Staying Sick but Feeling Better? – The Impact of Health Shocks on Health Perceptions and Behaviours

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Abstract

Objective: Severe health shocks may affect individuals' objective health and the perception thereof, but potentially in different ways. Specifically, individuals might either under- or overestimate the effect of a shock on their health and might be unresponsive to less salient gradual effects of the initial shock over time. Potentially biased responses in individuals' perceived health to a shock are important because people make decisions based on these. 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 combine three large Dutch health surveys from 2012, 2016 and 2020 with administrative data on hospital admissions, healthcare demand and death records from 1995 to 2020. We identify a sample of 7,900 heart attack and 5,600 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 8 years prior and 10 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 an immediate negative effect on self-assessed health decreases substantially, which is larger than the decrease in objective health (as measures by physical limitations). While individuals experience a gradually increasing objective burden of disease over time, reflected in an increasing prevalence of long-term physical disability, their self-assessed health does not adapt further after the response to the initial shock. The effects of the health shocks on smoking, alcohol use and heart-related medication use are in line with the pattern observed for subjective health.

Discussion: Our findings suggest that after a severe health shock like a heart attack or a stroke, individuals health perceptions respond more strongly than what would be expected based on the impact of these shock on physical limitations. After the initial shock, subjective health seems unresponsive to the further gradual decline in physical health. Our results on health behaviors confirm previous studies that find smoking behavior and medication use to be consistently affected by a health shock. Our results suggest that these behavior changes are aligned with the effect on subjective health. 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 individuals' choice of health insurance deductibles.

1 Introduction

The ability to accurately process information about one's health is a prerequisite for optimal choices, e.g. regarding life-cycle planning and investments in health, and a key assumption underlying many health-related policy reforms. Severe shocks such as heart attacks or strokes are salient signals providing information on risk factors with long-tern implications for survival and hence for life-cycle planning and behavior change. Whether such events lead to behavior change rests on whether subjective beliefs are updated accordingly.

This paper studies the role of subjective beliefs in explaining behavior change after a health shock, both in the short and in the long run. Thus, it informs about the ability of people to incorporate new, important information into their beliefs and the role that this ability plays in whether people adjust their behavior. We use linked administrative and survey data on people experiencing a heart attack (7,900 observations) or stroke (5,600 observations) for the first time. This data contains objective and subjective health and behavior choices between 8 years prior and 10 years after the event. We explore the causal effect of health shocks on how objective health and subjective health change and link the difference between these trends to changes in risky health behaviors, medication use and health insurance deductible choice. For this, we use a doubly robust event-study approach that exploits the exogenous timing of the occurrence of these shocks.

We find that objective health and subjective health perceptions are in sync before the health shock, but sharply diverge in the post-shock period. That is, initially the subjective perception declines relatively strongly compared to objective health. In addition, further declines in the objective health in subsequent years are not reflected in the subjective health trajectory. Individuals reduce risky behaviors and increase medication use in an immediate response to the shock, but. do not respond to the subsequent declines in objective health. Taken together, these findings suggest that individuals' perceptions overrespond to large health shocks, at least compared to their immediate effects on their physical health while the subsequent gradual decline after the initial shock is not accompanied by additional changes in health beliefs. This might explain their choices on risky behavior and medication use, which move in similar direction as subjective health. This implies that interventions targeted at changing health behavior may be most effective in the period right after a shock when people might be most susceptible to new information.

Our results are consistent with claims about how health perceptions change following health shocks (Groot 2000; Baji and Biró 2017; de Hond et al. 2019; Cubi-Molla et al. 2017)[1] and about how subjective health perceptions shape behavior (Arni et al. 2021; Biró 2016; Spitzer & Shaikh 2020; Harris 2017) and consumption, savings and labor supply decisions (Schünemann et al. 2017; Gan et al. 2015). Furthermore, there is a large literature on the impact of health shocks on household decision making, e.g. on healthcare use, savings and labor supply decisions (e.g. Garcia-Gomez et al. 2013, Fadlon and Nielsen 2019). However, aside from Arni et al. (2021) and Baji and Biró (2017), none of these has connected all three elements – the objective health shock, subjective perceptions, and health behavior – in one study. Our study further adds to the existing evidence on the long-run effects of heart attacks and strokes on health-related quality of life. These two conditions contribute much to the burden of disease in high-income economies (Pandaya et al., 2013; Roth et al., 2020).

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 Odermatt and Stutzer (2019) 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.

2 Data

2.1 Data Sources

We use the general population samples of the Dutch Health Monitor (*Gezondheidsmonitor*) of 2012, 2016 and 2020. 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% (2016/2020) 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%) followed by 1.39 million individuals yielding 539,000 respondents (ca. 39%) in 2020.

The merged samples from all 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 2020. 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 2020.

2.2 Outcome Measures: Health Beliefs and Behaviors

Our main outcome is an indicator of subjective health beliefs: self-assessed health. Self-assessed health is measured on a five-point likert scale ranging from best health (1: *Very Good*) to worst possible health (5: *Very Poor*).

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. Alcohol consumption is based on the self-reported number of drinks consumed in an average week. Self-reported data on individuals' height and weight is used to compute the body-mass index while physical activity is self-reported as days in a given week in which at least 30-60 minutes of moderate to strenuous physical activity are conducted. All of these behaviors are chosen as they play a key role in decreasing overall risk of cardiovascular disease and in particular to decrease the risk of subsequent heart attacks and strokes. Smoking and excessive alcohol consumption are important individual-level modifiable risk factors improving post-shock outcomes and singled out as key priorities for policy interventions. (Roth et al., 2020).

Smoking cessation, alcohol consumption and overall physical fitness are important behavioral changes individual can enact to improve their health outcomes and decrease cardio-vascular risk. Another important factor is the adherence to prescription medication regiments. Pharmaceutical innovations have been found to be a crucial driver of the increase in life expectancy in the US an in particular with respect to cardio-vascular health (Buxbaum et al., 2020). In Europe clinical guidelines recommend the sustained long-term use of anti-hypertensive/anti-thrombotic medications and statins to prevent subsequent heart attacks and strokes (Binno, 2016) and improve long-term survival. Adherence to long-term therapy is however often only partial with patients discontinuing therapy. This has been a persistent finding in the literature even when consumption is not associated with direct healthcare costs to the individual (Choudry et al, 2011). While adjustments in smoking behavior, alcohol consumption and physical fitness overall might have tangible short-term benefits to the individual adherence to medication therapy might not due to its preventive nature with few directly observable health improvements. As such especially for medication adherence health beliefs might play a crucial role in determining behavior as the consequences of non-adherence are not directly obvious.

2.3 Measure of objective health

As our primary measure of objective health, we use the number of self-reported functional limitations which can be divided into limitations to physical functioning and cognitive or sensory functioning. The five cognitive or sensory functions covered 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. The three domains of physical functioning are; 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. Each of these dimensions is surveyed using a question on the degree to which the activity described can be performed by the individual. The response options are whether an activity can be done without any limitation, with some effort, with high effort, or not at all. Throughout we are applying a simple definition of functional limitation in which an individual has indicated to be able to do an activity only with high effort or not at all. For some auxiliary analyses we are applying a lower reporting threshold of individuals indicating some effort, high effort or inability to conduct a given activity but unless stated otherwise the definition of more severe limitations applies.

2.4 Sample Selection and Time Structure

The analysis sample is restricted to participants in the Health Monitors of 2012/2016/2020 for which we have information our subjective and objective health measures and for whom the described administrative information is available. As we aim to compare the health perceptions and behaviors 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 2020 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]

Our identification strategy relies on the comparison of individuals having a heart attack or stroke in one year to those that will have a similar event in a future year. This requires us to observe individuals that despite their difference in the timing of their respective shock are comparably likely to suffer from their health shock when they do. Phrased differently, we want to avoid comparing for example an individual having a heart attack in 2009 at 45 years of age as an avid marathon runner to an individual having the same event in 2015 at 75 years of age after a history of chronic disease. We do so by exploiting rich administrative data in combination with the exogenous timing of heart attacks and strokes but as a more general step we restrict our sample of heart attack and stroke patients in the administrative data according

[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.

to certain characteristics. We only include individual that have a heart attack between the ages of 60 and 70 and stroke patients aged between 64 and 74. In addition we exclude individuals that have spent any time inside a nursing home before their health shock as for these medication data is incomplete as medications received within nursing homes are not recorded. Lastly, 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.

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 respective first admission for a heart attack or stroke where t is measured in years. We therefore construct three samples of individuals 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.

3 Methods

3.1 The effects of a health shock on objective and self-perceived health

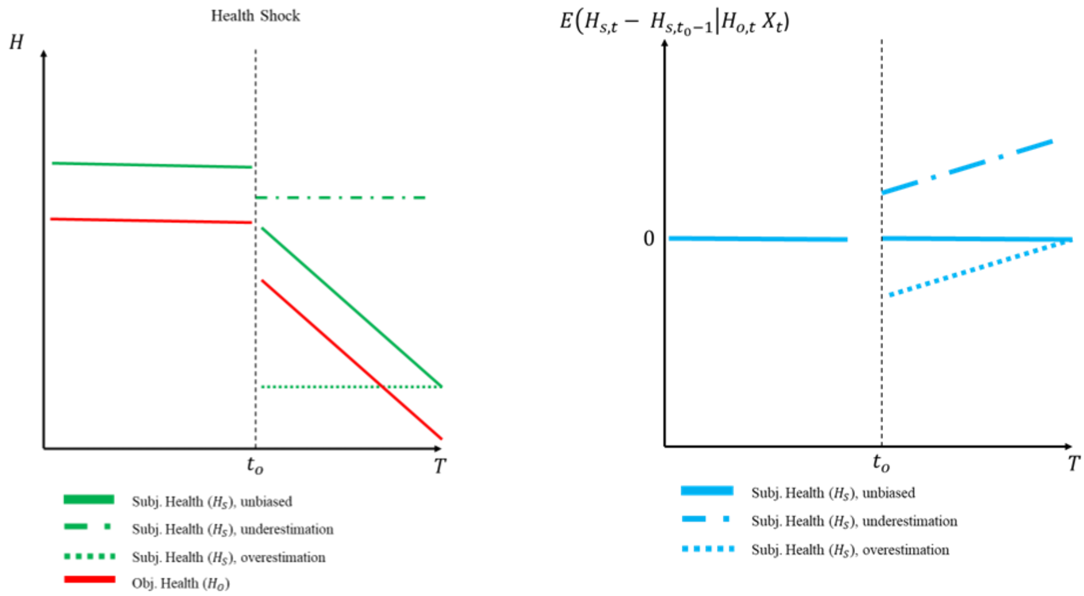
We identify a potential bias in health beliefs by exploiting an exogenous negative shock in objective health. The idea is that if health beliefs are unbiased, both objective and subjective health should decrease after the shock, but the relation (or mapping) between objective and subjective health should stay the same. Let H_o be objective health and $H_s$be subjective, then in case of unbiased health beliefs $E(H_s|H_o)$, the expected values of subjective health conditional on objective health, should be the same before and after the shock.

