Staying Sick but Feeling Better? – The impact of health shocks on health perceptions and behaviors

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Abstract

Objective: Severe health shocks may affect individuals' objective health and the perception thereof, but potentially in different ways. Specifically, self-perceived health might revert to pre-shock levels as individuals adapt to their new health state over time despite persistent effects on objective health. This difference is important given that individuals make decisions based on these biased subjective health perceptions. We explore how health perceptions, lifestyle behavior, and medication use change after experiencing a negative health shock that persistently affects objective health: an ischemic stroke or an acute myocardial infarction. We shed new light on post-health shock recovery and on the role of health perceptions and choices using a novel combination of detailed administrative and survey data.

Methods: We combined two large Dutch health surveys from 2012 and 2016 with administrative data on hospital admissions, healthcare demand and death records from 1995 to 2018. We identified a sample of 13,000 heart attack and 9,000 stroke patients providing survey responses on subjective outcome measures at different relative time points to their respective health shocks. The resulting repeated cross-section of heart attack/stroke patients is interviewed between 6 years prior and 7 years after their event. We use a doubly robust event-study approach that exploits the exogenous timing of the occurrence of these shocks to explore the causal effects of heart attacks and strokes on subjective outcome measures, risky health behaviors, and medication use over time.

Results: A heart attack or stroke has large immediate negative effects on subjective health perceptions as self-assessed health decreases substantially by one-third of a standard deviation in the year after a heart attack or stroke occurs. Despite these substantial initial differences, the effects attenuate quickly. While individuals experience an increased objective burden of disease over time, reflected in an increasing prevalence of long-term physical disability, their self-assessed health reverses towards pre-shock levels. Further we observe heterogenous impacts on a range of (risky) health behaviors with both health shocks leading to long-term decreased smoking prevalence of around 10-15 percentage points but only temporary decreases in alcohol consumption and no change in overweight rates or physical activity.

Discussion: Our findings suggest that even after a severe health shock like a heart attack or a stroke, individuals health perceptions return to pre-shock levels within a short period of time, despite an increasing burden of disease observed. Our results on health behaviors confirm previous studies that find smoking behavior to be consistently affected by a health shock. In line with the temporary effect on subjective health, we find that most effects on lifestyle behaviors are short-lasting. Only for smoking we observe a permanent decrease. In ongoing work, we aim to extend our analyses to the health perceptions and behaviors of cohabiting family members and to explore whether the observed pattern of adapted health perceptions also influence economic behaviors such as the decision to retire or rejoin the labor force, individuals' choice of health insurance deductibles or adherence to prescription medicine.

1 Introduction

In many economic models the ability of agents to accurately interpret and observe information about themselves is a necessary prerequisite to identify optimal choices. A classic example are health beliefs that inform life-cycle planning and investments in future health. However, the extent to which health beliefs adequately represent objective health and how these beliefs are formed over time remains underexplored. While health shocks are undesirable, they do provide information to individuals about their underlying health. Severe shocks with long-term implications, such as heart attacks or strokes, can act as salient signals highlighting individual-level risk. Whether or not such events lead to persistent behavior change rests on the extent to which subjective beliefs reflect this information. Does experiencing a severe health shock result in persistent changes in perceived health and risky health behaviors? Or do individuals return to previous beliefs leading only to short-term behavior change and biased self-perceptions? While these questions are highly relevant for the effective design of public health interventions targeting at-risk populations there is scarce evidence on the evolution of subjective beliefs following severe health shocks.

Studies from various domains have shown that individuals' frequently overestimate their own abilities. Being able to perform certain work-related tasks (Zell & Kirzan, 2014), gauge their level of or ability to conduct physical activities (Harris, 2017; Spitzer & Shaikh, 2020), identify being at risk of deteriorating health (Arni et al., 2021) or predict long-term survival (Bago d'Uva at al., 2020) have been shown to be prone to biased perceptions. These biases can have negative consequences. Optimal life-cycle decisions such as consumption and retirement planning (Schünemann et al., 2017), or savings decisions (Gan et al., 2015) rest on adequate perceptions of health and long-term survival. Also, current behavior might be influenced by perceptions. Arni et al. (2021) were the first to quantify and relate health perception bias to risky health behavior illustrating that overly optimistic perceptions correlate with adverse health habits while also lack of preventive care consumption (Biró, 2016; Spitzer & Shaikh, 2020) or overeating (Harris, 2017) have been shown to higher among individuals with biased self-perceptions.

How self-perceptions evolve following health events that provide objective information on individuals' health has received less attention. Early descriptive evidence from clinical settings suggests that individuals adapt even to very severe diseases by shifting their reference point

(Groot, 2000)[1]. However, robust evidence remains wanting. Baji and Biró (2017) explore the effect of suffering from a neoplasm, heart attack or stroke and report subjective health and survival probabilities to be only short-term effected by such events with suggestive evidence that preventive behavior follows the same pattern. Similarly, de Hond et al. (2019) find that after the onset of physical limitations self-assessed health reverts toward pre-onset levels. Cubi-Molla et al., (2017) on the other hand explore a range of diseases and find perceptions to revert to pre-shock levels over time although only over long time-periods. While these findings suggest another form of biased health perceptions, they also rely on a common research design to study the impact of health events on perceived health by using (two-way) fixed-effects models to analyze panel survey data. Population panel surveys provide the obvious benefit of observing the same individuals over time, they also have a common drawback of only covering a small number of individuals suffering from specific diseases and limited information on objective measures of health and healthcare use.

This study explores the causal impact of severe health shocks on subjective health and well-being measures and health behaviors over time by studying patients suffering from an ischemic heart attack or stroke. We focus on these conditions for three reasons. Firstly, cardiovascular diseases remain to be the leading contributor to the global burden of disease (Roth et al., 2020). Secondly, among cardiovascular diseases heart attacks (as a category of ischemic heart disease) and strokes are some of the most severe conditions that despite their reduced mortality continue to cause a growing number of disability-adjusted life years and have long-term implications for patients (Pandaya et al., 2013; Feigin et al, 2017; Roth et al, 2020). Last and most importantly, their onset is relatively unexpected (see for example Chandra & Staiger, 2007; Doyle, 2011; Nielsen & Fadlon, 2019; Hodor, 2021). The unexpected timing of heart attacks and strokes is at the core of our identification strategy in which we compare the self-reported outcomes of individuals interviewed up to 7 years after their heart attack or stroke to those not-yet affected by either of these events. We do so by using two large-scale general population surveys from the Netherlands to construct a repeated cross-section of 13,000 heart attack and 9,000 stroke patients interviewed at different time-points relative to their health shock. We combine this survey data with rich administrative data on objective measures of health such as observed

[1] This goes back to an early study by Brickmann et al. (1978) that has inspired a large literature on the impact of life events on subjective well-being measures often exploring the impact of health changes on life satisfaction over time. Clark et al. (2008), Oswald and Powdthavee (2009), Powdthavee (2009) and recently Odermatt and Stutzer (2019) for example have studied broader health states, such as becoming disabled, and report life satisfaction to (partially) revert to pre-shock levels while Powdthavee (2009) finds that adaptation in self-perceived health is the main driver of this dynamic.

hospitalizations and medicine use. To explore the causal impact of a severe health shock on self-assessed outcomes over time, we use a doubly robust event study design proposed by Callaway and Sant'Anna (2020).

Suffering from a heart attack or stroke has a strong initial negative effect on health perceptions. However, these initial effects attenuate over time. In the case of heart attacks, the initial effect decreases by two-thirds within a few years after the event. For strokes the effects are generally smaller and attenuate more quickly, becoming non-significant after a few years. With respect to broader subjective outcomes such as mental health we observe a comparable pattern with initial negative effects that attenuate quickly. This occurs despite individuals' health to remain low with an increasing prevalence of self-reported functional limitations being observed over time. However, while these patterns suggest health perceptions to only temporarily being affected health behaviors provide a more nuanced picture. Risky health behaviors like smoking, obesity, lack of exercise and excessive drinking contribute to avoidable mortality and morbidity (Cawley & Ruhm, 2011) and are leading risk factors for cardiovascular diseases (Roth et al., 2020). We observe a strong impact of both events on smoking rates with a large 10 to 15 percentage point drop, more than half of the observed pre-onset smoking rates. With respect to physical activity and overweight prevalence no effects are observed while alcohol consumption seems to be only temporarily affected.

Our study presents multiple contributions to the literature on the impact of health shocks on health perceptions and behavior. Firstly, we employ a novel approach that exploits the exogenous timing of certain health shocks among a group of individuals that will all eventually experience this shock. This is in contrast to other studies on the impact of health shocks on health perceptions and behavior that usually rely on the assumed exogeneity of the shock itself in combination with standard fixed-effects approaches. Secondly, the availability of rich administrative data allows us to control for many confounding factors or alternative explanations when exploring the dynamic impact of ill health. Thirdly, by focusing on heart attacks and strokes we contribute to the study of longer-term effects on health perceptions and behavior to these two conditions which contribute disproportionately to the burden of disease in high-income economies (Pandaya et al., 2013; Roth et al., 2020). Lastly, we connect the literature on the impact of health shocks to recent work on the relationship between biased health beliefs and risky health behaviors.

2 Data

2.1 Data Sources

We use the general population samples of the Dutch Health Monitor (*Gezondheidsmonitor*) of 2012 and 2016. The Health Monitor is a large-scale, nationally representative survey of the general adult population in the Netherlands (aged 18+) aimed at measuring health and well-being and organized by Statistics Netherlands (*Centraal Bureau voor de Statistiek*, CBS). Starting in 2012 it is conducted each four years. Individuals registered in their respective municipality are invited to participate. Only those individuals living in an institutionalized setting, such as permanent nursing home residents, are not approached. The collection of surveys is conducted by municipalities and spread out throughout the year. Individuals were invited by letter to participate in the online survey. A paper-based questionnaire was included in some regions with the initial contact while in others this was only send to those not responding to the initial invitation. The broad majority of responses were submitted online with in-person or phone-based interviews making up only 0.5% (2012) and 0.1% (2016) of the collected surveys (CBS, 2015; 2017). The 2012 Health Monitor was sent to approximately 700,000 individuals with 387,195 respondents (ca. 55%), while in 2016 1.15 million individuals were approached resulting in 457,153 respondents (ca. 40%).

The merged samples from both Health Monitors are linked at Statistics Netherlands to Dutch administrative records using pseudo-anonymized individual-level and household-level identifiers. This administrative data covers multiple dimensions; demographic background information (age, gender, and, if applicable, time of death), socio-economic variables (household income based on income tax data) and healthcare use (hospitalizations and medicine consumption). Table A1.1 in the Appendix provides an overview of the included data sources. The administrative data on medicine consumption we include in our analysis covers the period of 2006 to 2018. As parts of our analyses use lagged information on these indicators for up to three years this results in an effective observation period ranging from 2009 to 2018.

2.2 Outcome Measures

Our outcomes are two subjective indicators of individuals' health and well-being. Firstly, we use self-assessed health on a five-point scale ranging from best health (1: *Very Good*) to worst possible health (5: *Very Poor*). Secondly, we use a mental health questionnaire based on the Kessler Psychological Distress Scale (Kessler et al., 2002). Individuals respond to 10 questions

related to feelings of depression and anxiety in the past four weeks which are then scored based on a standardized scoring method that that results in a score ranging from 10 (best) to 50 (worse). We consider the raw scores as our main outcome measure for mental health but also consider a binarized outcome for scores exceeding, indicating heightened risk to suffer from depression/anxiety (Kessler et al., 2002).

Our analysis of health behaviors uses self-reported information collected as part of the health monitor surveys. Smoking status is based on individuals reporting to be smokers at the point of the survey without making a distinction on the intensity of their smoking habit. To measure the prevalence of overweight we calculate the body-mass-index based on self-reported height and weight and using a threshold of 25. Excessive alcohol consumption is measured by using the self-reported number of alcoholic drinks per week and applying a threshold of 14 for male and 7 for female respondents. Lastly physical activity is defined as a minimum of 3 days of moderate to strenuous activity a week that lasts for 30-60 minutes. All of these behaviors are chosen for their importance in preventing subsequent heart attacks or strokes and improving post-shock health outcomes in the longer run (Roth et al., 2020)

2.3 Sample Selection and Time Structure

The sample is restricted to participants in the Health Monitors of 2012 and 2016 for which we have information on both of our well-being measures and for whom the described administrative information is available. As we aim to compare the health perceptions, well-being and behavior of individuals in the years preceding a heart-attack or stroke occurrence to those that have suffered from a heart attack or stroke in the past we use hospital records from 1995 to 2018 to identify the universe of patients admitted to Dutch Hospitals for either condition. Using the International Classification of Disease (ICD) codes we identify for each patient the first admission for a heart attack or stroke which we define as the first occurrence.[2] In the case of both a heart attack and stroke occurring (in the same or at different years) that individual is excluded from the sample.

