthrosis', "intervertebral disc disorders" and fractures are the diseases with highest share of female patients. Patients with heart failure are the oldest on average, and are most often single. Medicine use is considerably higher in the disease groups than in the general population. Average net wealth us between 116 and 170 thousand euros across diseases and consists for a large part of the net value of the house. Average wealth on the savings account lies between 31 and 36 thousand euros. This high percentage of relatively old and single persons for heart failures translates in a relatively low average income and wealth. Table 2 shows the number of observations in each year p before and after admission, by disease.

Table 1: Summary statistics

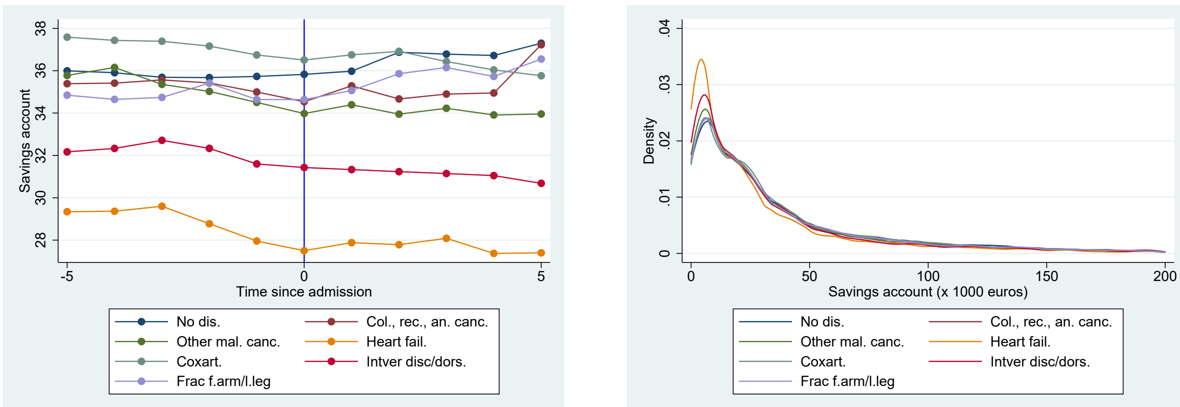
	No dis.	Col., rec., an. canc.	Other mal. canc.	Heart fail.	Coxart.	Intver disc/dors.	Frac f.arm/l.leg
gender (1: male; 2: female)	1.67	1.58	1.57	1.65	1.80	1.76	1.89
age	78.33	79.52	78.55	83.23	78.02	78.09	79.01
children: yes	0.85	0.87	0.85	0.86	0.88	0.89	0.84
single: yes	0.53	0.55	0.54	0.68	0.54	0.54	0.65
nummed	3.45	4.91	5.36	5.58	5.22	5.35	4.38
income	29.72	30.11	30.30	26.38	30.62	28.64	28.67
allwealth	152.41	149.21	147.94	115.97	169.68	127.53	150.65
finwealth	45.84	45.27	43.91	38.25	47.59	38.63	44.98
curaccount	35.86	35.30	34.42	30.90	36.28	30.80	35.22
Observations	8 420	7 103	12 159	14 386	25 687	10 242	7 781

Table 2: No. of observation in each time period, with $p = 0$ is the year of hospital admission

	No dis.	Col., rec., an. canc.	Other mal. canc.	Heart fail.	Coxart.	Intver disc/dors.	Frac f.arm/l.leg
$p = -5$	3798	3859	6004	7484	12852	4548	3818
$p = -4$	4581	4411	6987	8565	15049	5538	4514
$p = -3$	5436	5001	8137	9885	17618	6795	5469
$p = -2$	6366	5672	9373	11264	20207	7977	6303
$p = -1$	7362	6425	10764	12762	22965	9143	7048
$p = 0$	8451	7061	12114	14239	25629	10206	7764
$p = 1$	7674	6233	10753	11877	23211	9530	6794
$p = 2$	6969	5524	9817	10200	20828	8750	6001
$p = 3$	6295	4758	8723	8899	18208	7900	5284
$p = 4$	5594	3944	7597	7594	15518	6880	4543
$p = 5$	4899	3339	6518	6467	13052	5626	3883
Total	67425	56227	96787	109236	205137	82893	61421

Figure 3a shows the development of wealth (savings account) before and after admission. We again corrected for differences in age and calendar years here. Although there are clear differences in the wealth levels across disease groups and the control group, based on this purely descriptive graph there does not seem to be a large impact of any of the conditions on wealth. Figure 3b shows the distribution of wealth in the year of admission. Apart form the difference in levels, the shape of the distribution looks very similar across disease groups. Wealth is very unevenly distributed, with a large fraction of the population having less than 20,000 euros of savings.

Figure 3: Wealth (savings account) by disease.



(a) Savings account before and after admission. **(b)** Savings account. Distribution in $t = 0$.

In case of the "no disease" group, admission is a placebo admission. The disease groups are all separately matched to the "no disease" group by stratification based on calendar year and age. The density plot are made using a kernel density estimator.

4 Results

Our difference-in-timing methodology is flexible enough to estimate the effect of various health shocks on various outcome measures. First, we present the estimation results for the effect health, using the six diseases introduced in Section 3.2, on gross household income and savings account. Second, as a sensitivity analysis, we present the effect of a health shock on financial wealth, net total wealth and savings account (singles, survivors, individuals admitted five years later instead of three).

4.1 Income and savings account

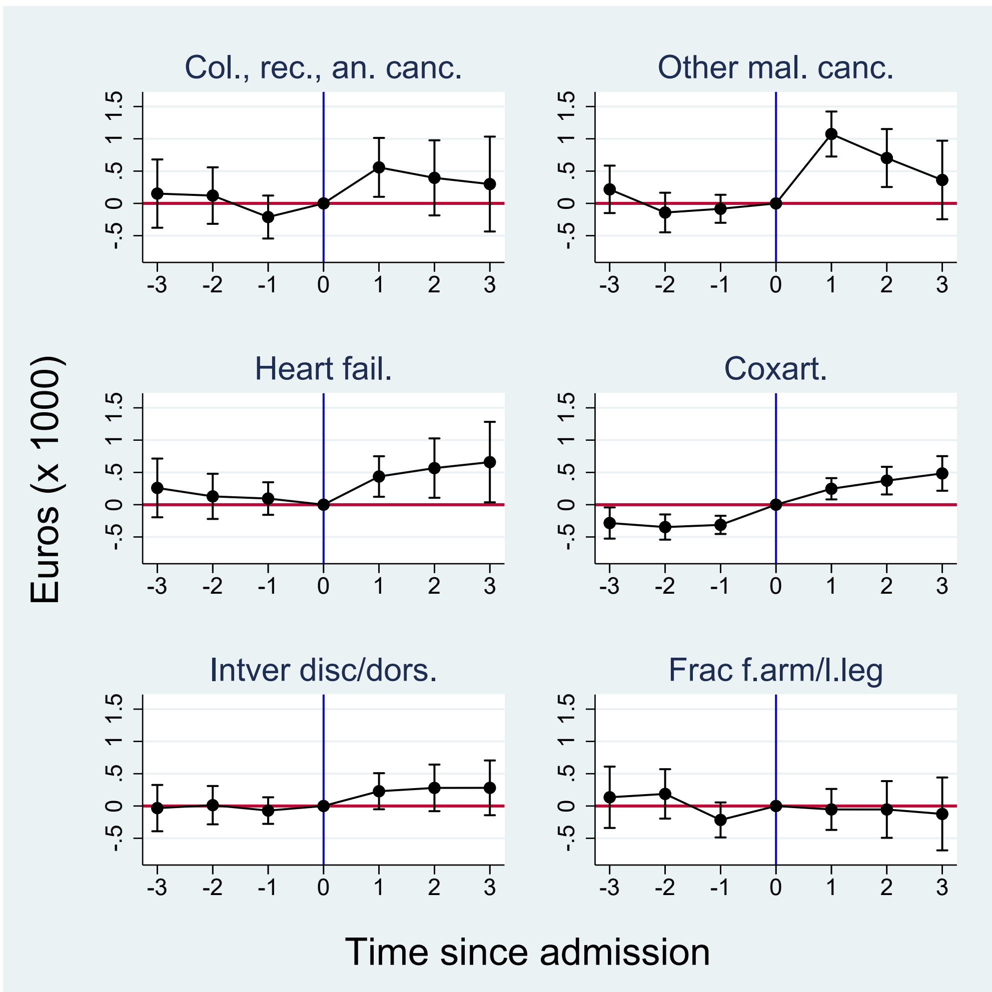
As we focus on the retired Dutch population, we expect that income protection for this group is high. We formally check this using Figure 4 where we present the estimation results of a health shock on gross household income[4] using the difference-in-timing methodology. From this figure we observe that for all diseases, except coxarthrosis, the pre-trend is, from a statistical point of view, indistinguishable from zero. After the health shock, we have the somewhat