Figure 1a illustrates three hypothetical scenarios for subjective health. The figure shows a health shock which has a progressively decreasing effect on objective health. In the hypothetical scenarios subjective health either moves proportional to the changes in objective health (unbiased), or individuals only changes their health belief in an immediate response to the shock and then leave their beliefs unaltered. This one-time adaptation in health is either too small (underestimation) or too large in comparison to the initial change in objective health. In case of the initial underestimation of the effect on objective health (and with no further adaptation of subjective health later on), the difference between subjective and objective health increases in the years after the shock. In case of an initial overestimation, the differences between subjective and objective health decreases over time as objective health `catches up' with the initially overstated decrease in subjective health.

The way we measure any discrepancies between subjective and objective health because of the health shock is by plotting $E\left(H_{s,t}\middle|H_{o,t}\right)$ over event-time *t* relative to the shock. We do this by running a linear regression, with $H_{s,t}$ as a function of $H_{o,t}$ and a set of additional controls X. In this regression we use the last year before the shock as the baseline. Figure 1b shows the pattern of the coefficients we would find in each of the three scenarios. If perceived health is unbiased, then we don't see any change in the relation between subjective and objective health compared to the baseline. If the initial adaption in self-deceived is too small, we see an increasing positive effect of subjective health conditional on objective health compared to the baseline. If the initial change in self-perceived is too large, we see a negative effect of the shock on subjective health conditional on objective health, which becomes smaller over time.

Figure 1: Three scenarios for the effect of health shocks on the relation between subjective and objective health

(a) Levels of objective and subjective health (b) Regression coefficients



3.2 Study design

Ideally, we would like to follow measures of objective and subjective health for the same individuals over time, before and after the health shock. Unfortunately, a longitudinal panel survey that is large enough to identify sufficiently many individuals experiencing a heart attack or stroke is not available. Instead, we identify the effect of a heart attack or stroke by comparing the objective and the self-perceived health of individuals in the years right after the health shock to the health of *different* but similar individuals in the years prior to the same shock. The main identifying assumption is that within our study period the timing of the shock is exogenous, so that individuals who have a heart attack or stroke at different times can be compared. This assumption is less stringent than the one needed for a comparison between individuals who receive a shock to individuals that never receive the shock. In the latter case we would have to assume that individuals have no private information about their risk of a heart attack, while in our case people can have this information as long as they do not know *when* they will have a heart attack.

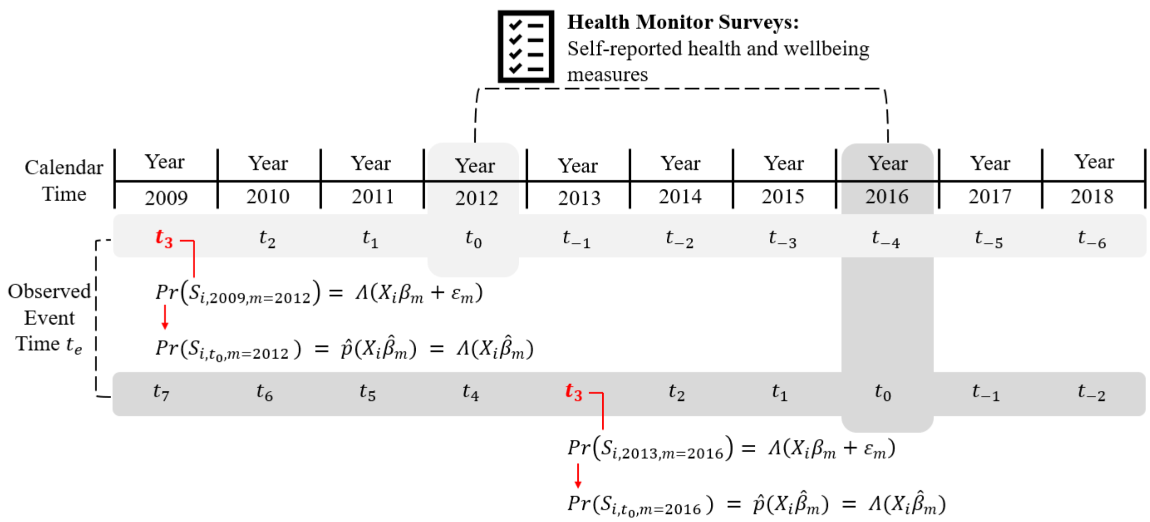
We use two large-scale general population health surveys from 2012, 2016, and 2020 that can be linked to administrative records on hospital admissions and their cause at the individual level for 1995 to 2020. This feature of our data allows us to observe individuals' objective and subjective health at different event-times t relative to their first-time admission for a heart attack or stroke. In our context t ranges from -8 through 3 for the 2012 sample, and -4 to 7 for the 2016 sample and 0 to 10 for the 2020 sample.[3]

The exogeneity of the timing of the shock should in principle ensure the comparability of the different individuals observed at different event-times. Still, to strengthen the credibility of the identification (and to increase power) we want to take any differences in observable characteristics across cohorts with the shocks at different times into account. To do this we ensure that individuals interviewed at different times to event have a comparable probability to suffer from a heart attack or stroke at their respective $t = 0$, the time their actual health shock occurs. We do this using the 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]

3.3 Empirical Application

Figure 2 provides a graphical overview of the data- and the different steps taken which are described in further detail below.

Figure 2: Study Design Overview -



Source: Own illustration. *Note:* Calendar year range is truncated and survey group 2020 is omitted for ease of interpretation.

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[3] The observed event-time is determined by the calendar time of the health shock (2009 to 2020) and the year of survey participation (2012/16/20). Health Monitor participants of 2012 we can for example observe individuals interviewed at event-times t_{-8} (health shock in 2020), up until t_3 (health shock in 2009).

[4] This doubly robust procedure combines propensity score-based methods to deal with covariates in event-study regressions proposed by Abadie (2005) with the outcome regression approach (Heckman et al., 1997). The doubly robust property from the fact that correct inference requires only one of the two specifications, the generalized propensity score estimation or the outcome regression, to be correctly specified (Sant'Anna and Zhao, 2020).

Step 1: estimating propensity scores

The estimation procedure of Callaway and Sant'Anna (2020) consist of two steps. In the first step we derive for each individual the probability of receiving the shock at their actual event-time $t = 0$. For example, suppose we have two individuals both interviewed in 2012. One has a heart attack in 2011, the other one in 2013. Then we observe health for the first person at event-time $t = -1$ and for the other at $t = 1$. To ensure comparability of these two individuals, we want to make sure that the *ex-ante* probability of having a heart attack at the time of the actual shock $t = 0$ is equal. For the first person, event time t=0 correspond to calendar time $y_0 = 2011$ and for the second one to $y_0 = 2013$.

We first need to estimate the probability of a heart attack or stroke occurring in a particular calendar year. For this, we estimate the probability of having a shock in some base year y^*. For this, we use a sample consisting of all individuals in our administrative data sample who had either a heart attack or stroke in y^* or later:

(1) $Pr(y_0 = y^*) = \Lambda(X\beta)$,

where Λ is a logit-function and X_i contains demographic and socio-economic information alongside information on healthcare use in the three years prior to y^*, so in y^*-1, y^*-2, and y^*-3. 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 disability benefits. Further, we include hospital admissions 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[6].

We can then use the estimated coefficients $\hat{\beta}$ from Equation (1) to predict for each individual in our health survey the probability of suffering from a heart attack or stroke in his or her actual event year y_0.We predict individuals' *ex-ante* probability of receiving the health shock 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.

[6] We use medication groups classified by 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).

year they actually receive it by using the same covariates as included in Equation (1) but measured in the three years prior to the year of their actual shock, so $y_0 - 1$, $y_0 - 2$, and $y_0 - 3$. This gives each individual's predicted probability of the shock happening in *calendar* year y_0, which is equal to *event* time t=0:

$$(2)\ \Pr\widehat{\left(S_{\iota,t_0}\right)} = \Lambda\left(X\hat{\beta}_m\right).$$

The estimation of the propensity score model is done separately for heart attacks and strokes. We also estimate the model and predict the propensity scores separately for the patients interviewed in the 2012, 2016, and 2020 health monitor. For the first group we use y^*=2009 as the base year in Equation (1), using a sample of all individuals receiving a heart attack or stroke between 2009 and 2020. For the second group we use y^*=2013, estimated on all individuals receiving a heart attack or stroke between 2013 and 2020, while for the last group we use y^*=2017 with the estimation sample being all patients suffering from either shock for the first time between 2017 and 2020. The focus on only comparing admitted vs not-yet-admitted is done to avoid including post-treatment covariates in the calculation of the generalized propensity score.[7]

Step 2: regression analysis

In the second step we estimate an event-study regression that uses the estimated propensity scores as weights. We also include control variables in these regressions (hence the term `doubly robust') to account for remaining imbalances on key variables. Using this pooled survey data, we regress self-perceived health $H_{s,t}$ on objective health $H_{o,t}$, a set of dummies measuring the time-distance e to the health shock $I(t = e)$ at the time of the survey together with a set of control variables X:

$$(3)\ H_{s,t} = \alpha + \sum_{e=-8,\ e\neq-1}^{10} \delta_e I(t = e) + \gamma H_{o,t} + X\beta + \varepsilon$$

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

[7] 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.

the shock, and survey year fixed-effects. 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. 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 objective health which we measure using self-reported functional limitations. 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.