Linking the hospital records to the participants of both Health Monitors allows us to identify individuals that have completed the self-reported surveys at relative time points t_i to their

[2] For heart attacks these are all diagnoses included under the ICD-9 three-digit code 410 and ICD-10 three-digit code I21. For strokes these are ICD-9 three-digit codes 433 and four-digit codes 4340, 4341, 4349, and ICD-10 three-digit codes I63 and I66. We currently do not differentiate between types of health shocks, for example STEMI or NSTEMI heart attacks.

respective first admission for a heart attack or stroke where t is measured in years. We therefore construct two groups of samples interviewed either before the heart attack or stroke occurs ($t_{<0}$) or thereafter ($t_{\geq 0}$). To explore whether individuals adapt over time after a severe health shock we compare the subjective health and well-being of individuals surveyed before to those surveyed after their health shock. As by definition individuals surveyed after their heart attack or stroke admission have survived their health shock this needs to be accounted for. To reflect this and make both groups more comparable we exclude all individuals that die within one year after their first admission. In a robustness check we further extend this condition to survival for longer time-periods. Lastly, we excluded all individuals that stayed in a nursing home at any point in the three years preceding their heart attack or stroke admission. The reason for this is that medication received in nursing homes is not observed by us.

3 Methods

3.1 Overview

To explore the causal effect of a heart attack or stroke on health over time, we compare the self-perceived health of individuals in the years right after a health shock to the health of different but similar individuals in the years prior to the same shock. We therefore rely on the exogeneity of the timing of a heart attack or stroke occurring which is a less restrictive assumption than the exogeneity whether an individual will suffer from a heart attack or stroke at all. To do so we use two large-scale general population surveys from 2012 and 2016 that can be linked to administrative records on hospital admissions and their cause at the individual level for 1995 to 2018. This feature of our data-generating process allows us to observe individuals at different time event-times t_e relative to their first-time admission for a heart attack or stroke. In our context e ranges from -6 through 3 for the 2012 sample and -2 to 7 for the 2016 sample.[3]

By focusing on individuals interviewed at relative time-points to their respective health shock we aim to ensure that the individuals interviewed before and after a heart attack or stroke occurs are highly comparable in (un-)observed characteristics. The assumption of exogenous timing conditional on an event occurring eventually is less restrictive than assuming exogeneity of the event itself. However, individuals interviewed at different event-times t_e might still differ, for example with respect to their underlying health before the event occurred. One way of doing this is to ensure that individuals interviewed at different at different time to event have a comparable probability to suffer from a heart attack or stroke at their respective t_0, the time their health shock occurs. To ensure the comparability of the different cohorts we observe we follow a two-step approach proposed by Callaway and Sant'Anna (2020) that combines inverse-probability weighting with an event-study design, a procedure referred to as "doubly robust" (Sant'Anna and Zhao, 2020).[4]

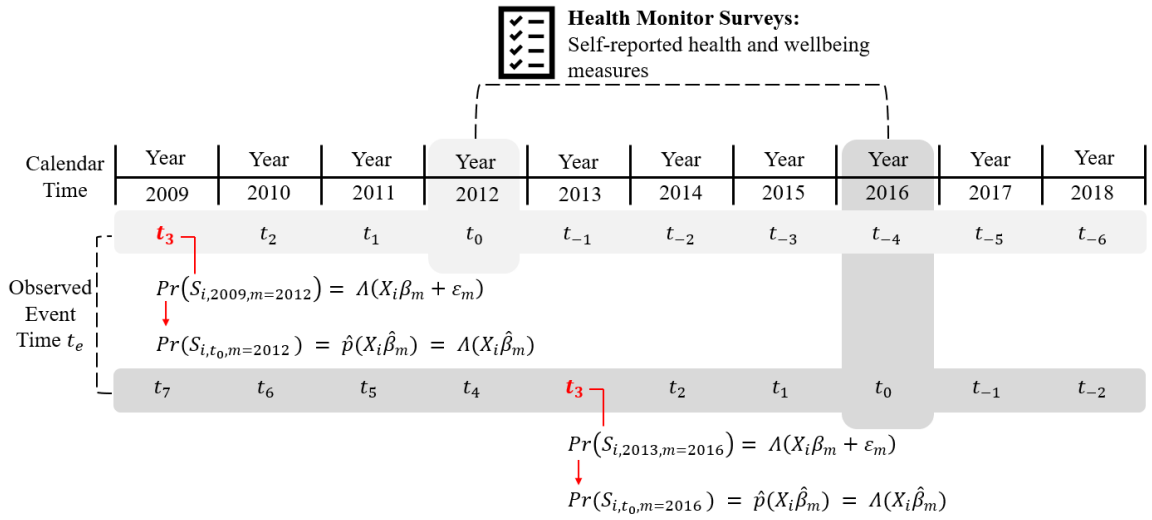
[3] The observed event-time is determined by the respective calendar time of their health shock which ranges from 2009 to 2018 and the calendar time of the survey participation which is 2012 and 2016. For individuals that participate in the Health Monitor of 2012 we can therefore observe individuals interviewed at event-times t_{-6} (health shock in 2018), up until t_3 (health shock in 2009). Individuals surveyed in 2016 on the other hand are observed at event-times t_{-2} (health shock in 2018), up until t_7, (health shock in 2009). Therefore, from each group of Health Monitor respondents we obtain ten repeated cross-sections covering a partially overlapping range of observed event-times (see also Figure 1).

[4] This doubly robust procedure combines propensity score-based methods to deal with covariates in event-study regressions proposed by Abadie (2005) with the contrasting outcome regression approach (Heckman et al., 1997). The doubly robust property from the fact that correct inference requires only

3.2 Empirical Application

Figure 1 provides a graphical overview of the data-generating process and the different steps taken which are described in further detail below.

Figure 1: Study Design Overview



Source: Own illustration.

In a first step we estimate a generalized propensity score model which will be used to calculate the propensity scores for the inverse probability weighting. To do so we make use of the extensive administrative data available to us. Using the entire population of individuals admitted to a hospital with a heart attack or stroke between 2009 and 2018 we estimate the probability of belonging to event-time group t_3. In other words, we estimate the probability to experience the respective health shock S_i in 2009 or 2013, for each of the Health Monitor groups (m) separately:

$$(1)\ Pr(S_{i,2009,\ m=2012}) = \Lambda(X_i\beta_m + \varepsilon_m) \text{ and } Pr(S_{i,2013,\ m=2016}) = \Lambda(X_i\beta_m + \varepsilon_m)$$

To do so we use demographic and socio-economic information alongside information on healthcare use in the three preceding years, 2006-2008 or 2010-2012. We choose these inputs into the propensity score model to capture common risk-factors for cardiovascular diseases.

one of the two specifications, the generalized propensity score estimation or the outcome regression, to be correctly specified (Sant'Anna and Zhao, 2020).

The most important of these are the presence of pre-existing conditions, for example hypertension or high cholesterol levels (Roth et al., 2020) while also socio-economic status has been found to be a significant risk factor (Schultz et al., 2018).

To estimate the generalized propensity score model, we include individual's age and gender, their position in the income distribution in the preceding year[5], and whether an individual is a pensioner, unemployed or receives incapacity benefits in the preceding year. Further we capture health prior to admission by including information on hospital admission for any of the disease categories of the International Shortlist for Hospital Morbidity (ISHMT) and the total length of stay for all admissions within a given year. We also include information on the consumption of medicines for specific chronic conditions according to the Anatomical Therapeutic Chemical Classification System (ATC). These include diabetes related drugs (A10), drugs to treat acid-related disorders (A02) and chronic obstructive pulmonary disease (R03), and drugs for chronic muscular or joint pain (M02) and rheumatic disease (M01). All of these are chosen to capture pre-existing conditions commonly found among older populations. Given our focus on heart attack and strokes we further include information on the consumption of medicine commonly prescribed to treat risk-factors for cardiovascular disease (Roth et al, 2020). These include drugs to counter hypertension (C02, C03, C07, C08), lipid modifiers and statins (C19), and antithrombotic drugs (B01). Lastly, as we use the Kessler Psychological Distress Scale as one of our main outcomes of interest, we also include whether individuals have been taking medicine to treat depression or anxiety. This includes antidepressants (N05B), anxiolytics (N05A) and combinations of both (N05C).

The estimation of this propensity score model is done separately for heart attacks and strokes. In both cases we use a logit model to predict the onset of each health shock using data from all individuals that will suffer from either of these health shocks between 2009 and 2018. Specifically, we predict the probability of a heart attack or stroke in calendar year 2009 (Health Monitor 2012) or 2013 (Health Monitor 2016) using a cross-section of all heart attack or stroke patients observed in this year. Importantly, the estimation for the latter group only contains individuals that have not yet suffered from a heart attack or stroke by 2013, as we aim to model a first-time admission only. This is done to avoid including post-treatment covariates in the

[5] To do so we calculate per-capita income for each individual using data from declared household-level income taxes and the municipal registry on the number of household members. We then divide incomes into quintiles based on the entire distribution of household incomes declared in the Netherlands in a given year.

calculation of the generalized propensity score.[6] The obtained coefficients $\widehat{\beta_m}$ estimated using equation (1) are then used to predict the estimated probability of suffering from a heart attack or stroke. We predict the occurrence of a health shock in each individual's respective t_0 using the same information on age, gender and health status up to three years before the respective event (t_{-1} to t_{-3}):

$$(2)\ Pr(S_{i,t_0,m}) = \hat{p}(X_i\hat{\beta}_m) = \Lambda(X_i\hat{\beta}_m) \text{ for } m \in \{2012, 2016\}$$

While equations (1) and (2) are structurally similar the data used in their estimation is different. In equation (1) we use the entire population of heart-attack and stroke patients between 2009 and 2018 to calibrate two versions of the generalized propensity score model. The resulting coefficients are then applied in (2) to the Health Monitor survey samples to predict individual-level propensity scores for both samples separately.

In a final step we estimate an event-study regression that uses the estimated propensity scores as weights. Using this pooled survey data, we regress our outcome measure on set of dummies measuring the time-distance to the health shock t_e at the time of the survey together with a set of control variables:

$$(3)\ y_i = \alpha + \sum_{e=-6}^{7} \delta_e\, t_e + \beta_1 female_i + \beta_2 onset_age_i + \beta_3 medicine_i + \beta_4 hospital_i + \beta_5 inpatient_days_i + \beta_6 disability_i + \beta_7 year_i + \varepsilon_i$$

Each observation is weighted by the inverse probability estimated using equation (2). The included control variables cover basic demographic information such as gender and the age at admission. Further we control for medicine use in the year preceding the hospital admission by including dummies for the use of anti-thrombotic and anti-hypertensive medication and statins. In addition, we also include information on the number of hospitalizations and the total number of inpatient days in the year preceding the admission. To capture the severity of the health shock we also include information on the number of inpatient days associated with the admission. Lastly, we include a dummy encoding whether an individual participated in the Health Monitor

[6] Previously treated individuals should not be included in the control group as their covariates might be affected by the previous treatment (Goodman-Bacon, 2021). In our context a previous heart-attack or stroke is likely to affect a range of covariates used in the estimation of the generalized propensity score and hence we condition for each estimation on the universe of patients that will be treated in the given year and those not-yet-treated.

of 2012 or 2016. We do not include the full range of control variables used for the generalized propensity score model (1) given the comparatively low sample size of the survey data versus the administrative data. Instead, we focus on those variables that are identified as most important given their predictive power in propensity score estimation and to address remaining imbalance between the cohorts.