[4]In our dataset we also have information on net household income as opposed to gross household income. However, there are some tax deductible expenses of specific costs of care which are being accounted for in the net household income. Consequently, net income potentially increases the first year(s) after a health shock.

surprising result that gross household income tends to increase for the treatment group, compared to the control group. This holds especially for diseases with a higher probability of dying within five years (see the upper panels and the left panel of the second row). Even though statistically significant, the effect on income appears appears to be small with points estimates of around 500 euros.

This finding appears to be driven by selective survival of individuals with a higher income. Even though we control for prior health and intensity of the treatment, there is likely to be heterogeneity in the severity of the health shock within each disease group. If income and the severity of the disease are related in an unobserved way, this might lead to individuals with a high income to be more likely to survive in the years after admission. If we impose the additional restriction on both the treatment and control group that we should observe the individuals for at least three years after the health shock (i.e. survive), the small income effect disappears (see Figure 13 in Appendix C). As we take gross household income into account in estimating the effect of health on wealth, this selective survival for income is not an issue for our main results. Still, we will also run our wealth estimates only using individuals who survive for at least three years after the health shock as a sensitivity test.

Figure 4: Results for difference-in-timing analysis for gross household income



The difference in gross household income between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

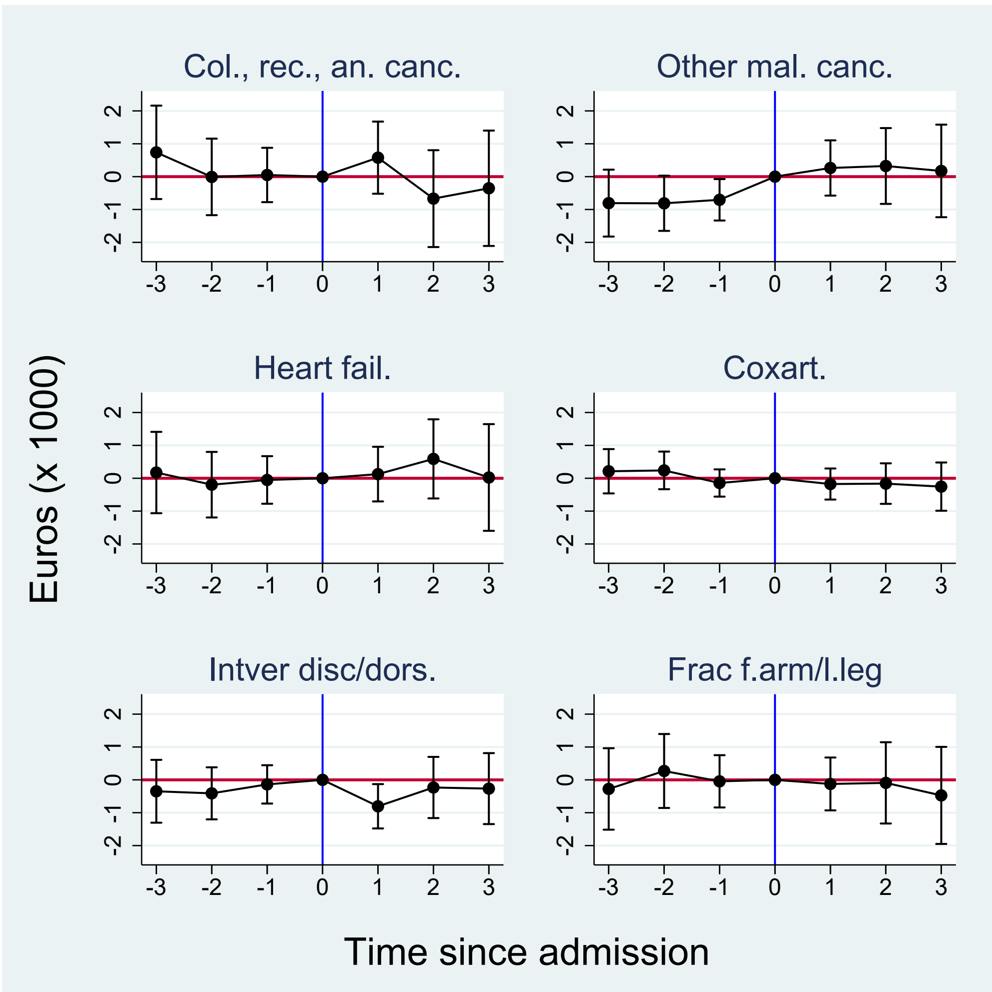
If there is an (immediate) effect of health on wealth, we would expect to first observe this for the savings account of the household[5]. Figure 5 present these estimation results. Note, here we compare individuals with a specific health shock to individuals from the same cohort that experience the same health shock, only three years later. The pre-trend generally matches the horizontal line at zero, except for the group “other malignant cancers” where it hints towards spending more, or saving less, than the control group the years prior to the health shock. As this is a very heterogeneous group[6], we simply might be comparing groups of individuals who ex-ante are not similar. After the health shock we generally not observe any statistically significant effects. The only exception is for the first year after “dorsalgia” and “interverbral disc disorder” (lower left panel) which have a relatively low mortality combined with a high disabling effect. Thus, this group might (temporarily) decrease savings, compared to the control group, to buy items that increase comfort in and around the house for them.

A potential explanation for the lack of significant results after the health shock, could be the inclusion of household with hardly any savings. We therefore re-estimate our model, including only households who have at least 40 000 euros on their savings account for at least one period in our dataset. The estimation results for this sub-sample are summarized in Figure 6. For the pre-trend, we now also have that for the group “dorsalgia” and “interverbal disc disorder” that the treatment group spends more, or saves less, than the control group. After the health shock we again, except for “dorsalgia” and “interverbral disc disorder”, do not find any statistically significant results. However, the estimates for “heart failure” (middle left panel) do suggest that the treated increase their savings compared to the control. This might be explained by the fact that “heart failure” has a strong disabling effect which could result in undertaking less leisure activities (such as travelling).