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 the propensity score matching and the distributions of the calculated propensity scores across the different samples (heart/stroke and health monitors 2012/2016/2020) in Appendix A2 with Figure A2.1 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 which is also reflected in the low number of individuals identified as off-support.

4.1 Event Study Regressions for Health

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.

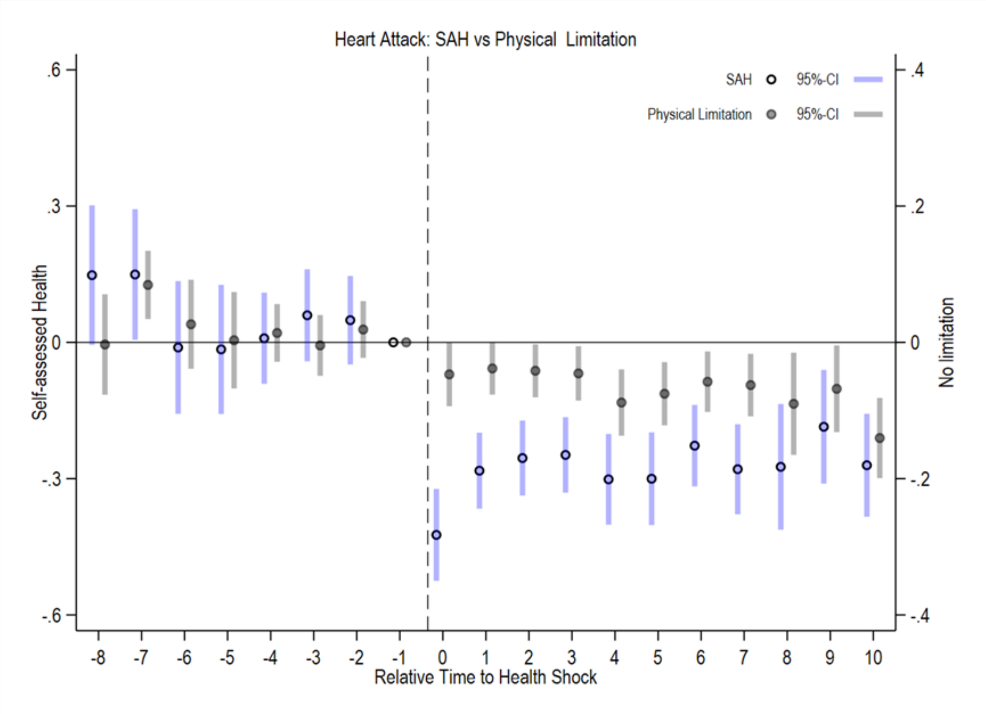
Time trends in subjective and objective health

Before we study the development of subjective health *conditional* on physical limitations, we first show the development of physical limitations themselves and of *unconditional* subjective health, in a similar way as in the example in Figure 1a. Figure 3 shows the development of both health measures before and after the health shock (relative to the last period before the shock) for heart attack (a) and stroke (b) patients in our sample. The estimates are derived using the doubly robust estimation method as in Equation (3), but using both subjective health and limitations as the outcome variable and without including dummies for the seven dimensions of functional limitations as a control variable. The vertical axis on the left-hand side depicts the coefficient size for the regression using self-assessed health as the outcome measure. The right-hand side is the coefficient for not reporting any physical limitation. Appendix A3 contains further results altering the reporting threshold for functional limitations and considering any limitation (A3.1), only physical (A3.2) or only cognitive/sensory (A3.3) limitations.

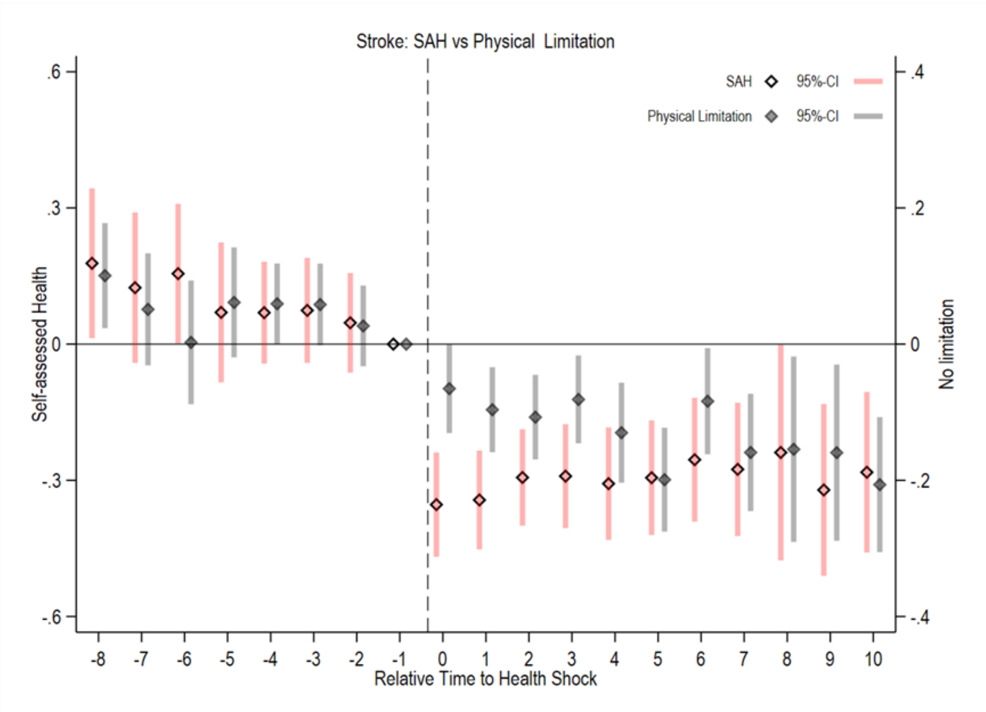
For both heart attacks and strokes, we do not see any significant trends in objective or subjective health prior to the shock. After the health shock, there is an immediate decline in objective health (as measured by physical limitations), in particular following strokes. In the years following the shock objective health declines further while the response in subjective health to the shock does not move in tandem with objective health. The initial decline in subjective health seems much stronger, but in consequent years remains stable or (in the case of heart attack) even seems to decrease.

Figure 3: Even Study Coefficients – Subjective and Objective Health Indicators

(a) Heart Attacks: Self-Assessed Health and Physical Functional Limitations



(b) Strokes: Self-Assessed Health and Physical Functional Limitations



Source: Own illustration.

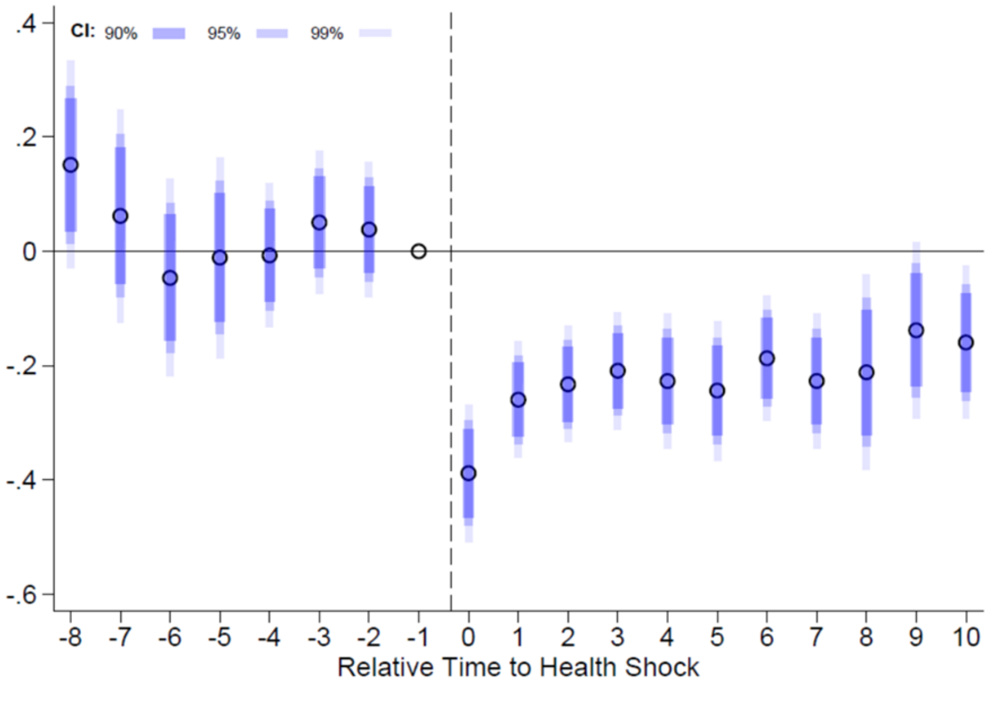
Time trends in subjective health conditional on objective health

To further study the diverging relation between objective and subjective health after the health shock, we now turn to the event-study of subjective health conditional on objective health, as in Equation (3). Figure 4 depicts the estimated event-study coefficients $\hat{\delta}_e$ separately for the heart attack (a) and stroke (b) samples.