The only control variable included that is measured in the survey-year is information on self-reported disability, measured using self-reported functional limitations.[7] Including this control variable is crucial for our empirical approach. Our aim is to explore whether individuals adapt to their deteriorating health and hence we need to control for the objective health of individuals at the time of their survey response. While reported functional limitations are also self-reported they are an important measure to capture individuals' objective health as they capture the actual consequences of chronic illness or disability for individuals' day-to-day life. However, we aim to extend this part of our analysis by also considering more objective measures on avoidable re-admission to a hospital and healthcare use in the future to not only rely on self-reported information to capture the evolution of subjective health after the initial shock.

[7] These are: not being able to follow a conversation of three or more persons; not being able to have a conversation with one person; not being able to read the small-print in newspapers; not being able to recognize someone's face at a distance of four meters or more; not being able to carry 5kg for 10 meters; not being able to reach the ground; not being able to walk 400 meters without stopping.

4 Results

In the main text we focus on the results obtained after conducting the inverse probability weighting. The interested reader can find the detailed information with respect to the calculation of propensity scores across the different samples (heart/stroke and health monitors 2012/2016) in Appendix A2 with Figure A2.2 depicting the detailed distributions by cohort. Across the different cohorts we observe a highly comparable distribution of calculated propensity scores indicating a good overlap and area of common support (A4) which is also reflected in the low number of individuals identified as off-support.

4.1 Weighted Differences across Covariates and Event-Time

Before exploring our main results of interest, it is useful to explore the outcome of the inverse probability weighting. Table 1 depicts the balancing table for the group of covariates also included in the event-study regression after weighting by the calculated propensity score.

Table 1: Weighted Covariate Means

Heart Attack Sample														
	Cohort (Years to Admission)													
Age/Gender at Admission	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Female	0.37	0.37	0.36	0.40	0.33	0.36	0.34	0.29	0.32	0.29	0.24	0.32	0.30	0.32
Age	73.43	71.80	72.24	72.13	71.57	71.01	70.31	69.10	69.19	68.56	66.40	64.71	65.76	64.44
Health in year before Admission														
Number of Hospitalisations	0.27	0.44	0.35	0.33	0.33	0.33	0.43	0.31	0.42	0.33	0.32	0.33	0.36	0.28
Total Length of Stay	0.68	1.09	1.12	1.05	0.87	0.88	1.05	0.87	1.09	0.93	1.11	0.86	1.09	0.73
Medication: Anti-Thrombotic	0.97	0.98	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.95	0.96	0.95	0.96	0.94
Medication: Anti-Hypertensive	0.93	0.93	0.92	0.95	0.92	0.93	0.94	0.92	0.93	0.93	0.94	0.94	0.93	0.93
Medication: Statins	0.96	0.96	0.95	0.95	0.93	0.94	0.94	0.94	0.95	0.93	0.96	0.93	0.94	0.93
Medication: Depression/Anxiety	0.14	0.15	0.12	0.14	0.14	0.14	0.12	0.14	0.15	0.16	0.12	0.17	0.14	0.15
Admission Related Information														
Inpatient Days	4.26	4.41	4.32	4.29	4.48	4.26	4.32	4.54	4.87	4.53	3.91	4.13	5.00	4.61
Observations	690	677	715	718	1576	1596	1242	1348	1269	1250	367	483	480	514

Stroke Sample														
	Cohort (Years to Admission)													
Age/Gender at Admission	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Female	0.47	0.48	0.54	0.46	0.47	0.49	0.45	0.48	0.44	0.41	0.37	0.45	0.47	0.39
Age	76.48	76.36	75.68	76.91	74.60	73.64	72.25	72.14	70.61	70.13	67.97	67.94	67.15	66.98
Health in year before Admission														
Number of Hospitalisations	0.42	0.44	0.42	0.51	0.45	0.39	0.33	0.38	0.40	0.35	0.50	0.45	0.34	0.44
Total Length of Stay	1.38	1.64	1.41	1.77	1.40	1.03	1.08	1.14	1.01	1.06	1.15	1.11	0.94	2.12
Medication: Anti-Thrombotic	0.97	0.97	0.97	0.97	0.96	0.95	0.96	0.96	0.96	0.95	0.95	0.95	0.95	0.96
Medication: Anti-Hypertensive	0.65	0.68	0.64	0.63	0.68	0.64	0.64	0.64	0.59	0.62	0.71	0.61	0.60	0.55

Medication: Statins	0.89	0.87	0.88	0.89	0.87	0.88	0.89	0.90	0.89	0.87	0.92	0.91	0.88	0.89
Medication: Depression/Anxiety	0.17	0.23	0.25	0.14	0.22	0.20	0.17	0.21	0.18	0.22	0.20	0.21	0.16	0.23
Admission Related Information														
Inpatient Days	4.77	5.16	5.16	5.40	4.75	4.77	4.73	5.02	5.06	5.15	5.27	4.63	5.26	6.10
Observations	669	624	537	515	1269	1162	865	832	743	604	235	288	294	219

Note: Shaded cells indicate that the standardized difference between the cohort group and the reference group (observed three years after the heart attack or stroke) exceeds the threshold value of 0.25 recommended by Stuart et al. (2013)

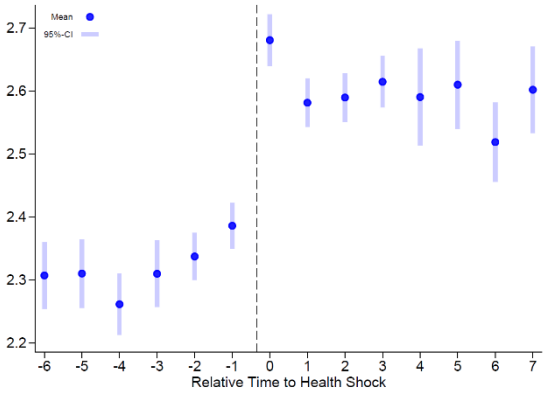
As can be seen there is a high level of balance with respect to the health status directly before an admission occurs as well as the severity of the health shock itself which we proxy using the number of inpatient days associated with the heart attack or stroke admission. The only variable in which we observe considerable covariate imbalance is with respect to the age-at-admission. We control for this remaining imbalance as age-at-admission is included in the event study-regression. When comparing this Table with the unweighted Table in Appendix A2.1 it becomes clear that already before the weighting we observed a similar level of balance. The weighting does however lead to individuals that have a high probability to suffer from a heart attack or stroke due to their poor underlying health are given a higher weight. This can be observed in the overall increased means for medication use in the weighted sample.

In a next step we explore the differences across event time in outcomes as well as the covariate balance after the initial step of calculating the inverse probability weights. Figure 2 depicts the weighted mean differences in outcomes (the unweighted equivalent can be found in Appendix Figure A2.1). For self-assessed health we can observe a clear decrease in self-assessed health (measured on a 5-point scale where higher points indicate worse health) related to the onset of a heart attack (panel A1, blue) or stroke (panel B1, red). We also observe self-assessed health to remain largely stable at the worse level also among the cohort of individuals surveyed 7 years after their heart attack. For our mental health outcome on the other hand (panels A2 and B2) we can observe no clear jump related to the heart-attack or stroke admission across the samples that is coinciding with the timing of the health shock. Only for the heart attack sample it seems that mental health outcomes worsen temporarily while among stroke patients the pattern indicates a more persistent transition into worse mental health.

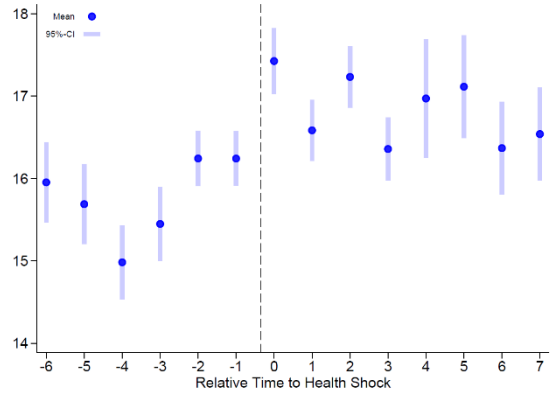
Figure 2: Weighted Mean Differences in Outcomes

A) Heart Attacks

A1) Self-Assessed Health

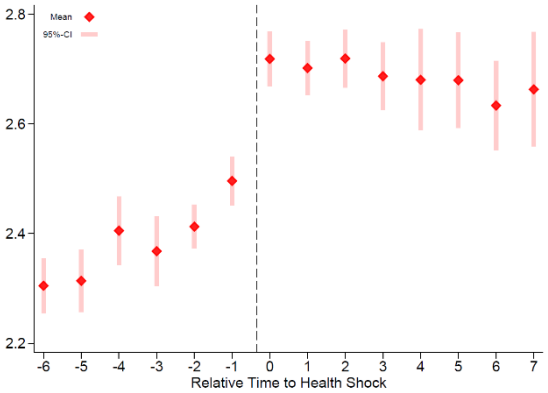


A2) Anxiety/Depression Risk Scores

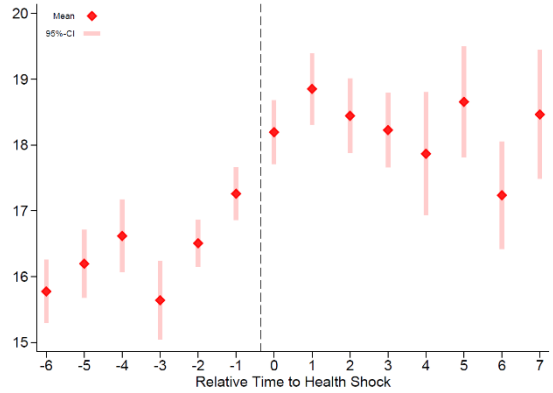


B) Strokes

B1) Self-Assessed Health



B2) Anxiety/Depression Risk Scores



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 95% confidence intervalls.

4.2 Event Study Regressions

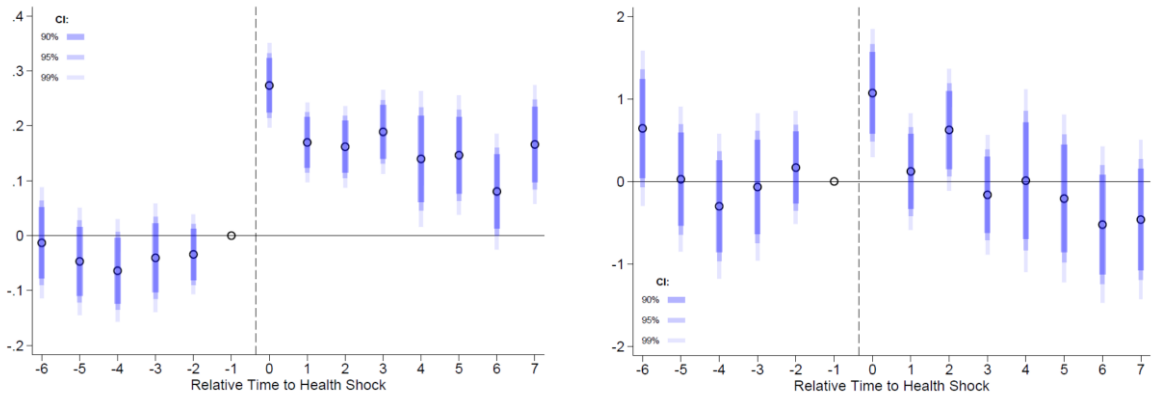
In the second step we estimate the event-study regression outlined in equation (3) to correct for remaining imbalances as well as controlling for health at the time of the survey response. Regression results are only displayed graphically with the full results depicted in Appendix A4. Figure 3 depicts the estimated event-study coefficients $\hat{\delta}_e$ separately for the heart attack (A, blue) and stroke (B, red) samples and using self-assessed health (A1/B1) or the anxiety and depression scores as the outcome measure (A2/B2). The detailed regression results can be found in Table A4.1 in the Appendix.