[5]The effect of a health shock on net (total) wealth will be discussed in Section 4.2

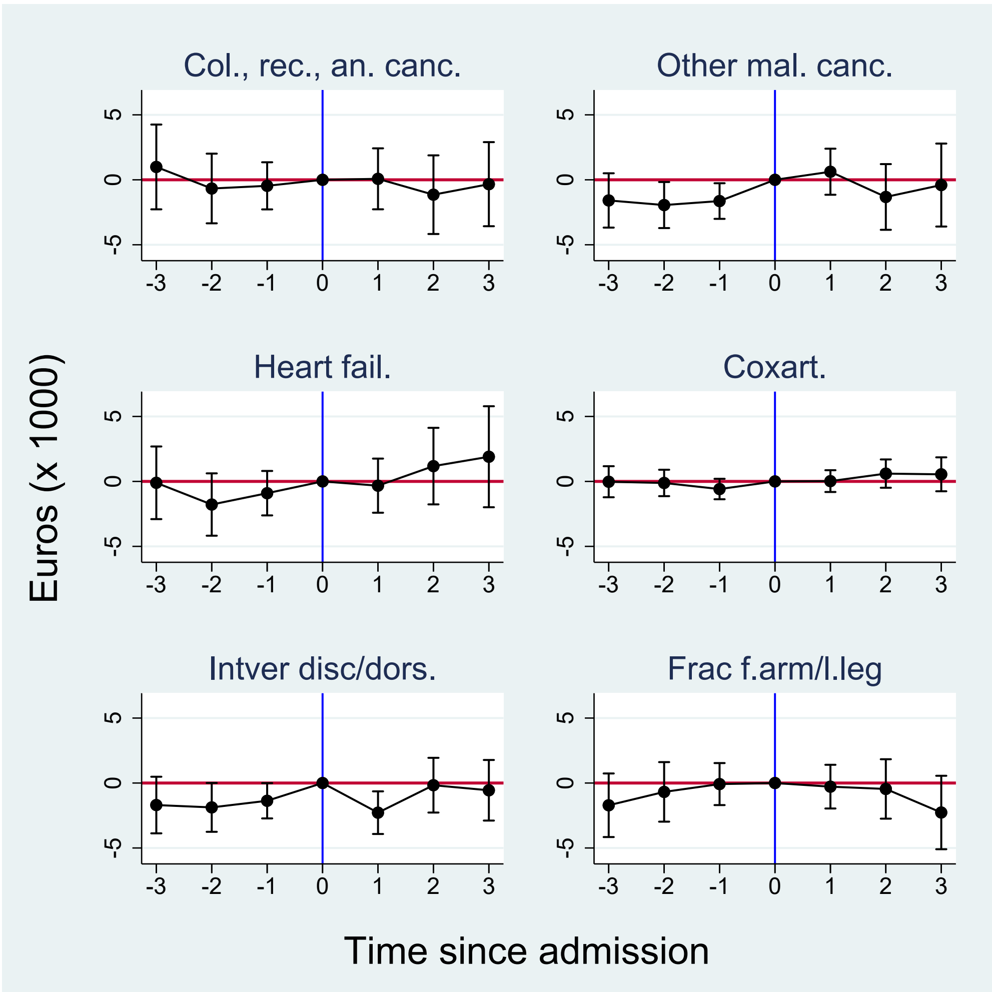
[6]The ISHMT classifications distinguishes between eight different group of cancers - see Table 3. Only if a cancer cannot be classified as belonging to one of these eight groups, its included in the group “other malignant cancers”.

Figure 5: Results for difference-in-timing analysis for savings account



The difference in savings account between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

Figure 6: Results for difference-in-timing analysis for savings account (at least 40 000 euros)

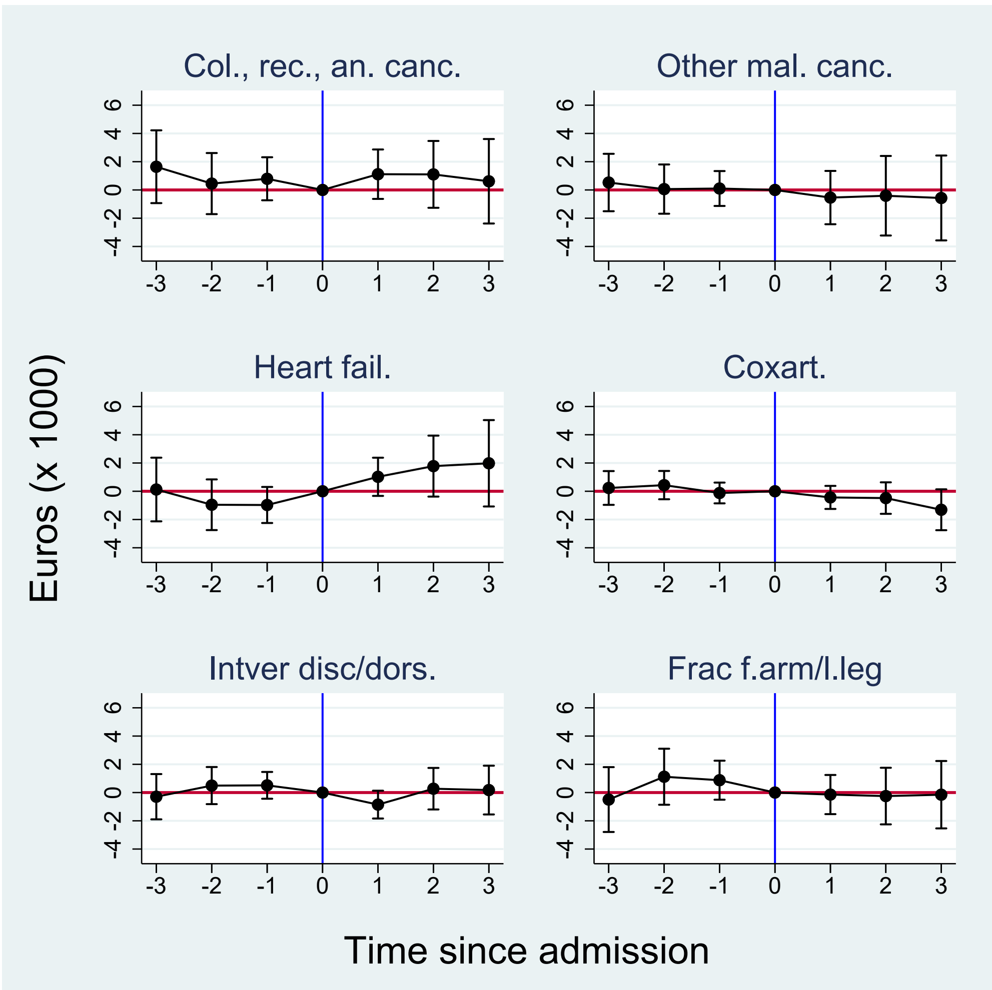


The difference in savings account between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