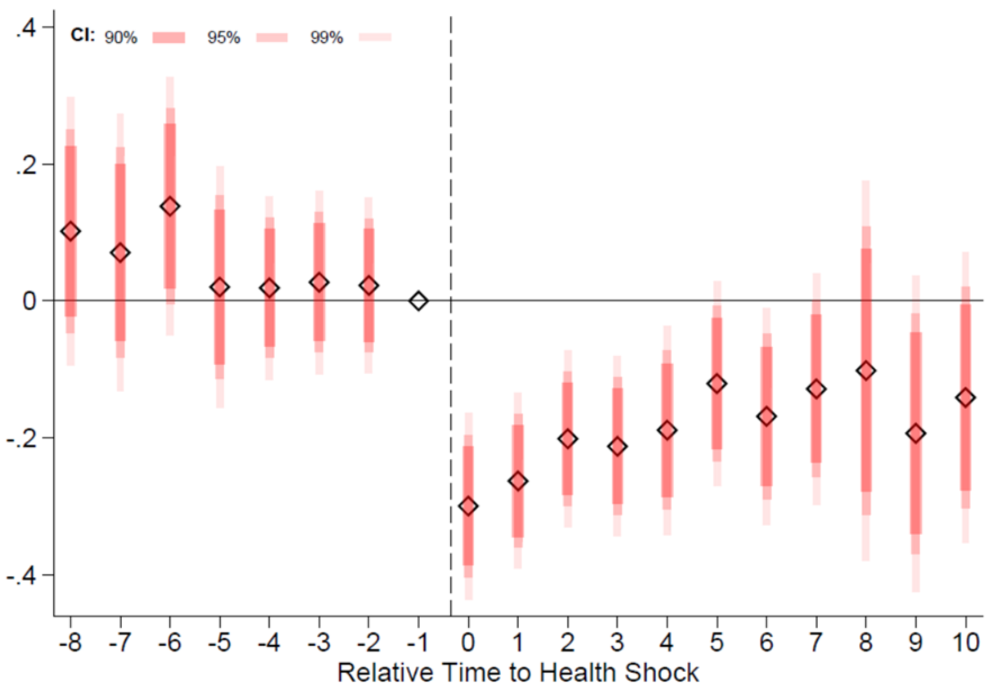
The time patterns in the figure reconfirm what we could already see in Figure 2. Prior to the health shock, the development of subjective health conditional on objective health is stable. After the shock, we see a decline in subjective health that is much larger than can be explained by the increase in physical limitations related to the onset of a heart attack or stroke. In the following years, this discrepancy between objective and subjective health gradually disappears (which is, based on Figure 2, mostly due to a combination of stable subjective health and further decreasing objective health).

Figure 4: Even Study Coefficients – Subjective Health conditional on Objective Health

(a) Heart Attacks: Self-Assessed Health



(b) Strokes: Self-Assessed Health



Source: Own illustration.

4.2 Other outcomes

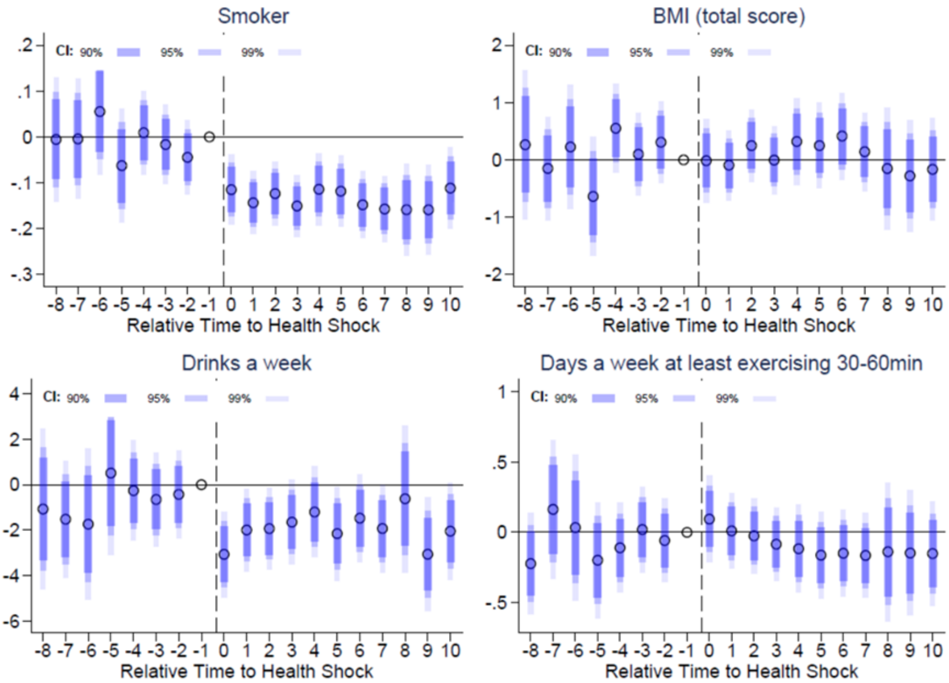
Health behaviors

The results indicate a substantial change in patients health perceptions following a heart attack or stroke that goes well beyond that would be expected given the realized change in physical health. To explore whether such a substantial adjustment in health beliefs is associated with adjustments in self-reported health behaviors we now turn towards these using the same event-study specification that condition on objective health at the time of the survey (equation (3)). Figure 5 depicts the results for all four outcomes related to health behavior (smoking, BMI, alcohol consumption, exercising).

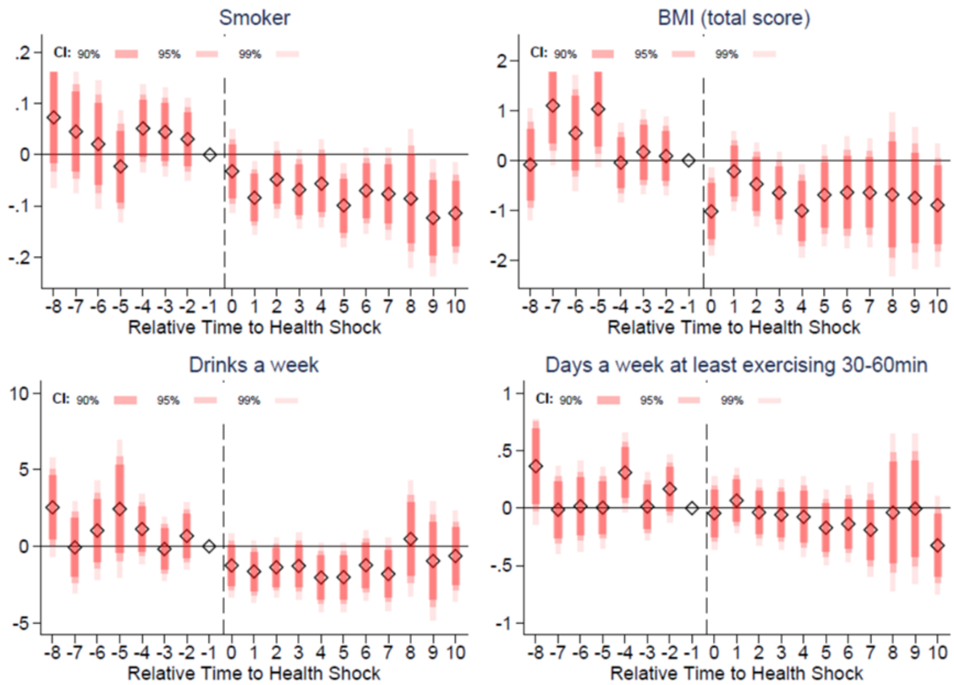
For both heart attacks and strokes, we do not observe any pre-trends. After the shock, we see an immediate decrease in smoking and alcohol consumption and a stably lower level of these behaviors in the consequent years. For heart attack patients the implied change in the smoking rate is substantial. About 37% of individual interviewed before a heart attack self-report do be smokers while the event study coefficient suggests a 11.5 percentage point drop rising to 16 percentage points over time. For strokes we also find some weak evidence for a similar pattern for BMI. No effects are found for exercising. As the plotted coefficients are conditional on physical limitations, the results show that the decrease in smoking and drinking is larger than would be expected based on objective health alone. The patterns for these behaviors condition on objective health is very similar to that for conditional subjective health. This provides suggestive evidence that the changes in behavior are driven by the change in subjective health and the information shock associated with suffering from a heart attack or stroke.

Figure 5: Even Study Coefficients – Health Behaviors conditional on Objective Health

(a) Heart Attacks: Smoking, overweight, alcohol consumption, and physical activity



(b) Strokes: Smoking, overweight, alcohol consumption, and physical activity



Source: Own illustration.

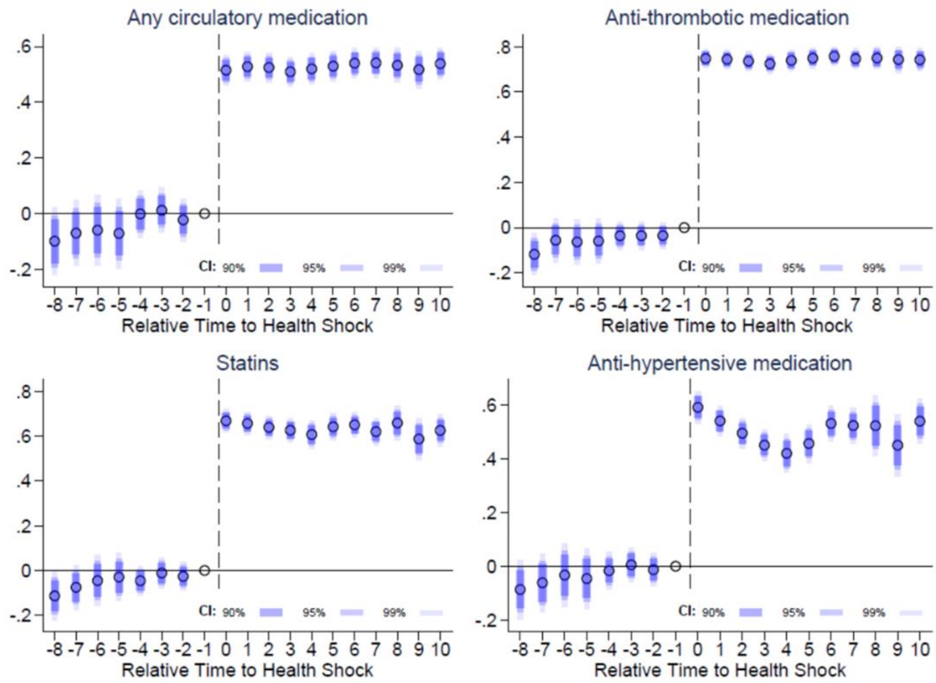
Medication use

Lastly, we turn towards preventive medication use. This data is not self-reported but based on administrative records on the usage of prescription medication in a given year. Based on this we construct a dummy variable indicating whether in a given year an individual has made use of any medication being either anti-thrombotic/anti-hypertensive or a statin, and each of these separately.