Figure 3: Event-Study Coefficients

A) Heart Attacks

A1) Self-Assessed Health

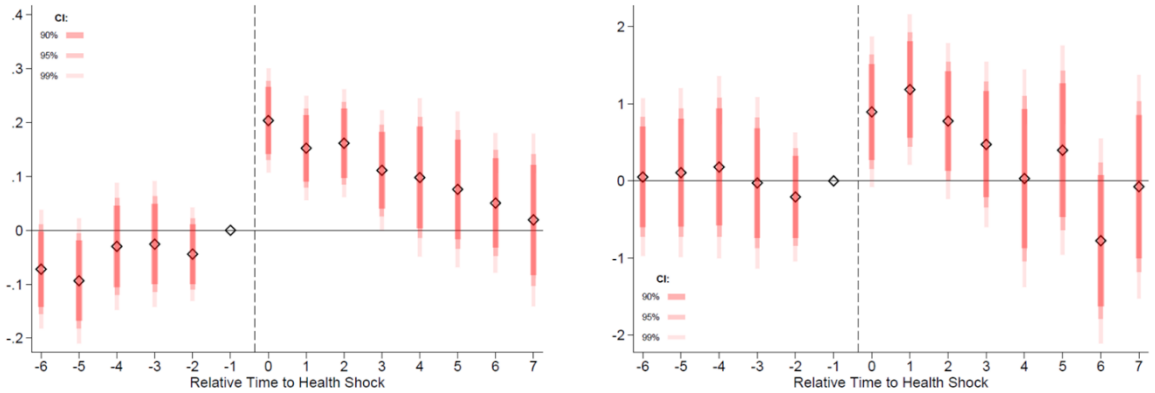
A2) Anxiety/Depression Risk Scores



B) Strokes

B1) Self-Assessed Health

B2) Anxiety/Depression Risk



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 90/95/99% confidence intervalls.

The regression results provide a different picture than the comparison of weighted means by event-time cohort. Given that we include information on individuals' health at the time of the survey response this is somewhat expected as this crucial control is not accounted for when comparing the weighted differences. For heart attacks and strokes we observe a strong initial effect of suffering from a heart attack on the reported self-assessed health. While the initial impact strongly decreases reported self-assessed health that effect is not persistent over time. For heart attacks the effect decreases, although it does not seem to vanish entirely but shrinks to about 50% its initial size. For strokes on the other hand there is a clear downward trend in the estimated event-time coefficients, which become insignificant already for the cohort interviewed four years after their health shock. Given the pre-shock mean of 2.73 and

standard deviation of 0.73 the initial effects are quite strong ranging from 37% (heart attacks) to 28% of a standard deviation.

With respect to our mental health outcome the picture is somewhat different. While for heart attacks we do observe an initial impact implying a one-point increase of the Kessler scores it quickly becomes insignificant. For strokes the picture is similar with an effect implying a one-point increase in the first year that slightly increases further in the second year before then also trending towards zero. As we use the full range of the Kessler score the effect sizes seem to be small given the mean of 16.08 and standard deviation of 6.58. However, when using a binary variable encoding the score to exceed 20, a commonly applied threshold value indicating heightened risk for anxiety or depression, we find that the effects are sufficiently large to significantly increase the likelihood to exceed this threshold (see Figure A3.1).

4.3 Risky Health Behaviors

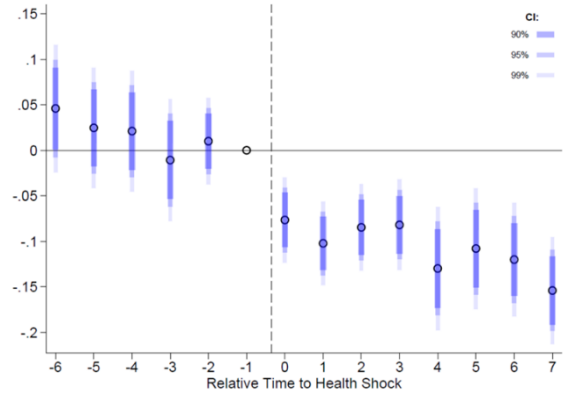
Our results indicate that following a heart attack or stroke self-assessed health and mental health outcomes are negatively impacted but this impact is only temporary. For mental health the negative effect attenuates more quickly than for self-assessed health. This finding is generally supportive of previous results for example by de Hond et al. (2019) finding that adaptation in broader well-being measures such as life satisfaction seems to precede adaptation in domain-specific outcomes such as self-assessed health. Previous studies have also found some evidence for health behaviors to exhibit a similar pattern over time with smoking rates only temporarily decreasing after a stroke, in line with observed subjective health assessments (Baji & Biro, 2018). Such a pattern would be in line with the theory that biased perceptions of ones' health can lead to risky health behaviors due to overconfidence (Arni et al., 2021). To explore this, we use self-reported information on four risky health behaviors included in the health monitor surveys: smoking, overweight, excessive alcohol consumption, and (lack of) physical activity.

The resulting coefficient estimates for our heart attack sample and all four outcomes are depicted in Figure 4. Detailed results can be found in Table A4.2 in the Appendix. For all behaviors we use a dummy-variable to ease interpretation of coefficient estimates as implied changes in the probability to engage in a specific activity. Across all four we can observe no pre-shock differences among the cohorts interviewed before their heart attack occurred. The impact of a heart attack on the different behavioral risk factors is heterogenous. For smoking status (Figure 4, panel A) we observe a strong initial effect implying a drop in the smoking rate of 7.65 percentage points, down from a pre-shock mean of 24%. This initial effect increases in

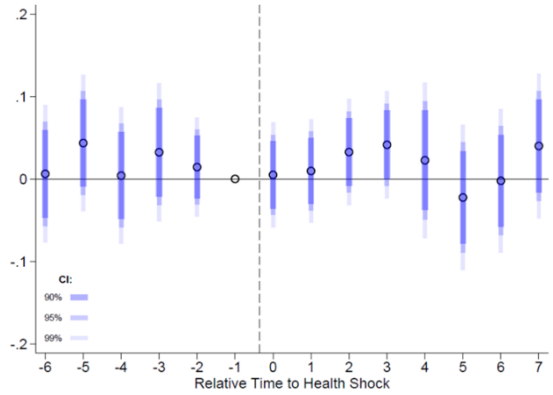
later cohorts to 15.4 percentage points at t_7. Also, for excessive drinking (panel C), defined as more than 14 drinks per week for men and 7 for women, we observe a decrease. In the year of admission, the effect is a drop of 4 percentage points (significant at the 10%-level) and increases gradually to 10.2 percentage points and strongly significant by t_5. For the two cohorts interviewed in subsequent years on the other hand no effect is observed. Likewise, we do not observe any evidence for lower rates of overweight individuals (panel B), a body mass index (BMI) of ≥25 or an increase in physical activity defined as more than three days of moderate activity per week (panel D).

Figure 4: Event-Study Coefficients Health Behaviors – Hearth Attack Sample

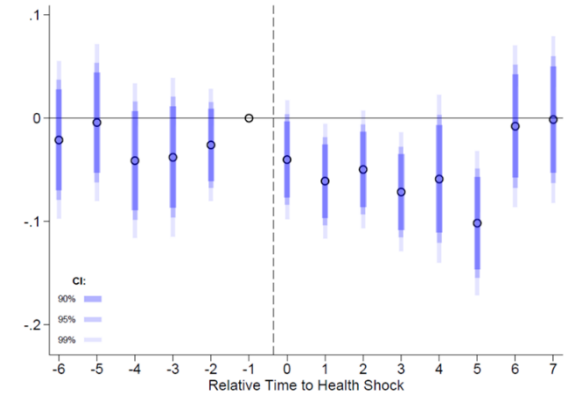
A) Smoking Status



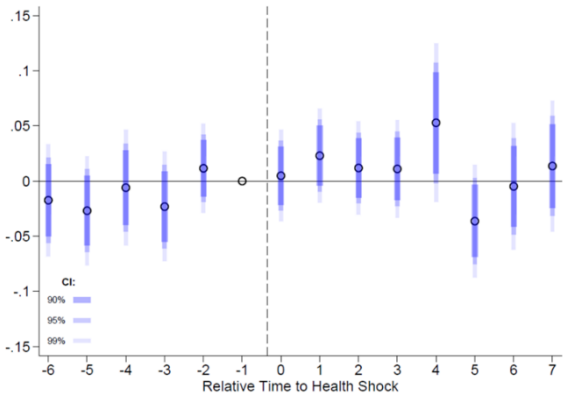
B) Being Overweight (BMI≥25)



C) Drinking more than 14(m)/7(f) units a week



D) ≥3 days Physical Activity per week



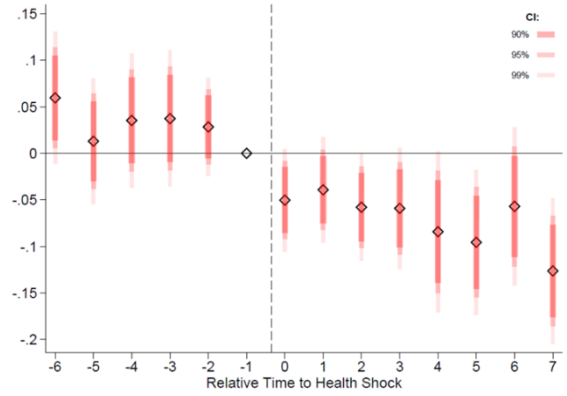
Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 90/95/99% confidence intervalls.

Figure 5 depict the estimated coefficients for all four behaviors using the stroke sample. Overall, the results are highly like those estimated for individuals suffering from a heart attack or stroke but differ in magnitude as already observed for self-assessed health. With respect to the number of people being overweight and those physically active we observe no effects. For smoking status and excessive drinking, the patterns are highly similar. Those

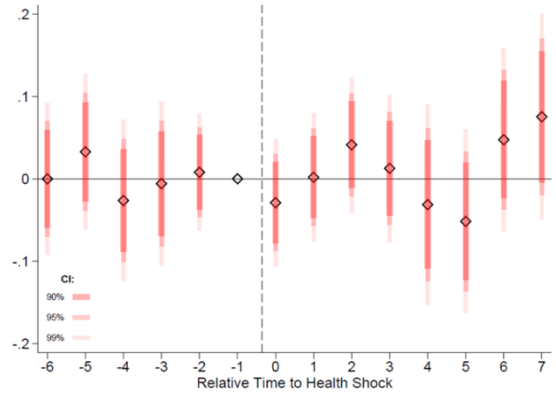
interviewed in the year of their stroke are 5.03 percentage points less likely to report to be a smoker which rises to 12.6 percentage points by t_7. With respect to excessive drinking on the other hand we observe a drop of 5.02 percentage points (significant at the 10% level) that rises to 11.1 percentage points by t_4 but also becomes insignificant as is the case in the heart attack sample. However, unlike our results for heart attacks the point estimates do not approach zero but shrink in size and become insignificant due to a widening of the confidence intervals. The detailed results can be found in Table A4.3 in the Appendix.

Figure 5: Event-Study Coefficients Health Behaviors – Stroke Sample

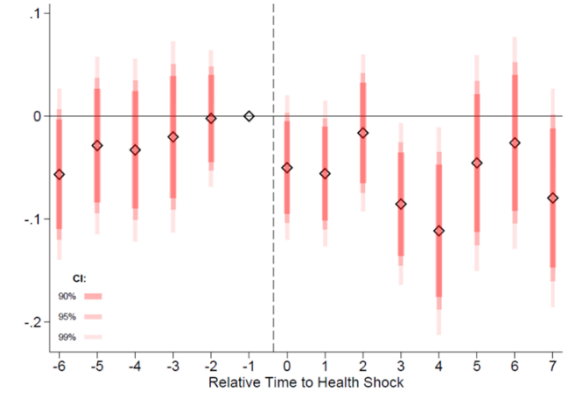
A) Smoking Status



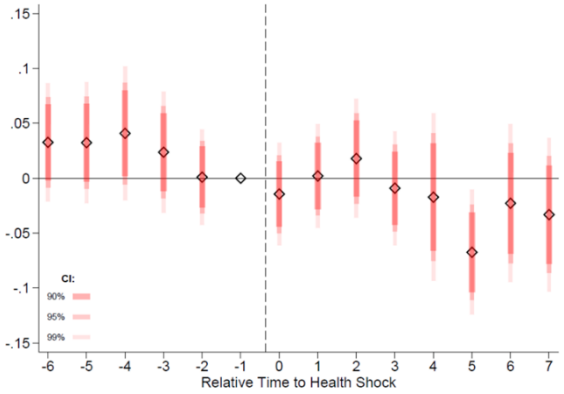
B) Being Overweight (BMI≥25)



C) Drinking more than 14(m)/7(f) units a week



D) ≥3 days Physical Activity per week



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 90/95/99% confidence intervalls.