4.2 Sensitivity analysis

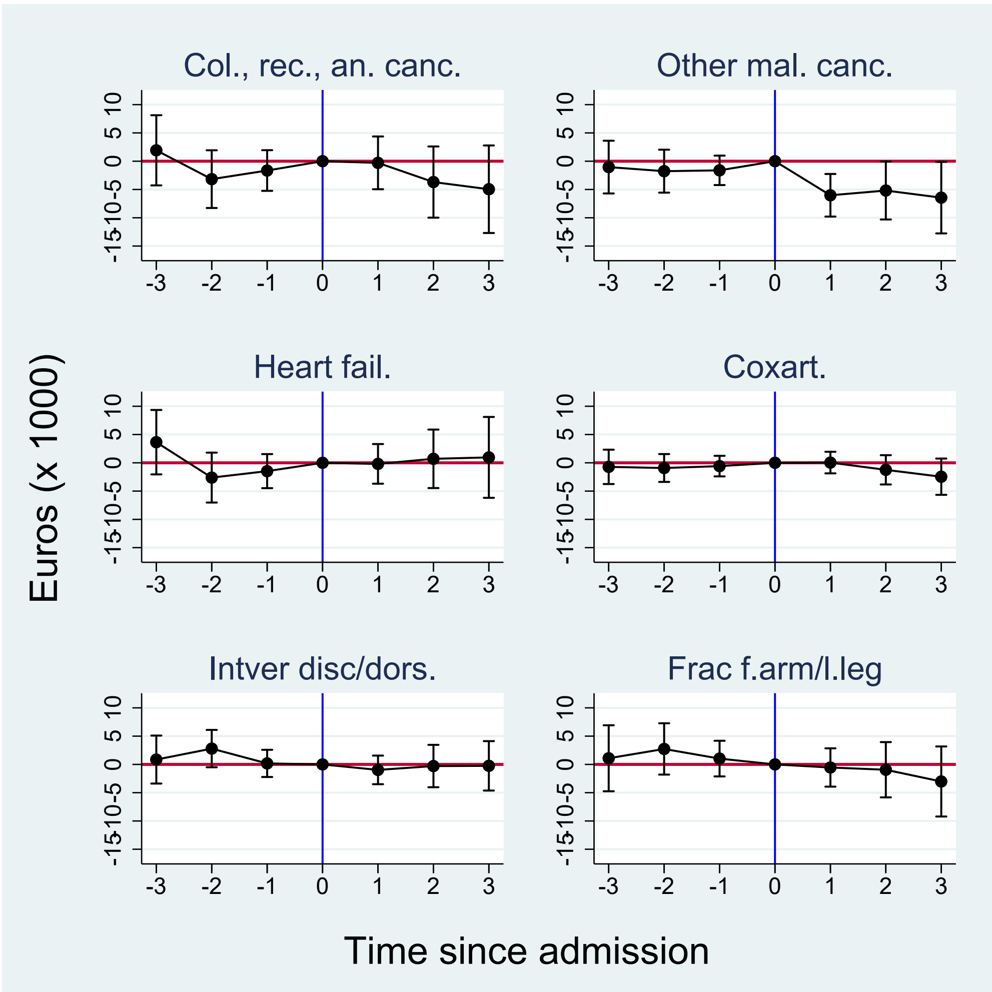
As a first sensitivity test, we consider different types of wealth. Wealth on the savings account is the most liquid, which is why we expected individuals to respond to health shocks through this channel. At the same time, most individuals hold a large part of their wealth in other assets, and might choose to use these other assets to make changes in their overall savings. Figure 7 and 8 show the results of the difference-in-timing analysis using financial wealth (savings account, stocks and bonds) and total net wealth (financial wealth and net value of the own house). Generally, we do not find significant effects. The exception are the two cancer groups, for which we find some evidence of dissavings in total net wealth (upper panels).

Figure 7: Results for difference-in-timing analysis for financial wealth



The difference in total net wealth between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

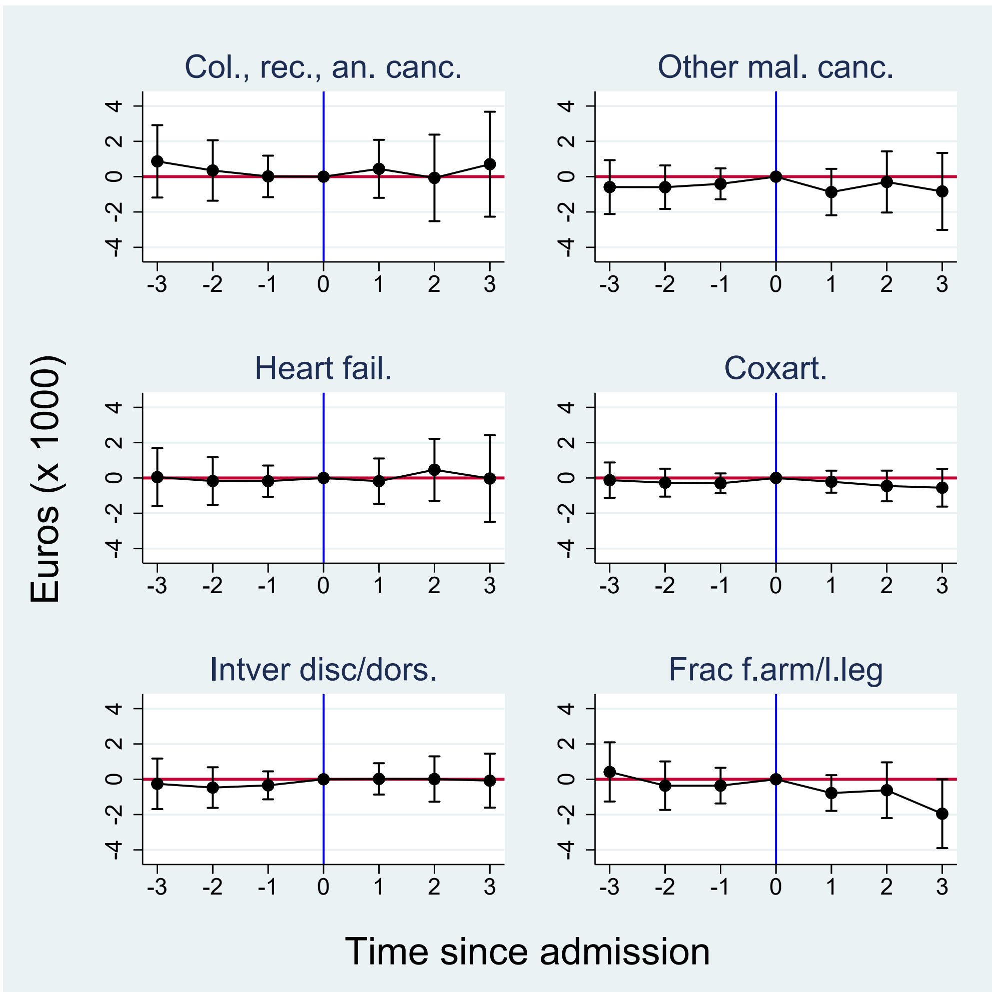
Figure 8: Results for difference-in-timing analysis for net total wealth



The difference in total net wealth between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

As a second sensitivity test, we again consider the savings account and in addition restrict our sample to singles only. We select individuals who are single during the whole observation period. For this group, we can be sure that any changes in wealth are driven by the saving decisions and circumstances of the individual himself and not his or her partner. Figure 9 shows the results. We do not find any significant effects.