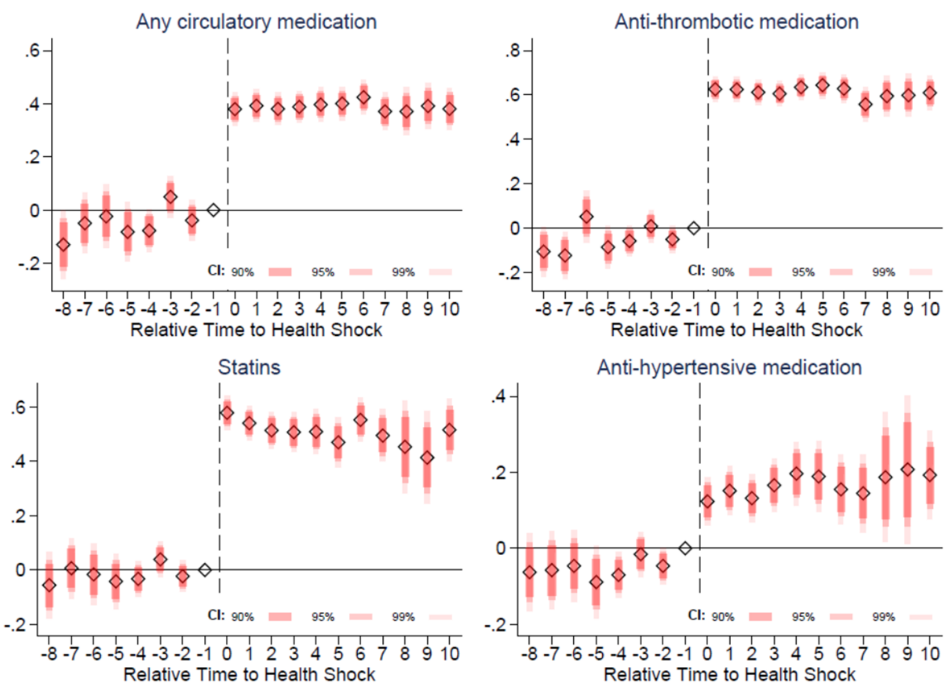
Figure 6 depicts the results for heart attacks (a) and strokes (b) for either medication or each separately. Again, we do not see any significant pre-trends in use prior to the health shock. After the shock, the use of heart-related medication increases substantially (between 60 and 75 percentage points). Interestingly, we do not see any decline in use in the following years suggesting that adherence is high. This high adherence might be related to the severity of the conditions, but also at least is in line with the stable level of subjective health.

Figure 6: Even Study Coefficients – Medicine consumption conditional on Objective Health

(a) Heart Attacks: Any circulatory medication, anti-thrombotic, statins, and anti-hypertensive



(b) Strokes: Any circulatory medication, anti-thrombotic, statins, and anti-hypertensive



Source: Own illustration.

4.3 Robustness checks

We perform a number of robust checks. First, we might be concerned about attrition bias due to death. In the baseline specification we only condition on survival for at least one year after the shock. To explore whether our results might be driven by the survival of healthier individuals we condition on survival until February 2022, the latest available mortality data from Statistics Netherlands. This results in dropping 551 (6.96%) individuals from the heart attack and 731 (13.02%) from the stroke samples. The results are barely affected by dropping the deceased individuals, providing confidence that the observed pattern of subjective health conditional on objective health is not driven by mortality induced attrition.

Second, given that we pool both health 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 years. The patterns of subjective health conditional on objective health are very similar between both health survey samples. Because of the smaller sample size of the 2012 survey, we do observe larger confidence intervals there.

Third, we assess the relevance of the propensity score weighting and of the selection of the base year. In our main analysis, we use two different base years to estimate the ex-ante likelihood of a heart attack or stroke on. We do this, so that for both samples this model is based on the group for which we observe health outcomes at the same event time (t=3). As an alternative, we use the same model for both groups. This does not affect the results. We also rerun the analysis without weighting, again finding very similar results.

5 Discussion & Conclusion

In this paper we investigate the effect of a heart attack or stroke on the subjective health perceptions and health behaviors of individuals relative to the effect on objective health. We exploit the exogenous timing of these health shocks to compare outcomes of individuals who already have suffered from a heart attack or stroke to different but similar individual 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, 2016 and 2020 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.

Our results indicate that immediately following a heart attack or stroke self-assessed health is negatively impacted, and this impact is stronger than that on physical limitations. After the initial shock, self-perceived health remains stable. Further gradual declines in objective health (as measured by physical limitations) do not induce individuals to change their health perceptions. Our results do not confirm earlier findings (e.g. by De Hond et al. (2019) for life satisfaction and Baji & Biro (2018) for subjective mortality probabilities) that individuals adapt over time to their new condition; In our case, self-perceived health never returns to pre-shock levels.

In the second part of our analysis, we turn to the effects of the shocks on health behaviors and medication use. Previous studies have o 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 (smoking, overweight, excessive alcohol consumption, physical activity) and heart-related medication use. 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. We find a similar, but smaller effect for alcohol use. We also observe a very substantial and persistent increase in heart-related medication use after the shock.

The effects on behavior *conditional* on physical limitations show a very similar pattern as those for conditional self-assessed health. This provides some first suggestive evidence that these behaviors are driven by health perception. This would be in line with previous findings suggesting that (biased) health beliefs impact health behaviors.

In ongoing work, we 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. In particular, we consider the impact of the health shocks on deductible choice for health insurance. Handel et al (2020) find that many individuals in the Netherlands choose a voluntary deductible that are suboptimal given their objective health risk. These suboptimal decisions might be driven by biased health beliefs.

Further we aim to connect our study to the literature on within-family health behavior spillovers and preventive behaviors. 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 potentially highly informative if lifestyles 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 & 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, highlighting 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 to illuminate this question.

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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)	Annual, 2006-2020	GBAPERSOONTAB (Municipal registry)
Gender	1 = Female	Annual, 2006-2020	
Mortality	1 = Died by March 2021, date of death	Annual, 2006-2020	GBAOVERLIJDENTAB (vital records)
Socio-Economic Status			
Household Income	Income quintiles based on entire population.	Annual, 2006-2020	INHATAB, INTEGRAAL HUISHOUDENS INKOMEN (household level tax declared income)
Labour Market Status	Receives pension, unemployment benefit, incapacity benefit.	Annual, 2006-2020	INPATAB, INTEGRAAL PERSOONLIJKE INKOMEN (personal level tax declared income and sources)
Healthcare Use			
Hospitalisations	Number of hospitalisations.	Annual, 1995-2020	LMR/LBZ Basis (hospital episodes statistic)
Hospital Diagnoses	Hospitalisation by ISHMT group.	Annual, 1995-2020	
Length of Stay	Length of stay by admission.	Annual, 1995-2020	
Total Length of Stay	Total length of stay.	Annual, 1995-2020	
Medicines Use	Medicine used by ATC group.	Annual, 2006-2020	MEDICIJNTAB (reimbursed medications)
Nursing Home use	Time spent in nursing home in days.	Annual, 2006-2019	ZORGMVTAB, GEBWLZTAB (nursing home admissions)
Self-Reported Outcomes			
Self-Assessed Health	5-point scale.	2012/2016/2020	Health Monitor 2012/2016/2020
Kessler Distress Scale	3-point scale.	2012/2016/2020	
Functional Limitations	Any limitation, limitation by dimension, total number of limitations.	2012/2016/2020	
Health Behavior	Self-reported smoking status, height/weight, alcoholic drinks per week, physical activity	2012/2016 /2020	

Table A1.2: Sample Size by Cohort

	Cohort (Years to Admission)																		
	-8	**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Heart Attack																			
2012	126	152	138	126	153	170	180	196	68	157	162	191							
2016					187	223	252	292	239	348	344	379	187	228	229	271			
2020									156	312	292	327	299	291	334	294	146	162	305
Total	126	152	138	126	340	393	732	488	463	817	798	897	486	519	563	565	146	162	305
																			7916
Stroke																			
2012	131	147	150	171	141	140	162	126	56	138	123	107							
2016					263	260	315	289	193	205	206	164	108	146	134	95			
2020									164	221	248	196	189	147	121	113	56	60	131
Total	131	147	150	171	404	400	477	415	416	564	577	467	297	293	255	208	56	60	131
																			5616

Appendix 2: Matching Details

Table A2.1: Unweighted Differences in Covariates

Heart Attack Sample																			
	Cohort (Years to Admission)																		
Demographics	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
Female	0.30	0.33	0.26	0.28	0.26	0.29	0.27	0.27	0.26	0.26	0.26	0.24	0.24	0.24	0.24	0.23	0.23	0.22	0.24
Age	65.23	65.13	65.34	65.19	65.36	66.09	65.96	66.12	65.96	65.69	65.70	65.33	65.13	64.86	64.93	64.59	64.61	64.52	64.63
Year before event																			
Hospitalisations	0.36	0.33	0.39	0.25	0.34	0.21	0.38	0.29	0.38	0.29	0.38	0.29	0.28	0.27	0.40	0.28	0.27	0.29	0.23
Total Length of Stay	1.02	0.92	1.12	0.49	1.12	0.63	0.84	0.75	0.88	0.99	1.07	0.93	0.96	0.60	0.79	0.65	0.84	0.46	0.62
Anti-Thrombotic	0.33	0.32	0.34	0.28	0.24	0.24	0.27	0.27	0.31	0.28	0.28	0.30	0.22	0.23	0.23	0.24	0.31	0.22	0.22
Anti-Hypertensive	0.50	0.48	0.51	0.39	0.37	0.36	0.39	0.35	0.38	0.37	0.38	0.41	0.37	0.34	0.34	0.35	0.37	0.36	0.35
Statins	0.36	0.33	0.40	0.29	0.27	0.34	0.32	0.33	0.37	0.31	0.32	0.33	0.30	0.30	0.28	0.28	0.36	0.28	0.23
At event																			
Inpatient Days	5.24	5.62	4.85	5.27	4.73	4.94	5.01	5.26	5.43	5.45	5.58	5.41	5.06	5.34	5.59	5.49	6.29	5.60	5.41
Observations	**126**	**152**	**138**	**126**	**340**	**393**	**732**	**488**	**463**	**817**	**798**	**897**	**486**	**519**	**563**	**565**	**146**	**162**	**305**