4.3 Physical Disability across Event-Time Groups

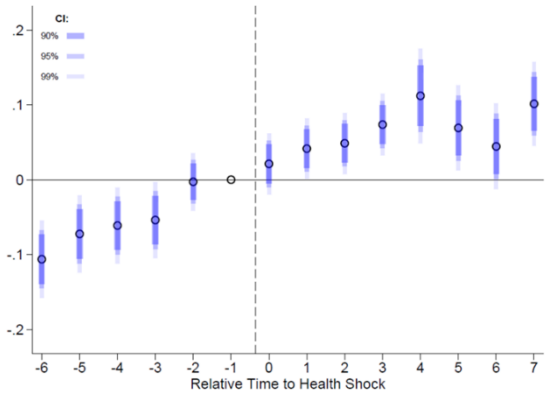
Our results indicate that individual return to pre-shock levels of self-assessed health in a relatively short period of time after suffering from a heart attack or stroke. Can we say this is adaptation? Ex-ante we would predict that a heart attack or stroke leads to long-lasting decreases individuals' objective health. In this case an improvement in individuals' self-

assessed health could be interpreted as adaptation. The combination of our event-study regression results with the weighted trends depicted in Figure 2 also confirm this. We do observe that self-assessed health is significantly worse after the health shock for both heart attacks and strokes. However, after controlling for disability in equation (3) we observe that there is an improvement as the initial effect decreases over time.

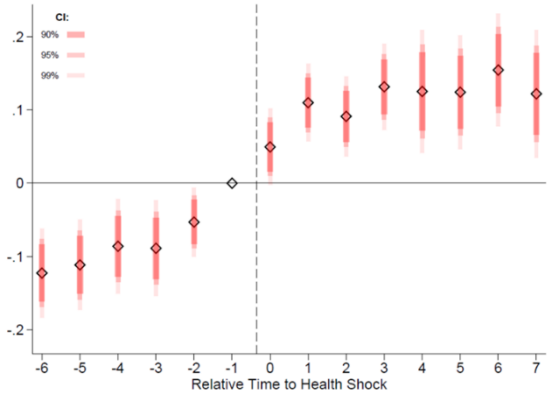
To explore this further we can also look directly at the patterns of reported disability. We do so be estimating equation (3) without including information on reported disability while using disability itself as the outcome of interest. If our doubly-robust approach works as intended we would expect to see a consistent trend of increasing functional limitations across time as this variation would be desired. Finding the opposite would indicate that later cohorts tend to be healthier than earlier cohorts and that the decrease in the estimated event-time coefficients is not attributable to time but to changes in the cohort composition. Figure 6 plots the coefficients from this exercise indicating for both the heart attack and stroke sample and confirms that the underlying physical health follows a downward trend in both cases. However, we do observe that for the latter time periods of $t_{\geq 5}$ this trend seems to be levelling off somewhat. Nonetheless the cohorts interviewed at these time-points still report a higher prevalence of functional limitations that those before the occurrence of the health shock. In the Appendix Figure A3.2 we show that the same pattern holds when considering the intensive margin of disability, the number of functional limitations, providing further support for our interpretation. Detailed results can be found in Table A4.4 in the Appendix.

Figure 6: Functional Limitations by Event Time

A) Heart Attack



B) Stroke



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate the 90/95/99% confidence intervalls.

While this suggests that we observe an increasing burden of disease among those individuals interviewed at increasing distance to their respective health shock we aim to explore this more directly in ongoing work. Functional limitations are an interesting *"objective"* outcome to consider but given health shocks we consider we aim to extend our analyses by considering the re-occurrence of subsequent health shocks or observed survival probabilities to explore post-shock health trajectories across cohorts using the available administrative data.

5 Robustness Checks

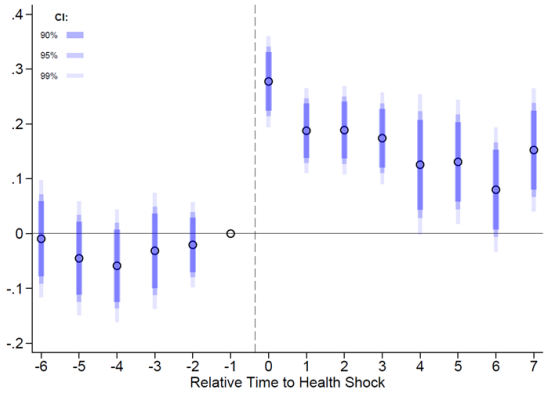
5.1 Mortality Induced Attrition

In the baseline specification we only condition on survival for at least one year. To explore whether our results might be driven by the survival of healthier individuals we condition on survival until March 2021 ($\approx 27\ months$), the latest available mortality data from Statistics Netherlands. This results in us dropping 2055 (15.90%) individuals from the heart attack and 2002 (22.61%) from the stroke samples. Figure 7 replicates the results from the event-study regression excluding deceased individuals. The detailed results are reported in Table A4.5. The results are barely affected by dropping the deceased individuals, providing confidence that the observed pattern of adaptation is not driven by mortality induced attrition alone.

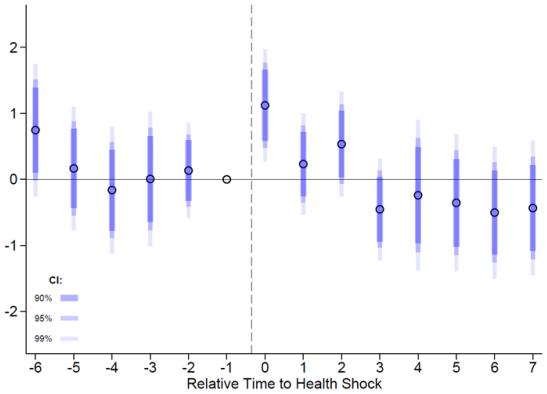
Figure 7: Event-Study Coefficients – Excluding Deceased Survey Respondents

A) Heart Attacks

A1) Self-Assessed Health

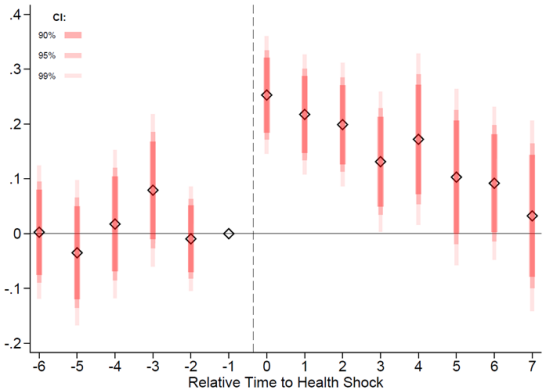


A2) Anxiety/Depression Risk

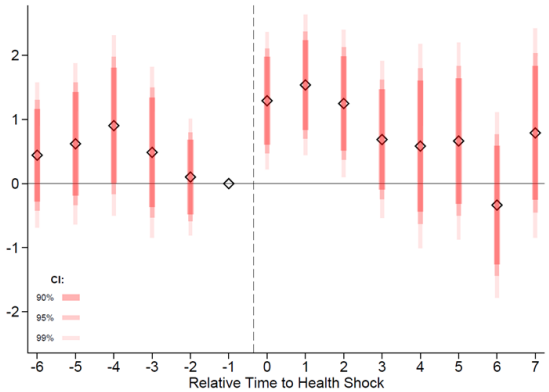


B) Strokes

B1) Self-Assessed Health



B2) Anxiety/Depression Risk



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 90/95/99% confidence intervalls.

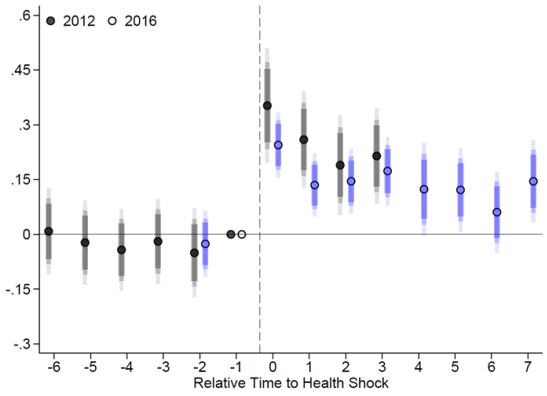
5.2 Treatment Effects by Survey Group

Given that we pool both surveys together some of our findings might be attributable to their joint analysis in a pooled sample. More explicitly, as one of the identifying assumptions of our methodology is the absence of compositional change over time (Callaway & Sant'Anna, 2020) we want to ensure that the observed patterns are not attributable for example to differences in the treatment of heart attacks or strokes in later year. To explore whether our findings also hold when considering both Health Monitor Surveys separately we run the event-regressions separately for each of the surveys. Figure 8 plots the resulting coefficients by Health Monitor survey for both our outcome measures and separately for heart attack and stroke samples. Detailed results can be found in Appendix Table A4.6.

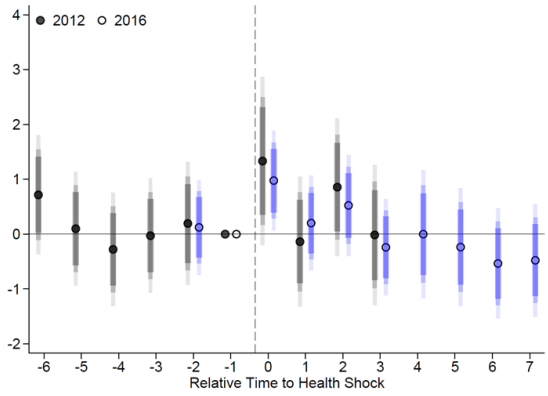
Figure 8: Event-Study Coefficients – Excluding Deceased Survey Respondents

A) Heart Attacks

A1) Self-Assessed Health

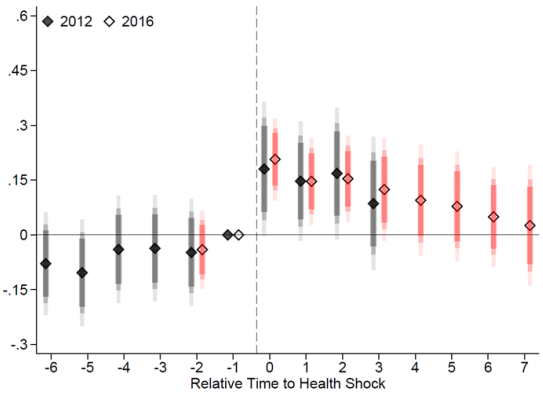


A2) Anxiety/Depression Risk

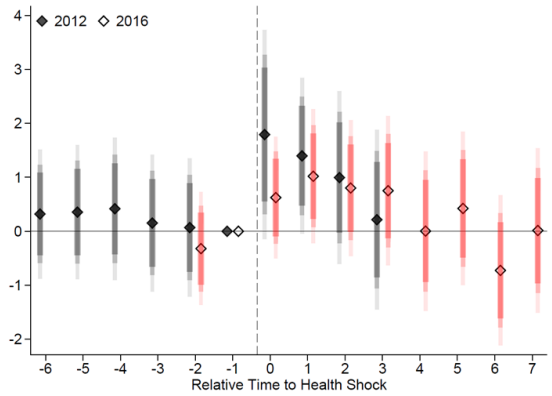


B) Strokes

B1) Self-Assessed Health



B2) Anxiety/Depression Risk



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 90/95/99% confidence intervalls.

6 Discussion & Conclusion

Suffering from a heart attack or stroke is a severe health shock. As such it provides information on individuals objective health status informing their subjective expectations. Subjective assessment of one's health status play a crucial role in individual-level decision making. If individuals adapt after a severe health shock by returning to pre-shock levels of perceived health despite continued ill health or even further deterioration this can have important consequences as at present a form of health perception bias. However, evidence on the causal impact of severe health shocks and the evolution of health perceptions and risky health behaviors over time remain scarce but provide important insights for the design of effective public health interventions.

In this paper we compare the subjective health perceptions, health behaviors and well-being outcomes of individuals directly before the onset of a heart attack or stroke to those surveyed up to 7 years after their respective health shock. We therefore exploit the exogenous timing of these events to compare outcomes of those who already have suffered from a heart attack or stroke to those that will suffer from either of these health shocks in the future. To do so we combine self-reported surveys from the Dutch Health Monitors of 2012 and 2016 with detailed administrative data on demographic information and healthcare use. Using an event-study approach developed by Callaway and Sant'Anna (2020) we estimate the effect of suffering from a heart attack or stroke on self-reported outcomes and behaviors over time.