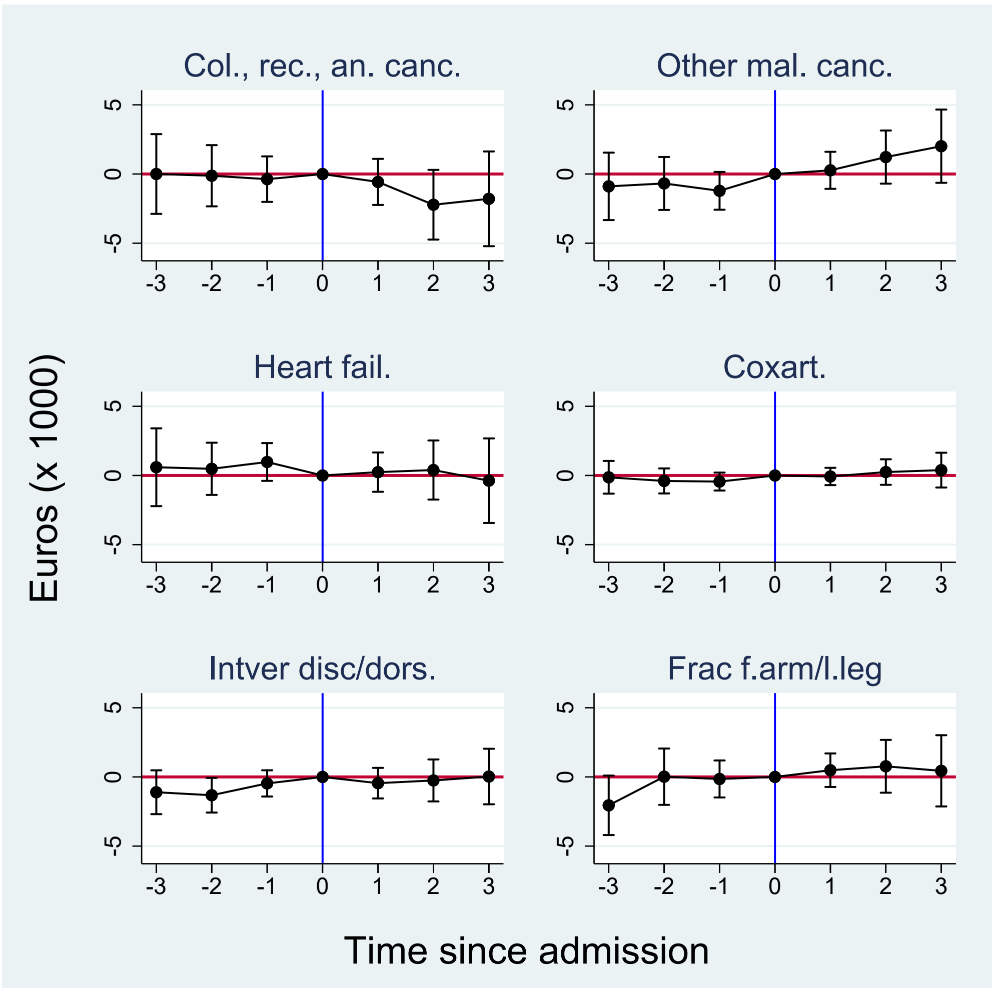
Figure 9: Results for difference-in-timing analysis for savings account, singles



The difference in wealth between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

As a third sensitivity test, we test whether our results are driven by selective survival. We restrict our sample to individuals who survive up to at least three years after the hospital admission. We put this restriction on both the intervention and the control group. Figure 10 shows the results. We do not find any effects. However, the estimates for the group "colon, rectal, and anal cancer" (upper left panel) do suggest that the treated decrease savings in the years after the health shock compared to the control.

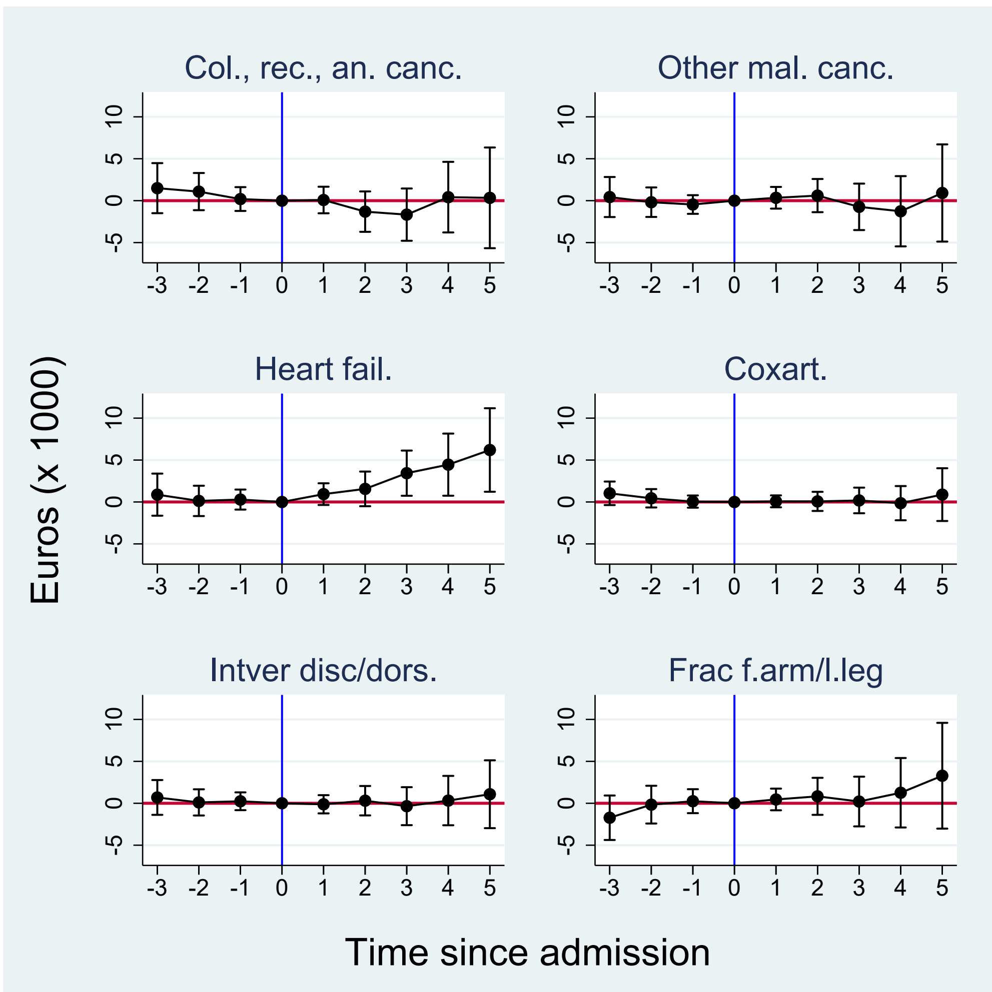
Figure 10: Results for difference-in-timing analysis for savings account, only individuals alive up to at least three years after admission



The difference in wealth between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

As a fourth sensitivity test, we change the time lag between the treatment and control group from 3 to 5 years. The advantage is that we can then identify effects over a longer period of time after admission. The disadvantage is that with a longer time between the two admissions, the assumption that individuals in the treatment group have the same expectation to get a health shock within that time as the control group, becomes less credible. Figure 11 shows the results. Only for heart failures do we find a significant effect: wealth tend to increase over the years after admission. We also found a similar pattern in our main analysis for households who have at least 40 000 euros on their savings account (Figure 6).