Stroke Sample																			
	Cohort (Years to Admission)																		
Demographics	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
Female	0.45	0.43	0.46	0.35	0.41	0.40	0.42	0.38	0.39	0.39	0.36	0.37	0.37	0.39	0.36	0.38	0.41	0.38	0.36
Age	70.31	70.61	70.00	69.93	69.79	70.17	69.88	69.45	69.68	69.14	69.09	69.12	69.01	68.89	69.23	68.93	68.61	69.06	68.19
Year before event																			
Hospitalisations	0.42	0.40	0.43	0.41	0.42	0.37	0.39	0.32	0.42	0.43	0.47	0.36	0.39	0.49	0.37	0.39	0.25	0.48	0.31
Total Length of Stay	1.32	1.24	1.40	1.62	1.16	1.27	0.90	0.87	1.49	1.32	1.21	1.07	1.15	1.43	1.00	1.82	0.56	1.34	0.54
Anti-Thrombotic	0.38	0.43	0.33	0.29	0.37	0.41	0.34	0.35	0.39	0.32	0.35	0.36	0.34	0.32	0.33	0.40	0.42	0.31	0.35
Anti-Hypertensive	0.49	0.54	0.44	0.39	0.53	0.52	0.45	0.46	0.50	0.40	0.42	0.44	0.46	0.46	0.37	0.46	0.48	0.41	0.44
Statins	0.39	0.42	0.37	0.37	0.33	0.47	0.39	0.38	0.40	0.34	0.37	0.35	0.36	0.36	0.32	0.37	0.33	0.37	0.37
At event																			
Inpatient Days	4.93	5.27	4.59	6.12	5.59	5.55	5.44	5.62	5.25	5.51	5.49	6.02	5.18	5.60	5.93	6.28	5.88	5.69	6.08
Observations	**131**	**147**	**150**	**171**	**404**	**400**	**477**	**415**	**416**	**564**	**577**	**467**	**297**	**293**	**255**	**208**	**56**	**60**	**131**

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)

Table A2.2: Weighted Differences in Covariates

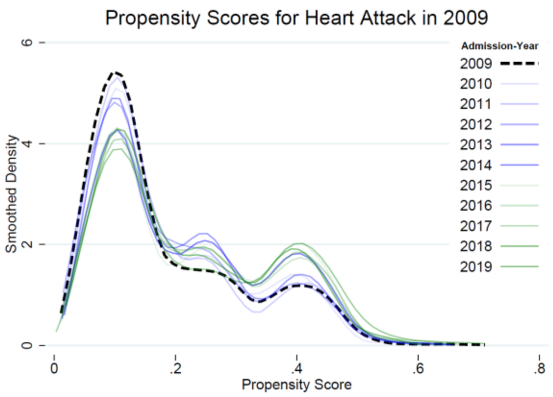
Heart Attack Sample																			
	Cohort (Years to Admission)																		
Demographics	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
Female	0.26	0.30	0.22	0.23	0.25	0.26	0.27	0.26	0.23	0.27	0.24	0.23	0.25	0.23	0.24	0.23	0.23	0.21	0.24
Age	66.79	66.70	66.88	66.63	66.96	67.33	67.17	67.23	67.13	66.13	66.12	65.76	65.24	65.11	65.10	64.92	64.35	64.20	64.36
Year before event																			
Hospitalisations	0.46	0.38	0.55	0.27	0.36	0.22	0.39	0.27	0.33	0.21	0.29	0.23	0.20	0.21	0.29	0.19	0.15	0.14	0.14
Total Length of Stay	1.36	1.02	1.70	0.63	0.93	0.71	0.90	0.77	0.81	0.63	0.78	0.68	0.58	0.39	0.51	0.44	0.36	0.22	0.43
Anti-Thrombotic	0.35	0.32	0.37	0.32	0.21	0.25	0.24	0.25	0.26	0.16	0.18	0.19	0.09	0.11	0.11	0.12	0.12	0.08	0.07
Anti-Hypertensive	0.50	0.49	0.51	0.44	0.38	0.39	0.38	0.34	0.37	0.31	0.32	0.35	0.31	0.28	0.26	0.27	0.25	0.25	0.24
Statins	0.37	0.35	0.39	0.31	0.26	0.34	0.30	0.29	0.33	0.20	0.23	0.23	0.17	0.19	0.17	0.17	0.18	0.14	0.10
At event																			
Inpatient Days	5.62	5.73	5.50	5.78	5.16	5.11	5.07	5.54	5.66	5.37	5.63	5.52	4.96	5.25	5.47	5.49	6.60	5.48	5.53
Observations	**126**	**152**	**138**	**126**	**340**	**393**	**732**	**488**	**463**	**817**	**798**	**897**	**486**	**519**	**563**	**565**	**146**	**162**	**305**

Stroke Sample																			
	Cohort (Years to Admission)																		
Demographics	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
Female	0.37	0.36	0.39	0.34	0.40	0.38	0.40	0.36	0.36	0.38	0.38	0.37	0.37	0.39	0.38	0.37	0.43	0.43	0.38
Age	71.52	71.72	71.33	70.95	70.98	71.34	71.02	70.77	71.06	69.75	69.67	69.69	69.14	69.27	69.56	69.01	68.37	68.72	67.95
Year before event																			
Hospitalisations	0.44	0.38	0.51	0.62	0.45	0.38	0.42	0.34	0.40	0.41	0.42	0.35	0.31	0.46	0.32	0.31	0.22	0.56	0.29
Total Length of Stay	1.43	1.01	1.86	2.48	1.31	1.36	0.87	0.79	1.26	1.17	1.08	0.91	0.93	1.02	0.70	1.07	0.47	1.37	0.49
Anti-Thrombotic	0.43	0.48	0.38	0.34	0.47	0.42	0.29	0.33	0.35	0.25	0.27	0.28	0.20	0.21	0.21	0.26	0.26	0.19	0.20
Anti-Hypertensive	0.51	0.56	0.46	0.46	0.61	0.55	0.44	0.47	0.53	0.39	0.41	0.42	0.43	0.45	0.34	0.46	0.46	0.38	0.44
Statins	0.44	0.45	0.42	0.39	0.42	0.44	0.35	0.34	0.37	0.29	0.31	0.29	0.26	0.26	0.24	0.28	0.22	0.29	0.28
At event																			
Inpatient Days	5.02	5.31	4.73	6.05	5.85	5.71	5.37	5.65	5.35	5.40	5.62	5.74	4.97	5.40	5.82	6.06	6.13	5.38	5.76
Observations	**131**	**147**	**150**	**171**	**404**	**400**	**477**	**415**	**416**	**564**	**577**	**467**	**297**	**293**	**255**	**208**	**56**	**60**	**131**

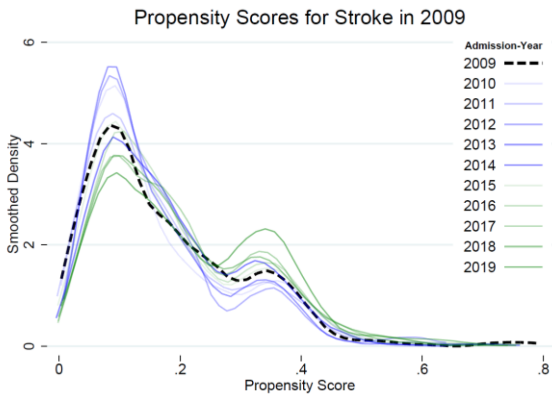
Note: Shaded cells indicate that the standardized difference between the cohort group and the reference group (observed three years after the heart attack or stroke) exceeds the threshold value of 0.25 recommended by Stuart et al. (2013)

Figure A3.1: Overview – Propensity Score Distributions by Survey and Event-Cohort