We find evidence that individuals suffering from a heart attack or stroke report decreased self-assessed health in the years directly after suffering from either of these health shocks. With respect to broader mental health outcomes, we observe only a very short-term negative effect. However, already within a few years adaptation seems to set in as the negative effects do not persist. We further find evidence that physical health deteriorates over time meaning that the finding of adaptation is not driven by an improvement in objective health. Taken together our results suggest that individual's self-assessed health is only temporarily affected even by severe health shocks such as heart attacks or strokes and a continued deterioration in physical health.

As this can be seen as a form of biased health beliefs, we further explore how risky health behaviors are affected by health shocks. Using data on smoking, overweight, alcohol consumption and physical activity we find evidence that behavioral changes occur but differ considerably across dimensions. In line with previous studies by Darden (2017), Arni et al. (2021) and Nie et al. (2021) we find a strong a persistent decrease in smoking prevalence

following a heart attack or stroke. These effects are considerable, indicating a 10-15 percentage point decrease. This implies a halving of the smoking prevalence with effects increasing over time. However, these persistent changes are not observed in other behavioral dimensions. For alcohol consumption we find smaller effects that are not persistent over time while we observe no changes for overweight or physical activity. These results are in line with previous findings suggesting that biased health beliefs and the resulting overconfidence in one's health increase the likelihood of adverse health habits only for certain risky health behaviors but not for smoking.

In ongoing work, we aim to extend our analyses to consider other economic and health related behaviors for which subjective perceptions of one's health are an important input for individual-level decision making. While smoking cessation is an important behavioral change improving individual-level outcomes following a heart attack or stroke another important behavioral factor is the adherence to medical recommendations. Given recommendations on the sustained use of prescription medicine such as statins or anti-hypertensive/thrombotic medication to prevent future events (Binno, 2016) we aim to explore whether our results on health behaviors also apply to medication adherence. In addition, we will explore whether individuals' copayment choice is also affected as one would expect if biased health belief is acted upon by individuals. Further we aim to explore the extent to which health outcomes in relation to heart attacks or strokes (e.g. subsequent avoidable hospitalizations or overall survival) develop after the initial shock to expand our analysis on the relationship between objective and subjective health indicators over time.

Lastly, we plan to connect our study to the literature on within-family health behavior spillovers and the value of health information. A common finding in the literature on risky and preventive health behaviors is the correlation between these habits within households. A range of studies have documented persistent correlations among spouses and between children and parents (see for example recently Banks et al., 2021 or Bouckaert et al., 2021). Health shocks to family members are therefore highly informative if lifestyle habits are strongly overlapping across individuals implying similar risk profiles for future health shocks. In line with this, recent studies have found strong causal evidence on how family health shocks shape direct family members health behaviors. Fadlon and Nielsen (2019) use Danish administrative records to explore the impact of health shocks on family members' and coworker's preventive health behaviors. Their results suggest a strong impact of health shocks on preventive care use and medication demand and highlights the time after such a shock as a window of opportunity for

public health interventions to spur behavior change. Hodor (2021) confirm these results with US data while Hoagland (2021) provides some cautionary insights by highlighting an increasing use of low-value care, suggesting that family members' health shocks can also be a noisy signal leading to costly over-consumption. While these results are highly consistent it is less clear whether experiencing such a shock also changes the perception of family members about their own health or rather increases the salience of the negative consequences of sustained risky health behavior. Using our unique combination of high-powered survey and administrative data we will extend our analysis to those individuals cohabiting with heart attack and stroke patients and their children to explore the broader impact of family health shocks on health perceptions and behaviors of family members.

In closing we find that even after suffering from a severe health shock individuals tend to only temporarily report significantly lower self-perceived health, a finding supportive of the hypothesis that individuals' perceptions adapt to ill health. Our results for health behaviors suggest that indeed adaptation coincides with only a partial habit change in risky health behaviors underlining the need for public health interventions to inform individuals about the need to make long-term changes to their behavior to improve post-event outcomes.

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Appendix 1: Dataset Details

Table A1.1: Data Sources

Variable	Measure	Time	Statistics Netherlands Dataset
Demographic Information			
Age	Age at onset (continous/5-year groups)	2006-2018	GBAPERSOONTAB (Municipal registry)
Gender	1 = Female	2006-2018	
Mortality	1 = Died by March 2021, date of death	2006-2018	GBAOVERLIJDENTAB (vital records)
Socio-Economic Status			
Household Income	Income quintiles based on entire population.	2006-2018	INHATAB, INTEGRAAL HUISHOUDENS INKOMEN (household level tax declared income)
Labour Market Status	Receives pension, unemployment benefit, incapacity benefit.	2006-2018	INPATAB, INTEGRAAL PERSOONLIJKE INKOMEN (personal level tax declared income and sources)
Healthcare Use			
Hospitalisations	Number of hospitalisations.	1995-2018	LMR/LBZ Basis (hospital episodes statistic)
Hospital Diagnoses	Hospitalisation by ISHMT group.	1995-2018	
Length of Stay	Length of stay by admission.	1995-2018	
Total Length of Stay	Total length of stay.	1995-2018	
Medicines Use	Medicine used by ATC group.	2006-2018	MEDICIJNTAB (reimbursed medications)
Nursing Home use	Time spent in nursing home in days.	2006-2018	ZORGMVTAB, GEBWLZTAB (nursing home admissions)
Self-Reported Outcomes			
Self-Assessed Health	5-point scale.	2012/2016	Health Monitor 2012/2016
Kessler Distress Scale	3-point scale.	2012/2016	
Functional Limitations	Any limitation, limitation by dimension, total number of limitations.	2012/2016	
Health Behavior	Self-reported smoking status, height/weight, alcoholic drinks per week, physical activity	2012/2016	

Table A1.2: Sample Size by Cohort

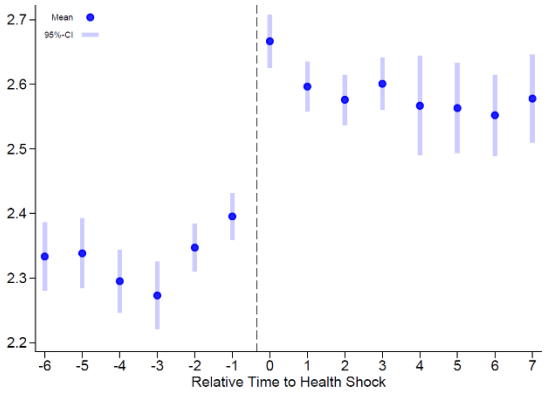
	Cohort (Years to Admission)													
	-6	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Heart Attack														
2012	690	677	715	718	654	642	312	418	430	450				
2016					922	954	930	930	839	800	367	483	480	514
Total	690	677	715	718	1576	1596	1242	1348	1269	1250	367	483	480	514
														12925
Stroke														
2012	669	624	537	515	455	379	225	306	280	257				
2016					814	783	640	526	463	347	235	288	294	219
Total	669	624	537	515	1269	1162	865	832	743	604	235	288	294	219
														8856

Appendix 2: Matching Details

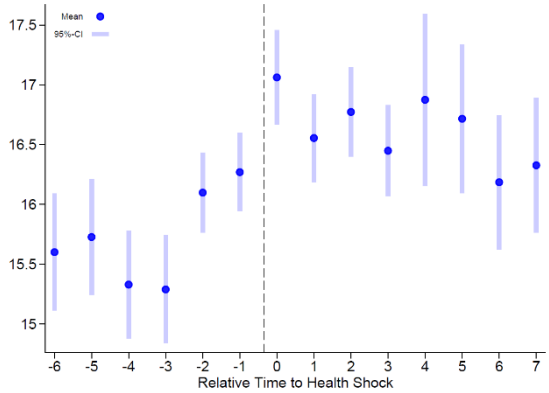
Figure A2.1: Unweighted Mean Differences in Outcomes

A) Heart Attacks

A1) Self-Assessed Health

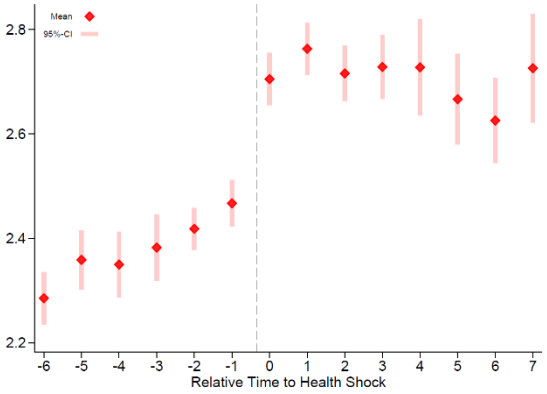


A2) Anxiety/Depression Risk

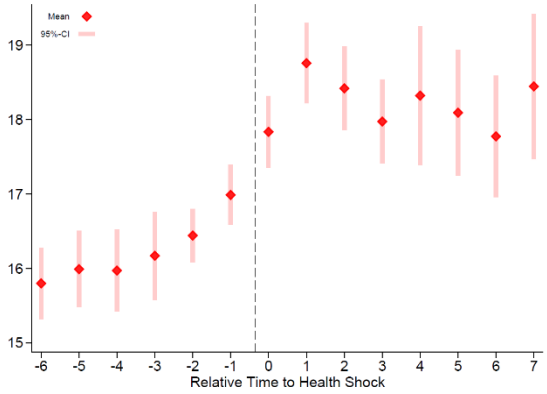


B) Strokes

B1) Self-Assessed Health



B2) Anxiety/Depression Risk



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate 95% confidence intervalls.

Table A2.1: Unweighted Differences in Covariates

Heart Attack Sample

	Cohort (Years to Admission)													
Age/Gender at Admission	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Female	0.35	0.36	0.35	0.38	0.33	0.34	0.33	0.28	0.30	0.28	0.26	0.31	0.27	0.27
Age	73.10	72.21	71.72	71.83	71.41	70.78	69.68	68.88	68.39	68.21	66.26	65.20	65.94	64.27
Health in year before Admission														
Number of Hospitalisations	0.36	0.52	0.41	0.40	0.38	0.42	0.44	0.38	0.42	0.38	0.47	0.37	0.37	0.34
Total Length of Stay	1.03	1.44	1.45	1.35	1.11	1.21	1.21	1.12	1.20	1.04	1.40	0.95	1.06	0.91
Medication: Anti-Thrombotic	0.80	0.81	0.77	0.75	0.76	0.76	0.76	0.73	0.73	0.72	0.73	0.70	0.73	0.68
Medication: Anti-Hypertensive	0.76	0.79	0.73	0.74	0.73	0.74	0.74	0.71	0.71	0.70	0.72	0.68	0.70	0.66
Medication: Statins	0.77	0.79	0.74	0.73	0.72	0.73	0.73	0.71	0.71	0.69	0.73	0.68	0.71	0.66
Medication: Depression/Anxiety	0.13	0.14	0.12	0.12	0.12	0.13	0.11	0.12	0.12	0.12	0.10	0.13	0.11	0.12
Admission Related Information														
Inpatient Days	4.52	4.55	4.43	4.55	4.46	4.21	4.48	4.61	4.76	4.64	3.84	4.19	5.09	4.72
Observations	690	677	715	718	1576	1596	1242	1348	1269	1250	367	483	480	514

Stroke Sample

	Cohort (Years to Admission)													
Age/Gender at Admission	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Female	0.48	0.46	0.50	0.44	0.47	0.46	0.43	0.43	0.42	0.41	0.37	0.41	0.42	0.40
Age	76.30	75.58	74.83	74.97	74.48	73.72	72.04	71.54	70.48	69.30	68.26	67.71	67.81	66.19
Health in year before Admission														
Number of Hospitalisations	0.45	0.46	0.39	0.51	0.50	0.40	0.39	0.41	0.48	0.37	0.49	0.44	0.36	0.40
Total Length of Stay	1.63	1.73	1.34	1.81	1.46	1.13	1.29	1.30	1.20	1.18	1.16	1.08	1.05	1.77
Medication: Anti-Thrombotic	0.77	0.77	0.76	0.79	0.77	0.75	0.77	0.76	0.76	0.73	0.77	0.75	0.75	0.79
Medication: Anti-Hypertensive	0.57	0.61	0.58	0.59	0.61	0.58	0.58	0.56	0.55	0.53	0.64	0.56	0.54	0.53
Medication: Statins	0.67	0.66	0.67	0.70	0.67	0.67	0.68	0.68	0.68	0.65	0.72	0.69	0.67	0.70
Medication: Depression/Anxiety	0.15	0.20	0.18	0.14	0.17	0.15	0.14	0.16	0.15	0.17	0.16	0.16	0.12	0.21
Admission Related Information														
Inpatient Days	5.30	5.39	5.45	5.52	5.23	5.33	4.68	5.24	5.30	5.63	5.46	5.43	5.72	6.43
Observations	669	624	537	515	1269	1162	865	832	743	604	235	288	294	219

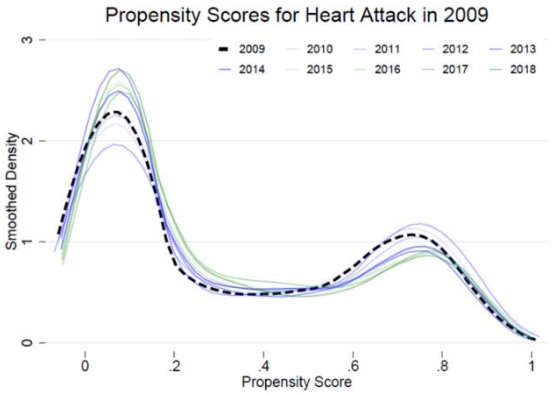
Note: Shaded cells indicate that the standardized difference between the cohort group and the "treated" reference group (observed three years after the heart attack or stroke) exceeds the threshold value of 0.25 recommended by Stuart et al. (2013). The standardized difference is calculated by taking the mean difference between the "untreated" and "treated" group and dividing it by the standard deviation of the latter.