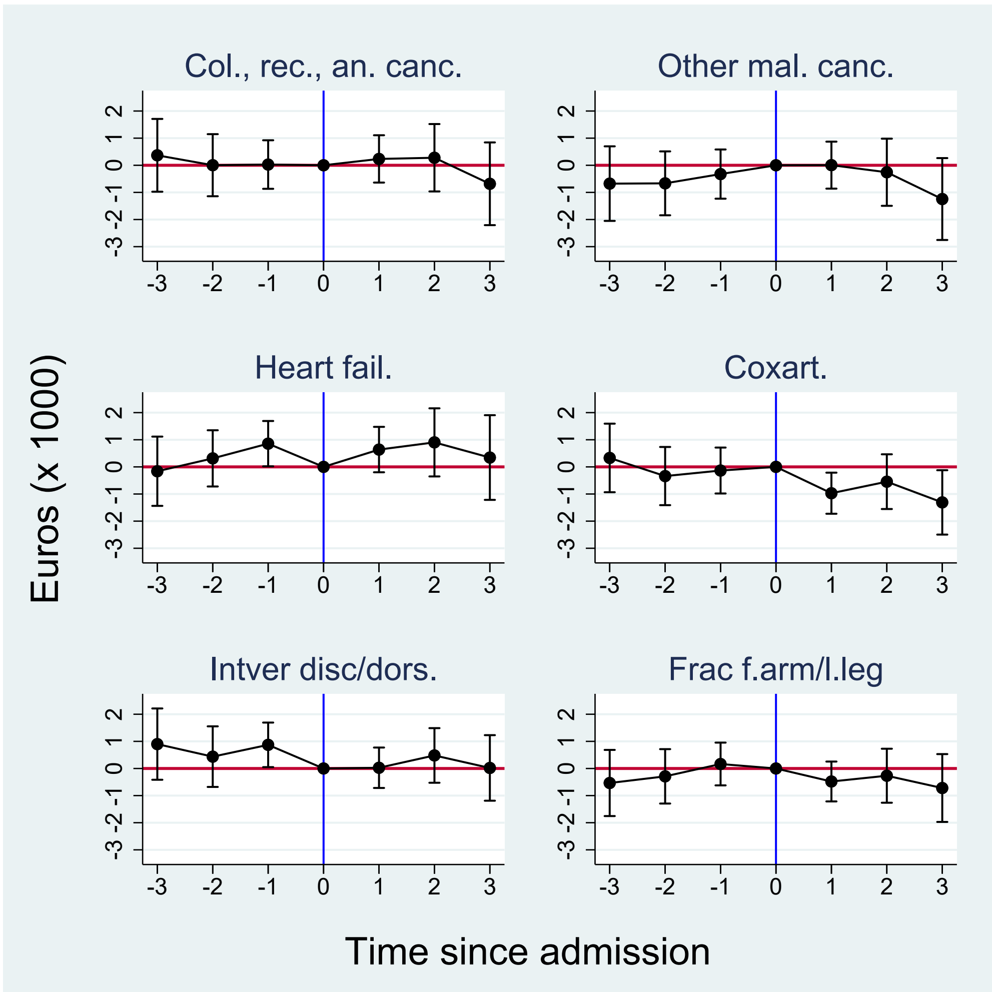
Figure 11: Results for difference-in-timing analysis for savings account. $k = 5$



The difference in wealth between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

Finally, we apply a standard difference-in-difference design instead of the difference-in-timing design. For each disease group, we use the randomly selected not-admitted population (with a placebo admission) as the control group. We do not find any significant effects (Figure 12), although we observe some suggestive evidence for decreasing wealth pattern for the two cancers. We found a similar pattern for total net wealth in a difference-in-timing design - see Figure 8.

Figure 12: Results for difference-in-difference analysis for savings account.



The difference in wealth between time of admission and t, between the group and the no-disease group (δ_p) and 95-% confidence intervals.

5 Discussion

The interaction between health shocks and wealth has been argued many times to be an important factor in the saving and insurance decisions for older individuals. In this paper, we have investigated this relation for six severe conditions among the elderly in the Netherlands. All of these conditions affect survival, disability, and the reliance on care, but to different extents. Based on theory, we would therefore expect different effects across diseases. For instance, a health shock that has a strong negative effect on survival, but not on disability or reliance on care, could be expected to decrease wealth holdings as the expected time left to consume lifetime wealth decreases sharply. Similarly, health shocks with small effects on mortality, but large effects on disability might increase savings, as they could induce people to leave strategic bequests.

In contrast to these expectations, we generally do not find an effect on wealth for any of the conditions. Even in the rare instances we find a significant effect, the size (in absolute numbers) is small. This finding holds if we compare individuals admitted to the hospital for a particular condition to individuals that share the same risk, but are admitted three (or five) years later (difference-in-timing), or if we compare them with the general population (difference-in-difference). Moreover, we do not find any effects for subgroups for which we would expect the bequest motive to be less dominant: individuals without a partner, or individuals without children.

We do find some evidence of heterogeneity in the effect on wealth. For the condition "colon, anal, and rectal cancer" and "other malignant cancers" we see some indications that individuals spend down on total wealth after admission. This finding would correspond to theoretical expectations: individuals who experience one of these health shocks, might know that changes for survival are slim and therefore want to decumulate wealth. More research is needed to see whether they consume this wealth themselves, or provide inter-vivos transfers to their children. We also find some evidence that individuals experience a heart failure increase their liquid wealth, which might be due to either reduced spending possibilites or increases bequest motive due to the severe disabling nature of this disease.

Our overall conclusion, based on these results, is that, at least in a social system like the system in place in the Netherlands, where the effect of health on income and out-of-pocket medical spending is relatively low, older individuals seem to stick to a pre-determined level of consumption regardless of their health. It might still be the case that, within this pre-determined overall level of consumption, individuals shift from one type of consumption to another (as found by Van Ooijen et al., 2018), but the health effects on survival and disability do not seem to affect the trade-off between saving and consumption overall.

A behavioral explanation for this finding might be that individuals engage in mental accounting (Thaler, 1999). Instead of making a joint re-assessment of all their saving and consumption decisions, individuals stick to the overall amounts of funds they have previously dedicated to either saving or wealth, and only change the reallocation within each of these two categories. Another interesting mechanism that is worthwhile to explore further is that individuals might not (fully) update their expectations of survival (and future health) after a health shock. Baji and Bíró (2018), for instance, find that after a health shock, people initially lower their survival expectations, but in the longer run they return to the same expectation they had prior to the shock. De Hond et al. (2019) find a similar pattern for life satisfaction in the years after the first occurrence of functional limitations.

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A Classification of diseases

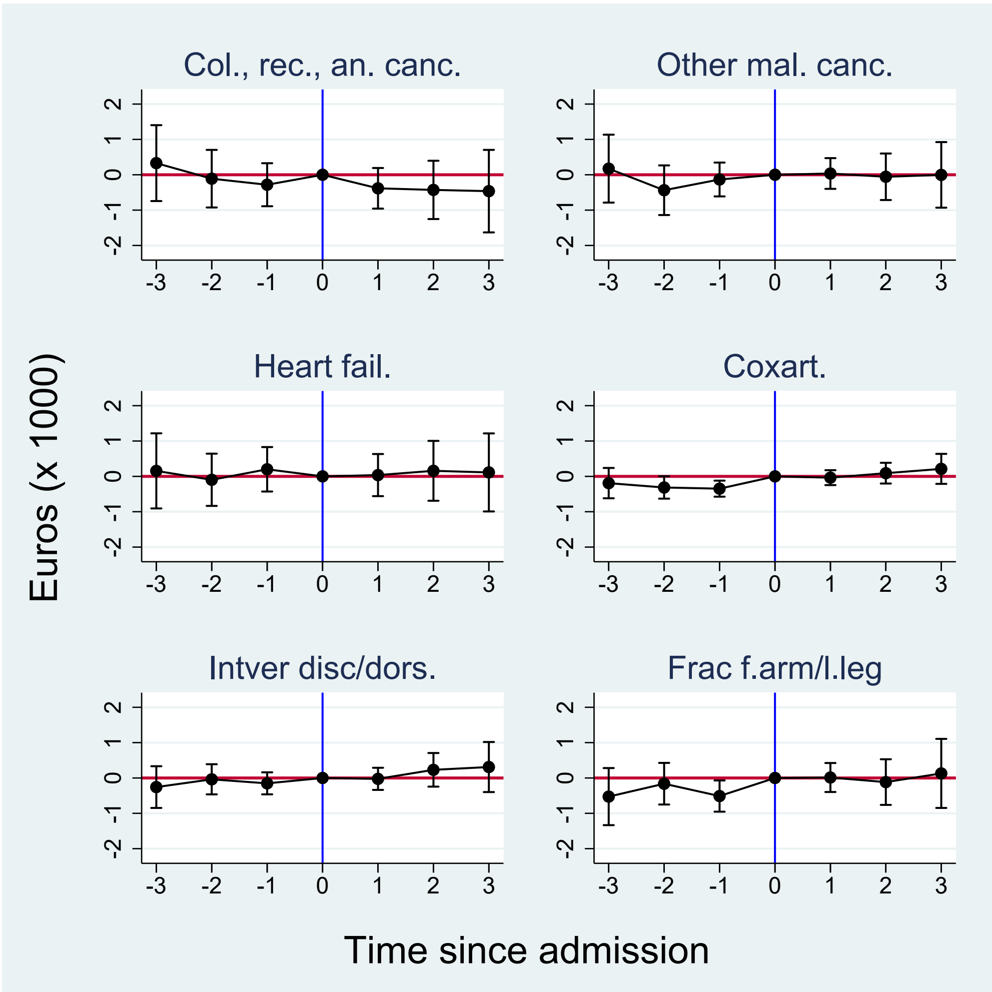
Table 3: Overview of ISHMT codes.