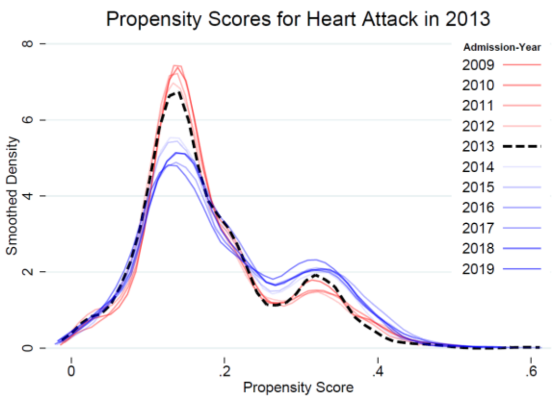
(a) Heart Attacks – Gemon 2012



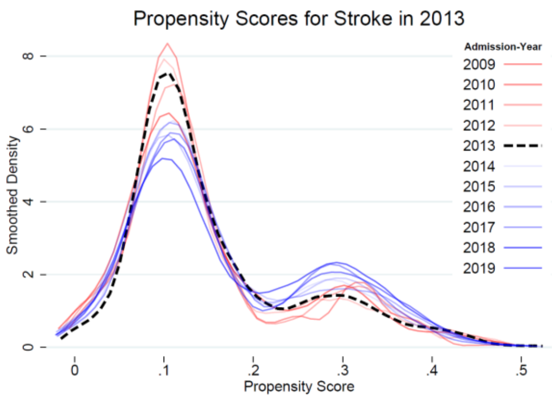
(b) Strokes – Gemon 2012



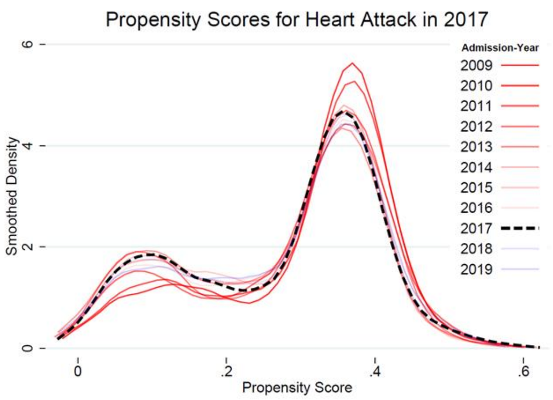
(c) Heart Attacks – Gemon 2016



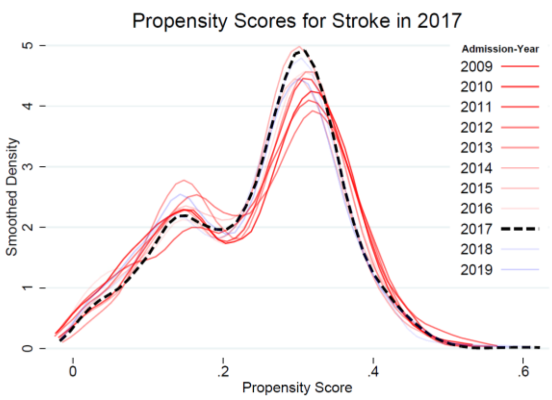
(d) Strokes – Gemon 2016



(e) Heart Attacks – Gemon 2020

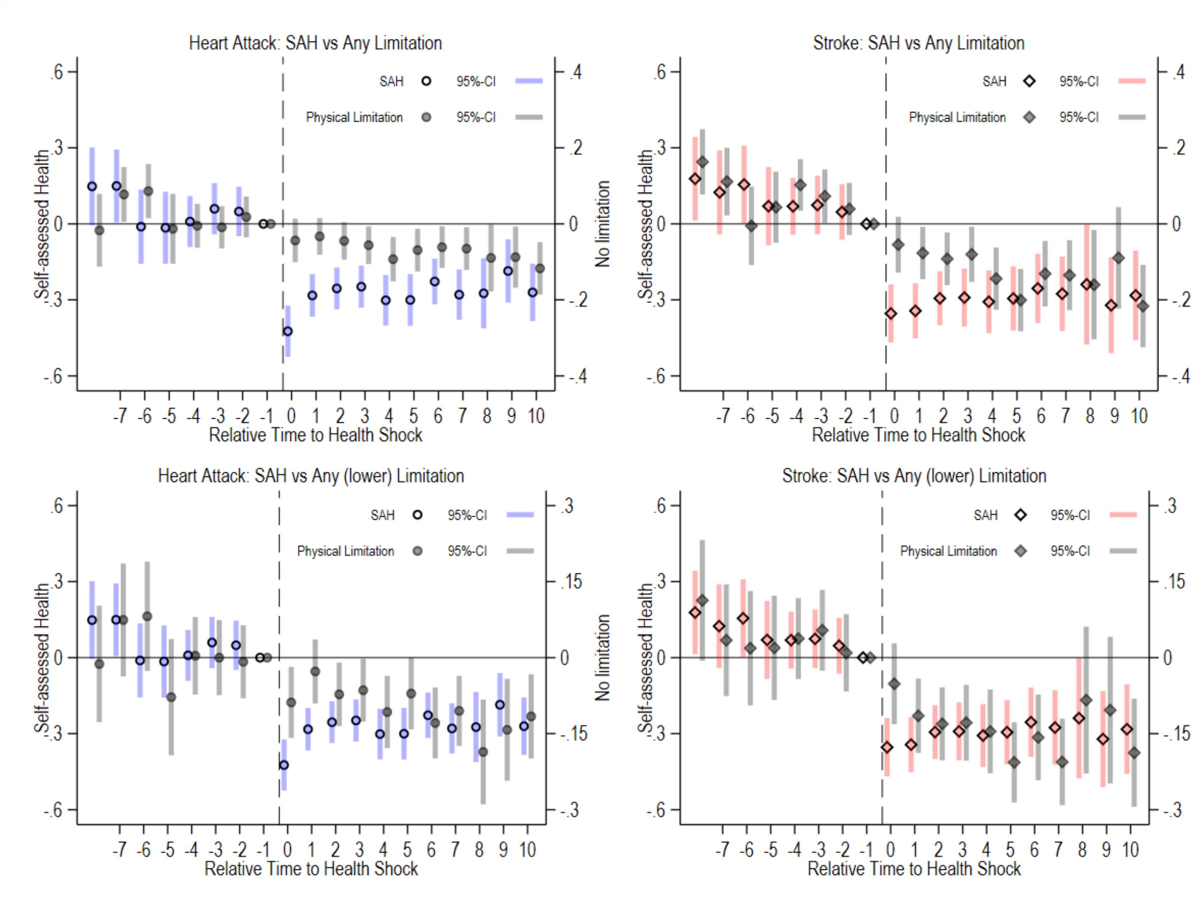


(f) Strokes – Gemon 2020



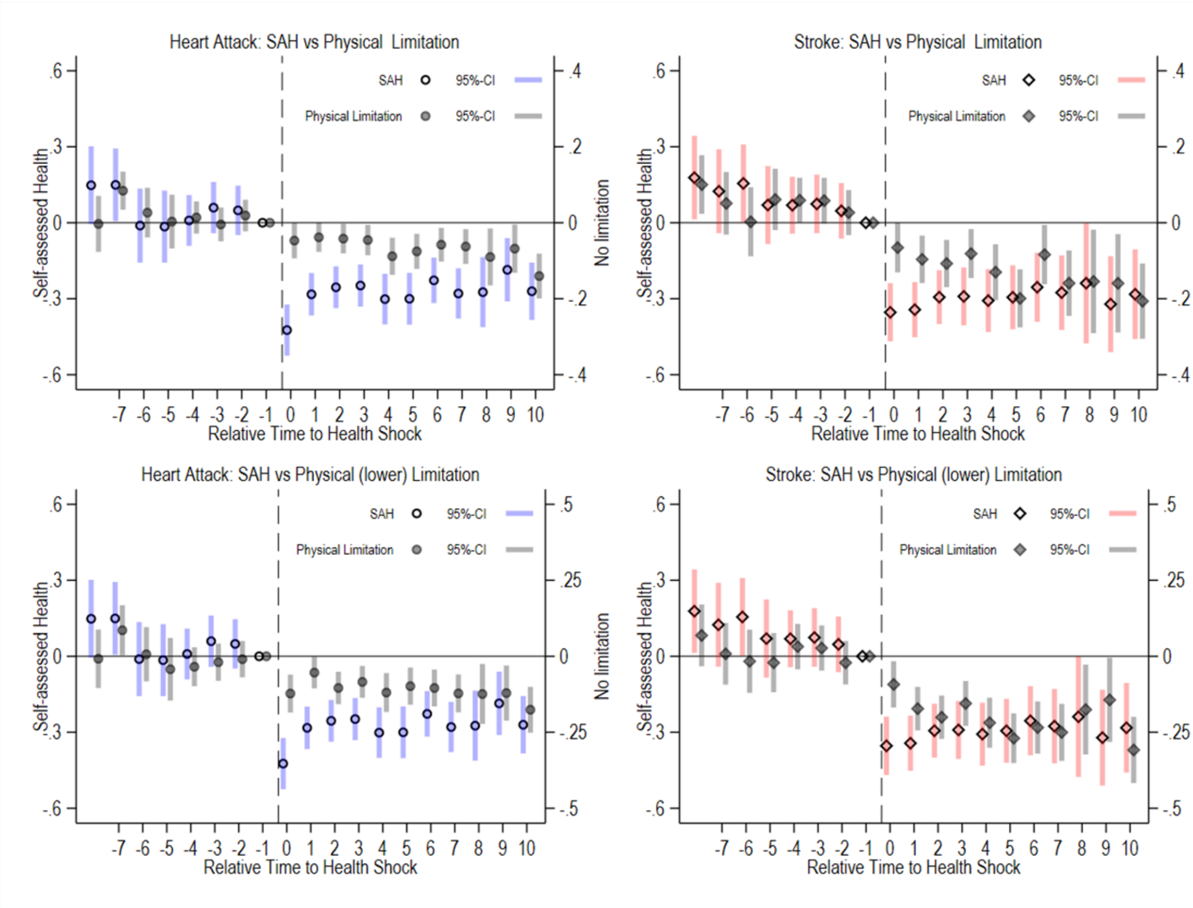
Appendix 3: Additional Results

Figure A3.1: Overview - Self-Assessed Health and Any Functional Limitations



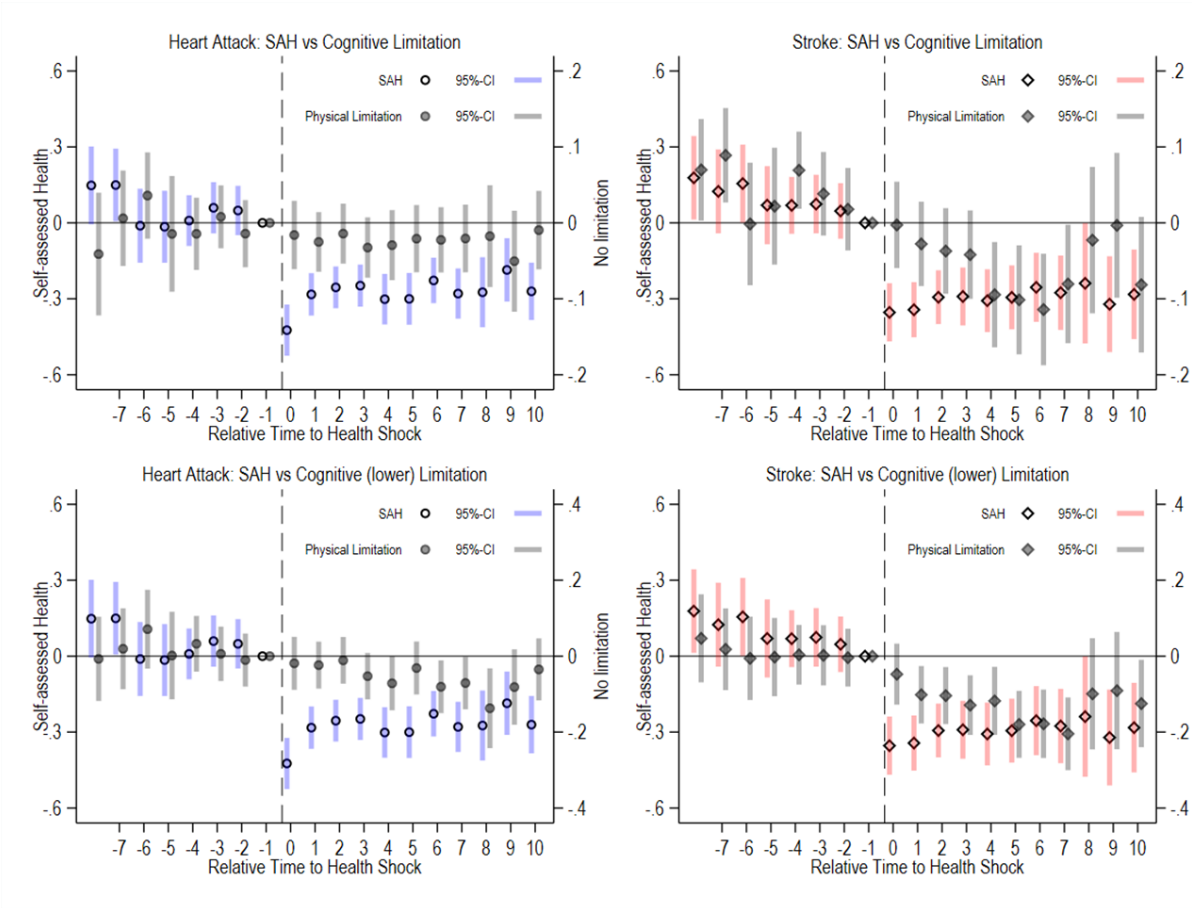
Source: Own illustration.

Figure A3.2: Overview - Self-Assessed Health and Physical Functional Limitations



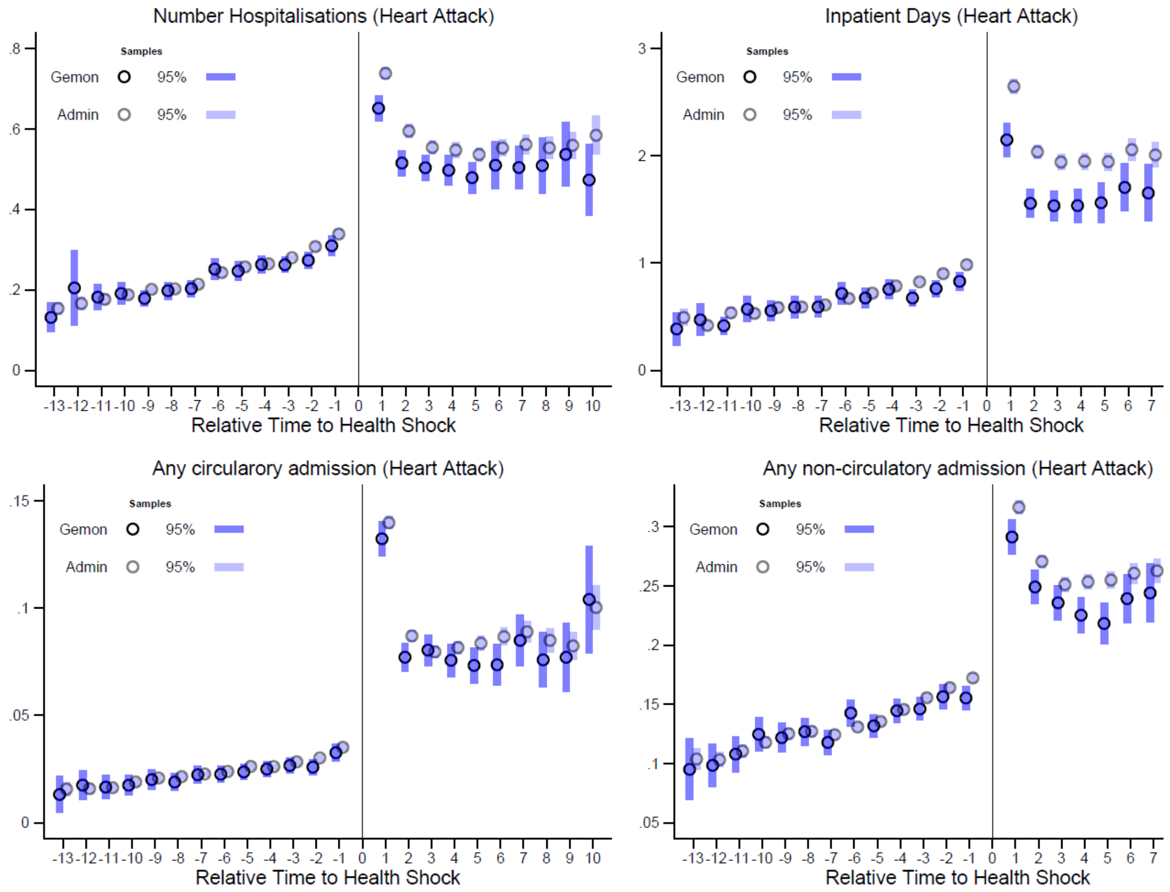
Source: Own illustration.

Figure A3.3: Overview - Self-Assessed Health and Cognitive Functional Limitations



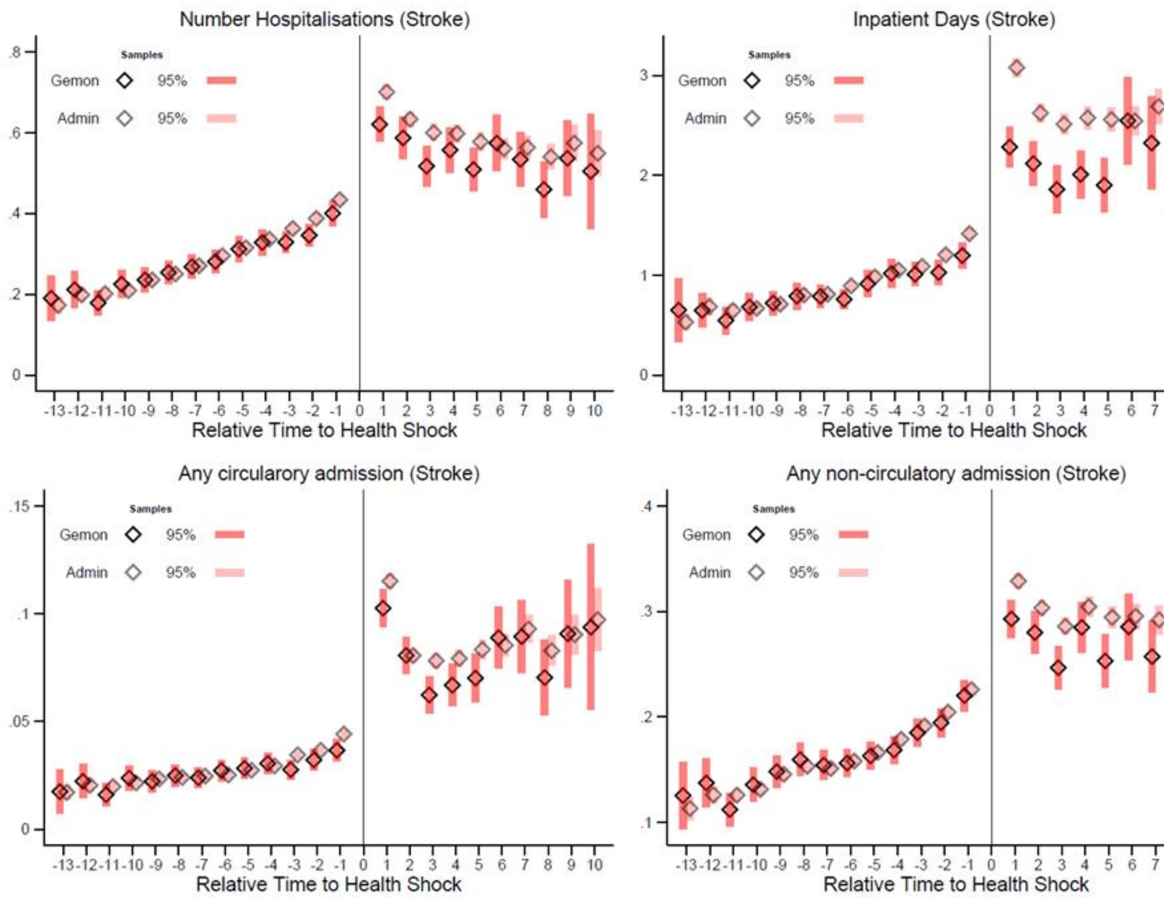
Source: Own illustration.

Figure A3.4: Heart Attacks – Hospitalisations and Inpatient Days



Source: Own illustration. *Note:* This descriptive data is not just the survey cross-section but the longitudinal administrative data. The transparent dots and bars are the mean and 95% confidence intervals for the entire sample of patients. The more strongly coloured dots and bars are the coresponding estimates for the survey sample. Time point t_0 is ommitted on purpose as for all patients at this time point a hospitalisation occurs.

Figure A3.5: Strokes – Hospitalisations and Inpatient Days



Source: Own illustration. *Note:* This descriptive data is not just the survey cross-section but the longitudinal administrative data. The transparent dots and bars are the mean and 95% confidence intervals for the entire sample of patients. The more strongly coloured dots and bars are the coresponding estimates for the survey sample. Time point t_0 is ommitted on purpose as for all patients at this time point a hospitalisation occurs.