The propensity score distributions by survey sample and event-time group are depicted in Figure A2.2 for heart attacks (A) and strokes (B). In each panel the thick black dashed line indicates distribution for the reference year used in equation (2) when estimating the coefficients for the generalized propensity score model. Depicted are only the merged survey respondents and not the distributions for the entire sample of heart attack or stroke patients.

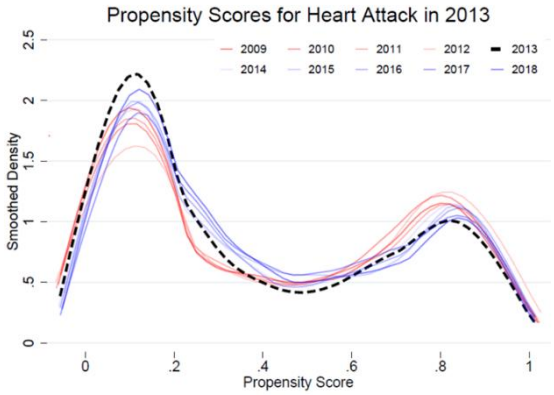
Figure A2.2: Propensity Score Distributions

A) Heart Attacks

A1) 2012 Sample

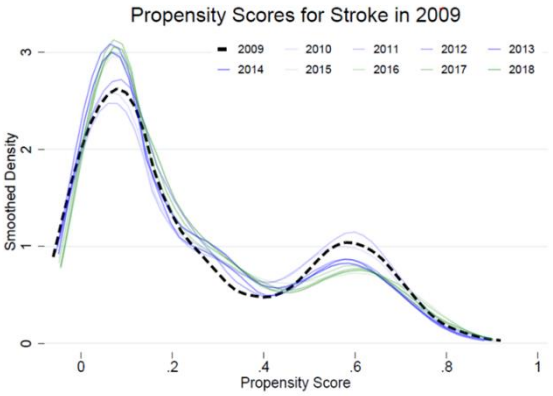


A2) 2016 Sample

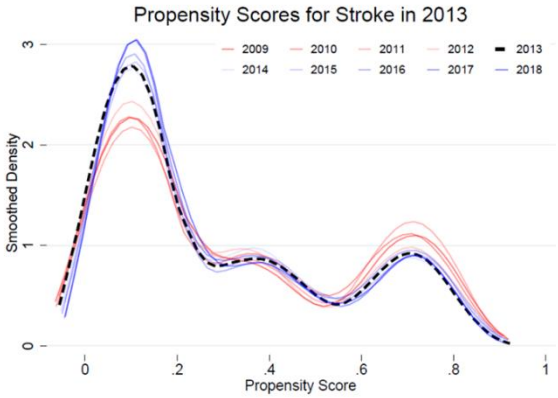


B) Strokes

B1) 2012 Sample



B2) 2016 Sample



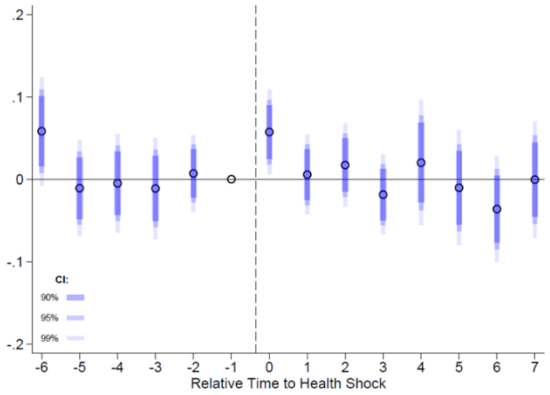
Source: Own calculations based on data from Statistics Netherlands.

Across survey samples we can observe a highly comparable distribution of propensity scores indicating a good overlap or common support (Assumption A4). The number of individuals identified as off support is very low with 23/15 heart attack and 30/22 stroke patients (2012/2016) being dropped as they are out of range. Across samples we observe a bimodal distribution of propensity scores. This is due to a small set of control variables that have a high predictive power, mainly previous admission for a related condition and whether individuals already take medications related to pre-existing conditions, most importantly related to cardio-vascular health.

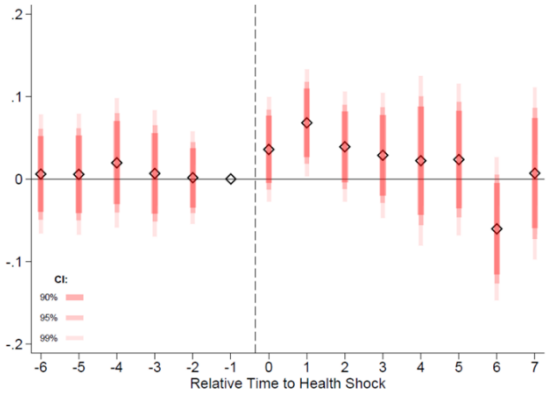
Appendix 3: Additional Results

Figure 3.1: Coefficients for Kessler Scores ≥ 20

A) Heart Attack



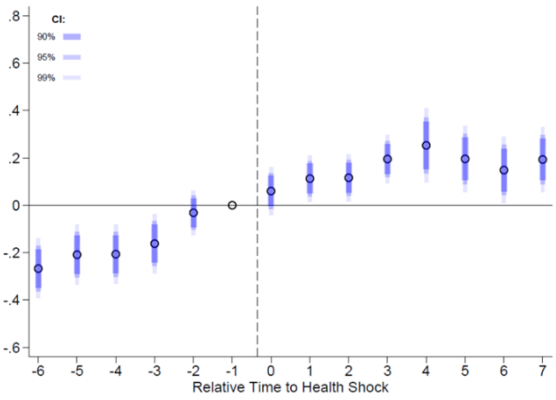
B) Stroke



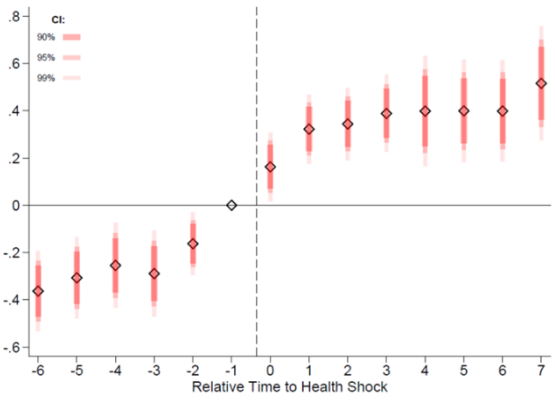
Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate the 90/95/99% confidence intervalls.

Figure 3.2: Coefficients for Number of Functional Limitations by Event Time

A) Heart Attack



B) Stroke



Source: Own calculations based on data from Statistics Netherlands. *Note:* Bars indicate the 90/95/99% confidence intervalls.

Appendix 4: Detailed Regression Results

Table 4.1: Baseline Regression Results

	Self-Assessed Health		Depression Score		Depression Score >20	
Time to Health Shock	**Heart Attack**	**Stroke**	**Heart Attack**	**Stroke**	**Heart Attack**	**Stroke**
6 years before	-0.0132	-0.0721*	0.644*	0.0499	0.0583**	0.00594
	(0.0391)	(0.0425)	(0.364)	(0.395)	(0.0256)	(0.0279)
5 years before	-0.0470	-0.0935**	0.0262	0.107	-0.0109	0.00562
	(0.0378)	(0.0448)	(0.341)	(0.423)	(0.0226)	(0.0283)
4 years before	-0.0641*	-0.0299	-0.301	0.180	-0.00493	0.0196
	(0.0361)	(0.0457)	(0.339)	(0.458)	(0.0231)	(0.0304)
3 years before	-0.0405	-0.0257	-0.0675	-0.0264	-0.0112	0.00670
	(0.0381)	(0.0451)	(0.346)	(0.430)	(0.0238)	(0.0296)
2 years before	-0.0343	-0.0441	0.168	-0.208	0.00705	0.00157
	(0.0281)	(0.0334)	(0.265)	(0.322)	(0.0178)	(0.0217)
Year of admission	0.274***	0.204***	1.073***	0.895**	0.0573***	0.0358
	(0.0298)	(0.0373)	(0.300)	(0.377)	(0.0199)	(0.0246)
1 year after	0.170***	0.152***	0.122	1.185***	0.00564	0.0681***
	(0.0279)	(0.0373)	(0.274)	(0.378)	(0.0188)	(0.0252)
2 years after	0.162***	0.161***	0.625**	0.776**	0.0173	0.0390
	(0.0288)	(0.0386)	(0.287)	(0.391)	(0.0196)	(0.0258)
3 years after	0.189***	0.111***	-0.163	0.473	-0.0187	0.0288
	(0.0295)	(0.0431)	(0.280)	(0.416)	(0.0187)	(0.0294)
4 years after	0.140***	0.0979*	0.00940	0.0312	0.0201	0.0221
	(0.0477)	(0.0569)	(0.431)	(0.546)	(0.0293)	(0.0397)
5 years after	0.147***	0.0760	-0.208	0.398	-0.0103	0.0236
	(0.0422)	(0.0557)	(0.394)	(0.526)	(0.0270)	(0.0357)
6 years after	0.0804**	0.0505	-0.524	-0.776	-0.0362	-0.0605*
	(0.0409)	(0.0500)	(0.368)	(0.515)	(0.0248)	(0.0336)
7 years after	0.166***	0.0194	-0.463	-0.0749	-0.000514	0.00699
	(0.0417)	(0.0620)	(0.374)	(0.563)	(0.0273)	(0.0404)
Observations	12,925	8.856	12,925	8.856	12,925	8.856

Source: Own calculation based on data from Statistics Netherlands. Note: Including controls for age at admission (5-year groups), gender, hospitalisations and total length of stay in the year before admission, anti-thrombotic, hypertensive, and statin use in the year before admission, inpatient days associated with admission, reported functional limitations at survey. Standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1