Code	Heading	Code	Heading
0101	Intestinal infectious diseases except diarrhoea	1008	Other diseases of the respiratory system
0104	Septicaemia	1101	Disorders of teeth and supporting structures
0106	Other infectious and parasitic diseases	1103	Diseases of oesophagus
0201	**Malignant neoplasm of colon, rectum and anus**	1104	Peptic ulcer
0202	Malignant neoplasms of trachea, bronchus and lung	1105	Dyspepsia and other diseases of stomach and duodenum
0203	Malignant neoplasms of skin	1106	Diseases of appendix
0204	Malignant neoplasm of breast	1107	Inguinal hernia
0205	Malignant neoplasm of uterus	1108	Other abdominal hernia
0206	Malignant neoplasm of ovary	1109	Crohn's disease and ulcerative colitis
0207	Malignant neoplasm of prostate	1110	Other noninfective gastroenteritis and colitis
0208	Malignant neoplasm of bladder	1111	Paralytic ileus and intestinal obstruction without hernia
0209	**Other malignant neoplasms**	1112	Diverticular disease of intestine
0210	Carcinoma in situ	1113	Diseases of anus and rectum
0211	Benign neoplasm of colon, rectum and anus	1114	Other diseases of intestine
0213	Other benign neoplasms and neoplasms of uncertain or unknown behaviour	1117	Cholelithiasis
0301	Anaemias	1118	Other diseases of gall bladder and biliary tract
0401	Diabetes mellitus	1119	Diseases of pancreas
0402	Other endocrine, nutritional and metabolic diseases	1120	Other diseases of the digestive system
0501	Dementia	1201	Infections of the skin and subcutaneous tissue
0506	Other mental and behavioural disorders	1203	Other diseases of the skin and subcutaneous tissue
0603	Epilepsy	**1301**	**Coxarthrosis [arthrosis of hip]**
0604	Transient cerebral ischaemic attacks and related syndromes	1302	Gonarthrosis [arthrosis of knee]
0605	Other diseases of the nervous system	1303	Internal derangement of knee
0701	Cataract	1304	Other arthropathies
0702	Other diseases of the eye and adnexa	1306	Deforming dorsopathies and spondylopathies
0800	Diseases of the ear and mastoid process	**1307**	**Intervertebral disc disorders**
0901	Hypertensive diseases	**1308**	**Dorsalgia**
0902	Angina pectoris	1309	Soft tissue disorders
0903	Acute myocardial infarction	1310	Other disorders of the musculoskeletal system and connective tissue
0904	Other ischaemic heart disease	1401	Glomerular and renal tubulo-interstitial diseases
0905	Pulmonary heart disease and diseases of pulmonary circulation	1402	Renal failure
0906	Conduction disorders and cardiac arrhythmias	1403	Urolithiasis
0907	**Heart failure**	1404	Other diseases of the urinary system
0908	Cerebrovascular diseases	1405	Hyperplasia of prostate
0909	Atherosclerosis	1406	Other diseases of male genital organs
0910	Varicose veins of lower extremities	1409	Menstrual, menopausal and other female genital conditions
0911	Other diseases of the circulatory system	1410	Other disorders of the genitourinary system
1001	Acute upper respiratory infections and influenza	1901	Intracranial injury
1002	Pneumonia	1902	Other injuries to the head
1005	Other diseases of upper respiratory tract	**1903**	**Fracture of forearm**
1006	Chronic obstructive pulmonary disease and bronchiectasis	1904	Fracture of femur
1007	Asthma	**1905**	**Fracture of lower leg, including ankle**

*Notes:*OECD Health Statistics 2019, June 2019. http://www.oecd.org/health/health-data.htm

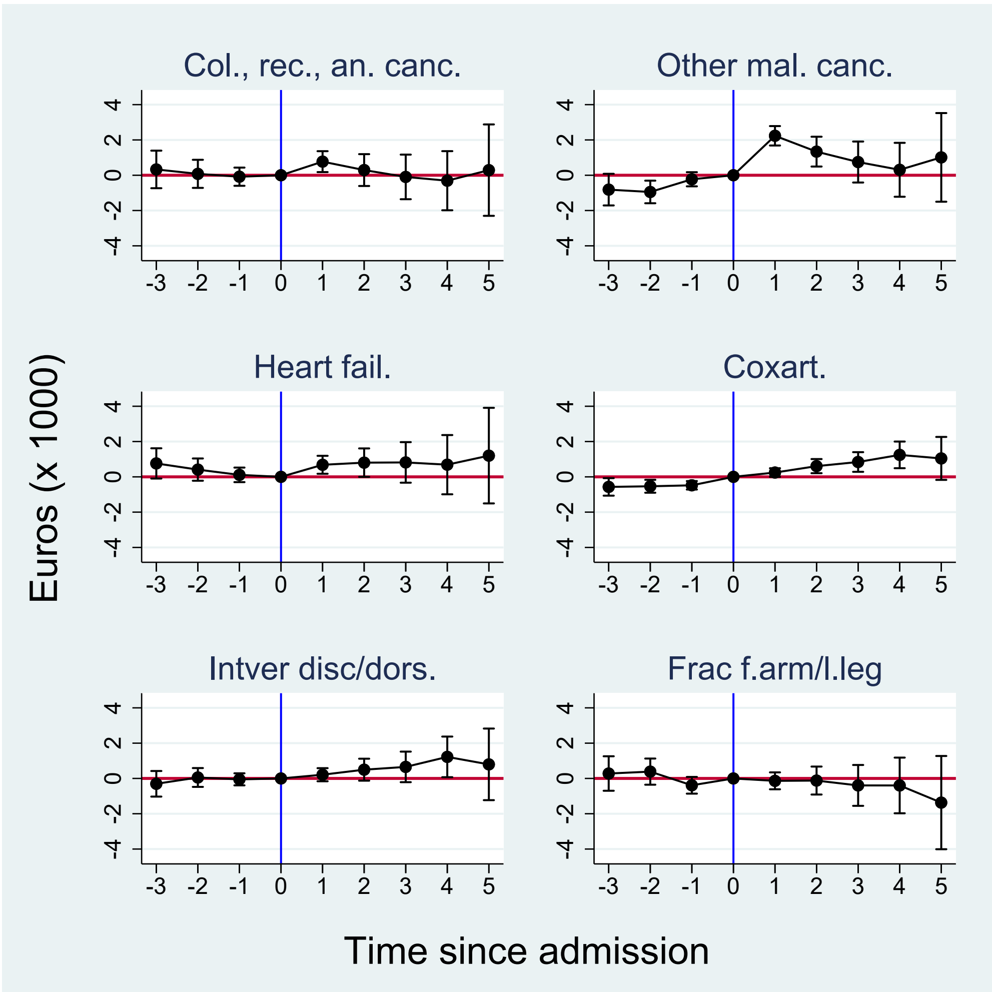
B Additional estimation results for income

Figure 13: Results for difference-in-timing analysis for gross household income. Survivors/



The difference in income between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

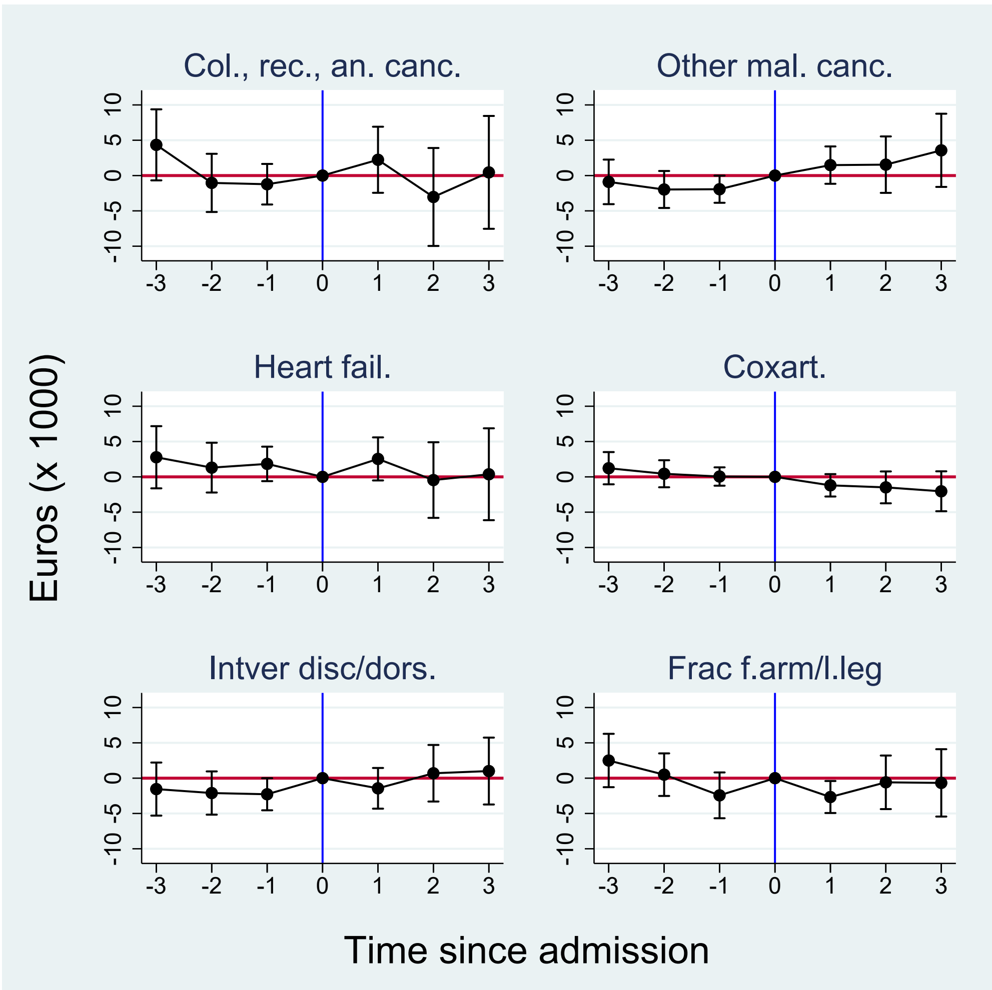
Figure 14: Results for difference-in-timing analysis for gross household income. $k = 5$



The difference in income between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

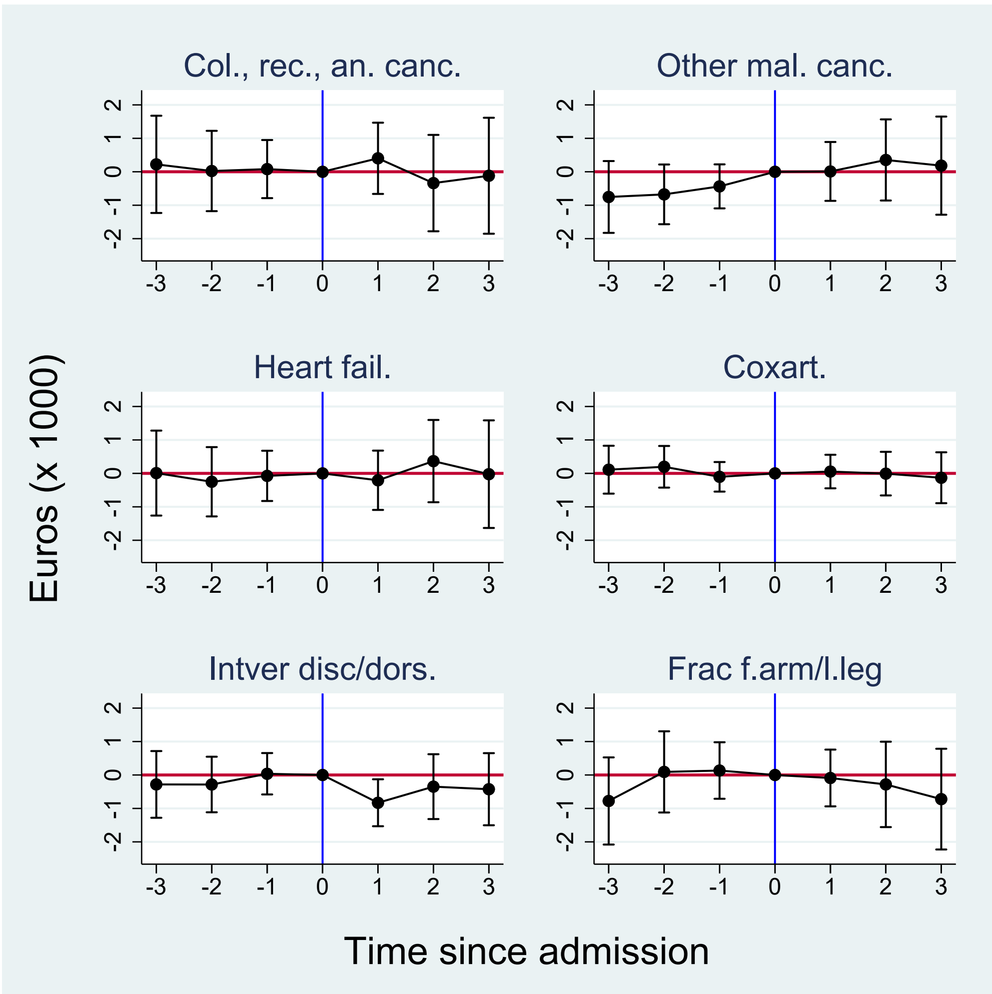
C Additional estimation results for wealth: individuals with and without children

Figure 15: Results for difference-in-timing analysis for wealth (savings account). Individuals without children



The difference in income between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.

Figure 16: Results for difference-in-timing analysis for wealth (savings account). Individuals with children



The difference in income between time of admission and t, between the group admitted at t and the control group admitted at $t + k$ (δ_p) and 95-% confidence intervals.