Table A4.2: Baseline Regression Results Heart Attack Sample - Health Behaviors

	Heart Attack			
Time to Health Shock	**Smoking**	**Overweight**	**Drinking**	**Phys. Activity**
6 years before	0.0460*	0.00616	-0.0212	-0.0173
	(0.0271)	(0.0323)	(0.0295)	(0.0197)
5 years before	0.0247	0.0435	-0.00426	-0.0269
	(0.0256)	(0.0320)	(0.0293)	(0.0191)
4 years before	0.0211	0.00408	-0.0411	-0.00594
	(0.0257)	(0.0320)	(0.0289)	(0.0204)
3 years before	-0.0107	0.0324	-0.0379	-0.0231
	(0.0259)	(0.0325)	(0.0297)	(0.0193)
2 years before	0.0100	0.0144	-0.0260	0.0116
	(0.0185)	(0.0233)	(0.0210)	(0.0156)
Year of admission	-0.0765***	0.00500	-0.0401*	0.00487
	(0.0181)	(0.0247)	(0.0222)	(0.0161)
1 year after	-0.102***	0.00965	-0.0609***	0.0231
	(0.0177)	(0.0244)	(0.0215)	(0.0165)
2 years after	-0.0846***	0.0327	-0.0496**	0.0119
	(0.0184)	(0.0249)	(0.0220)	(0.0163)
3 years after	-0.0819***	0.0415*	-0.0714***	0.0111
	(0.0192)	(0.0252)	(0.0222)	(0.0172)
4 years after	-0.130***	0.0227	-0.0589*	0.0529*
	(0.0262)	(0.0366)	(0.0314)	(0.0278)
5 years after	-0.108***	-0.0224	-0.102***	-0.0363*
	(0.0257)	(0.0341)	(0.0269)	(0.0198)
6 years after	-0.120***	-0.00225	-0.00780	-0.00471
	(0.0242)	(0.0338)	(0.0302)	(0.0222)
7 years after	-0.154***	0.0400	-0.00135	0.0137
	(0.0227)	(0.0340)	(0.0311)	(0.0230)
Observations	12,764	12,457	11,955	12,256

Source: Own calculation based on data from Statistics Netherlands. Note: Including controls for age at admission (5-year groups), gender, hospitalisations and total length of stay in the year before admission, anti-thrombotic, hypertensive, and statin use in the year before admission, inpatient days associated with admission, reported functional limitations at survey. Standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1

Table A4.3: Baseline Regression Results Stroke Sample - Health Behaviors

	Stroke			
Time to Health Shock	**Smoking**	**Overweight**	**Drinking**	**Phys. Activity**
6 years before	0.0596**	-0.000142	-0.0566*	0.0327
	(0.0275)	(0.0358)	(0.0321)	(0.0209)
5 years before	0.0130	0.0327	-0.0285	0.0324
	(0.0260)	(0.0366)	(0.0334)	(0.0214)
4 years before	0.0353	-0.0264	-0.0328	0.0409*
	(0.0279)	(0.0379)	(0.0344)	(0.0236)
3 years before	0.0373	-0.00591	-0.0201	0.0237
	(0.0284)	(0.0387)	(0.0359)	(0.0214)
2 years before	0.0283	0.00791	-0.00220	0.00101
	(0.0204)	(0.0276)	(0.0256)	(0.0168)
Year of admission	-0.0503**	-0.0292	-0.0501*	-0.0144
	(0.0213)	(0.0301)	(0.0271)	(0.0180)
1 year after	-0.0392*	0.00180	-0.0558**	0.00207
	(0.0218)	(0.0302)	(0.0274)	(0.0183)
2 years after	-0.0579***	0.0413	-0.0163	0.0180
	(0.0222)	(0.0319)	(0.0296)	(0.0210)
3 years after	-0.0591**	0.0126	-0.0853***	-0.00902
	(0.0253)	(0.0349)	(0.0304)	(0.0201)
4 years after	-0.0842**	-0.0314	-0.111***	-0.0173
	(0.0335)	(0.0473)	(0.0390)	(0.0296)
5 years after	-0.0957***	-0.0518	-0.0454	-0.0675***
	(0.0302)	(0.0432)	(0.0406)	(0.0220)
6 years after	-0.0570*	0.0474	-0.0259	-0.0228
	(0.0328)	(0.0433)	(0.0398)	(0.0279)
7 years after	-0.126***	0.0753	-0.0794*	-0.0331
	(0.0302)	(0.0484)	(0.0410)	(0.0271)
Observations	8.726	8,434	8,054	8.387

Source: Own calculation based on data from Statistics Netherlands. Note: Including controls for age at admission (5-year groups), gender, hospitalisations and total length of stay in the year before admission, anti-thrombotic, hypertensive, and statin use in the year before admission, inpatient days associated with admission, reported functional limitations at survey. Standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1

Table 4.4: Regression Results for Functional Limitations

	Any Limitation		Number of Limitations	
Time to Health Shock	**Heart Attack**	**Stroke**	**Heart Attack**	**Stroke**
6 years before	-0.106***	-0.123***	-0.267***	-0.363***
	(0.0199)	(0.0235)	(0.0487)	(0.0653)
5 years before	-0.0724***	-0.111***	-0.209***	-0.307***
	(0.0200)	(0.0239)	(0.0490)	(0.0666)
4 years before	-0.0612***	-0.0860***	-0.207***	-0.255***
	(0.0196)	(0.0250)	(0.0481)	(0.0695)
3 years before	-0.0538***	-0.0887***	-0.162***	-0.289***
	(0.0196)	(0.0253)	(0.0480)	(0.0704)
2 years before	-0.00275	-0.0530***	-0.0317	-0.163***
	(0.0148)	(0.0182)	(0.0362)	(0.0507)
Year of admission	0.0213	0.0495**	0.0599	0.163***
	(0.0158)	(0.0202)	(0.0388)	(0.0562)
1 year after	0.0416***	0.110***	0.113***	0.322***
	(0.0155)	(0.0204)	(0.0379)	(0.0568)
2 years after	0.0487***	0.0912***	0.116***	0.344***
	(0.0157)	(0.0211)	(0.0385)	(0.0588)
3 years after	0.0737***	0.132***	0.195***	0.388***
	(0.0158)	(0.0226)	(0.0388)	(0.0630)
4 years after	0.112***	0.125***	0.253***	0.398***
	(0.0245)	(0.0325)	(0.0601)	(0.0905)
5 years after	0.0692***	0.124***	0.196***	0.400***
	(0.0221)	(0.0300)	(0.0542)	(0.0835)
6 years after	0.0445**	0.154***	0.149***	0.399***
	(0.0222)	(0.0298)	(0.0543)	(0.0829)
7 years after	0.101***	0.122***	0.193***	0.516***
	(0.0217)	(0.0336)	(0.0531)	(0.0935)
Observations	12,925	8.856	12,925	8.856

Source: Own calculation based on data from Statistics Netherlands. Note: Including controls for age at admission (5-year groups), gender, hospitalisations and total length of stay in the year before admission, anti-thrombotic, hypertensive, and statin use in the year before admission, inpatient days associated with admission. Standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1

Table 4.5: Baseline Regression Results excluding Deceased

	Self-Assessed Health		Depression Score		Depression Score >20	
Time to Health Shock	**Heart Attack**	**Stroke**	**Heart Attack**	**Stroke**	**Heart Attack**	**Stroke**
6 years before	-0.00938	0.00267	0.746*	0.443	0.0656**	0.0377
	(0.0414)	(0.0470)	(0.389)	(0.439)	(0.0270)	(0.0312)
5 years before	-0.0450	-0.0350	0.166	0.622	-0.00319	0.0323
	(0.0403)	(0.0513)	(0.363)	(0.488)	(0.0240)	(0.0329)
4 years before	-0.0586	0.0175	-0.162	0.905*	0.000213	0.0632*
	(0.0397)	(0.0524)	(0.370)	(0.546)	(0.0247)	(0.0359)
3 years before	-0.0313	0.0793	0.00672	0.487	0.00903	0.0440
	(0.0410)	(0.0539)	(0.394)	(0.517)	(0.0273)	(0.0357)
2 years before	-0.0204	-0.00942	0.134	0.103	0.00459	0.0208
	(0.0300)	(0.0369)	(0.277)	(0.353)	(0.0189)	(0.0239)
Year of admission	0.277***	0.253***	1.121***	1.293***	0.0601***	0.0563**
	(0.0322)	(0.0415)	(0.327)	(0.416)	(0.0214)	(0.0282)
1 year after	0.188***	0.217***	0.233	1.540***	0.00867	0.0937***
	(0.0300)	(0.0424)	(0.296)	(0.425)	(0.0202)	(0.0284)
2 years after	0.189***	0.199***	0.534*	1.250***	0.0132	0.0660**
	(0.0312)	(0.0438)	(0.306)	(0.446)	(0.0208)	(0.0295)
3 years after	0.174***	0.131***	-0.453	0.688	-0.0315	0.0359
	(0.0322)	(0.0495)	(0.297)	(0.475)	(0.0203)	(0.0342)
4 years after	0.126**	0.172***	-0.240	0.585	0.0113	0.0575
	(0.0496)	(0.0605)	(0.441)	(0.619)	(0.0311)	(0.0457)
5 years after	0.131***	0.103*	-0.354	0.665	-0.00928	0.0434
	(0.0439)	(0.0624)	(0.403)	(0.595)	(0.0288)	(0.0406)
6 years after	0.0801*	0.0919*	-0.502	-0.336	-0.0376	-0.0328
	(0.0439)	(0.0541)	(0.386)	(0.561)	(0.0264)	(0.0374)
7 years after	0.152***	0.0324	-0.434	0.791	-0.00406	0.0402
	(0.0435)	(0.0673)	(0.394)	(0.633)	(0.0287)	(0.0457)
Observations	10,870	6.854	10,870	6.854	10,870	6,854

Source: Own calculation based on data from Statistics Netherlands. Note: Including controls for age at admission (5-year groups), gender, hospitalisations and total length of stay in the year before admission, anti-thrombotic, hypertensive, and statin use in the year before admission, inpatient days associated with admission, reported functional limitations at survey. Standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1

Table 4.6: Baseline Regression Results by Survey Sample

	Self Assessed Health				Depression Score			
	Heart Attack		Stroke		Heart Attack		Stroke	
Time to Health Shock	2012	2016	2012	2016	2012	2016	2012	2016
6 years before	0.00835	-	-0.0786	-	0.716*	-	0.320	-
	(0.0459)		(0.0547)		(0.420)		(0.464)	
5 years before	-0.0225	-	-0.103*	-	0.0996	-	0.356	-
	(0.0447)		(0.0564)		(0.402)		(0.483)	
4 years before	-0.0424	-	-0.0397	-	-0.278	-	0.418	-
	(0.0432)		(0.0569)		(0.400)		(0.511)	
3 years before	-0.0194	-	-0.0369	-	-0.0279	-	0.153	-
	(0.0447)		(0.0563)		(0.404)		(0.491)	
2 years before	-0.0506	-0.00570	-0.0481	-0.0403	0.195	0.123	0.0693	-0.321
	(0.0471)	(0.0332)	(0.0567)	(0.0410)	(0.435)	(0.334)	(0.497)	(0.406)
Year of admission	0.352***	0.228***	0.180**	0.207***	1.332**	0.977***	1.792**	0.624
	(0.0607)	(0.0325)	(0.0712)	(0.0435)	(0.595)	(0.351)	(0.751)	(0.436)
1 year after	0.259***	0.121***	0.147**	0.147***	-0.137	0.201	1.397**	1.020**
	(0.0508)	(0.0314)	(0.0633)	(0.0459)	(0.460)	(0.334)	(0.559)	(0.481)
2 years after	0.190***	0.134***	0.168**	0.154***	0.857*	0.523	0.996	0.802
	(0.0527)	(0.0330)	(0.0698)	(0.0459)	(0.486)	(0.356)	(0.619)	(0.489)
3 years after	0.215***	0.142***	0.0858	0.124**	-0.0144	-0.240	0.215	0.752
	(0.0505)	(0.0335)	(0.0708)	(0.0546)	(0.495)	(0.341)	(0.646)	(0.535)
4 years after	-	0.107**	-	0.0948	-	-8.61e-05	-	0.00394
		(0.0456)		(0.0590)		(0.452)		(0.572)
5 years after	-	0.104**	-	0.0782	-	-0.236	-	0.423
		(0.0413)		(0.0580)		(0.416)		(0.551)
6 years after	-	0.0420	-	0.0495	-	-0.534	-	-0.726
		(0.0398)		(0.0527)		(0.389)		(0.540)
7 years after	-	0.121***	-	0.0258	-	-0.477	-	0.0143
		(0.0411)		(0.0640)		(0.397)		(0.591)
Observations	5,706	7,703	4,247	4,609	5,706	7,219	4,247	4,609

Source: Own calculation based on data from Statistics Netherlands. Note: Including controls for age at admission (5-year groups), gender, hospitalisations and total length of stay in the year before admission, anti-thrombotic, hypertensive, and statin use in the year before admission, inpatient days associated with admission, reported functional limitations at survey. Standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1