1-2019

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Published in Health Economics,
Issue 28, January 2019, Pages 23–43
DOI 10.1002/hec.3824

Monthly Spending Dynamics of the Elderly Following a Health Shock: Evidence from Singapore

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9 July 2018

Accepted at Health Economics

Abstract

We use novel longitudinal data from 19 monthly waves of the Singapore Life Panel to examine the short-term dynamics of the effects health shocks have on household health and non-health spending and income by the elderly. The health shocks we study are the occurrence of new major conditions such as cancer, heart problems, and minor conditions (e.g. diabetes, and hypertension). Our empirical strategy is based on an event study approach that exploits unanticipated changes in health status through the diagnosis of new health conditions. We find that major shocks have large and persistent effects while minor shocks have small and mainly contemporaneous effects. We find that household income reduces following a major shock for males but not females. Major health shocks lead to a decrease in households' non-health expenditures that is particularly pronounced for cancer and stroke sufferers, driven largely by reductions in leisure spending. The financial impact of major shocks on medical saving account balances occur to those without private health insurance, while the impact is on cash balances for privately insured individuals.

Keywords: Health shocks; Health expenditure; Consumption; Insurance; Panel data.
JEL: I10, D12, J14.

Acknowledgements and Contacts
*Corresponding author, TC Cheng (terence.cheng@adelaide.edu.au). We thank two anonymous referees for their comments and suggestions. We gratefully acknowledge the helpful comments from participants at the 8th Workshop on the Economics of Health and Wellbeing, the 8th Australasian Workshop on Econometrics and Health Economics, and research seminars at Michigan Ann Arbor, McMaster, Toronto, University Technology Sydney. This research was supported by the Singapore Ministry of Education (MOE) Academic Research Fund Tier 3 grant MOE2013-T3-1-009.

1. Introduction

Unanticipated health events can have serious consequences on the economic well-being of individuals and households. The occurrence of serious illness can leave households to cope with large medical expenditures, especially when access to health insurance is poor, and when publicly funded health care programs are inadequate or absent. Ill health can limit the ability of individuals to work and generate income, which in turn can affect household consumption.

The importance of understanding the adverse effects of health shocks is more pertinent for elderly individuals, as ageing has become a more prevalent phenomenon in many countries[1] and acute health events become increasingly common at older ages. Exposure to financial risks from illness increases dramatically with age, as approximately half of lifetime medical expenditure is incurred after the age of 65 (Alemayehu and Warner 2004). While previous studies have documented that new health events result in cumulative income losses and increases expenses among aged population,[2] evidence, as based on infrequent surveys, may suffer from two significant drawbacks. First, long recall period may lead to significant non-random measurement errors of actual expenditures. Second, time-averaged measures can conceal significant short-term volatility in income and expenditure that are vital in determining the welfare of risk-averse individuals.

In this paper, we analyse the impact of health shocks on households' expenditures using new high-frequency longitudinal data of the elderly from the Singapore Life Panel (SLP). The SLP is unique in its tracking, on a monthly basis, of income, expenditure, health and labour market status of individuals 50 years and over in Singapore. The survey collects rich information on the different types of medical and non-medical spending by households, and captures information on a variety of major and minor chronic health conditions (e.g. cancer, heart problems, diabetes, hypertension). The distinctive feature of the SLP lies in the availability of monthly information on households, which permits us to obtain more accurate measures of expenditures and examine the short-term dynamics of health shocks on household's medical and non-medical expenditures, and income.

[1] For instance, the proportion of individuals over the age of 65 in the U.S. rose from 8% in 1950 to 13% in 2010 and is expected to rise to over 20% by 2030 as the Baby Boomer generation continues to age (Lee 2014).

[2] For example, Smith (2005) and French et al. (2004) have used the biennial Health and Retirement Survey (HRS) to document evidence on the impact of new health events on medical expenditures and income.

We find that major adverse health shocks (cancer, heart disease, and stroke) have large and persistent effects while minor shocks (such as diabetes and hypertension) have small and mainly contemporaneous effects. For example, individuals with major conditions, health spending increases by as high as 79 percent, and heightened spending is observed up to 6 months after the shock. We also find that household income reduces following the onset of a major shock for males but not for females. Major health shocks lead to a decrease in households' non-health expenditures that is particularly pronounced for cancer stroke sufferers, largely driven by reductions in spending on leisure.

Our study contributes to the literature on assessing the economic impacts of ill health in the following ways. First, as stressed earlier, short-term income and expenditure volatility are crucial determinants of the welfare of risk-averse individuals. Previous literature has mainly focused on medium- or long-term consequences of a health shock due to data availability. This approach, however, conceals possible short-term volatile dynamics that may reduce expected utility among risk-averse households even though the impacts on time-averaged income and consumption remain the same. In addition, short-term spike in spending may further deteriorate household welfare under the condition of liquidity constraints and financial constraints. The unique monthly SLP survey data that we use to conduct our analysis helps to contribute to the literature by uncovering possible short-term dynamics following a health shock. The implications of the analysis are important for policy makers in designing necessary tools to help vulnerable households to cope with temporary or persistent financial difficulties following a health shock.

Second, the SLP data allow us to explore the impact of adverse health events with more precisely measured consumption information with a wide range of categories. The high frequency nature of the data helps to overcome potential measurement errors as often associated with traditional consumption measures. These measurement errors tend to be non-random as households may systematically under-report spending when long recall period blurs memory. In this paper, we examine individual specific time variation in detailed health and non-health spending categories before and after receiving a health shock.[3] One month recall period in the data collection procedure allows us to obtain this detailed information with greater precision. The detailed spending categories collected in the SLP allow us to better examine substitution between health and non-health consumption, and how this varies with spending categories and types of health shocks. Overall, our estimated consumption responses are more

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[3] Details of the categorical spending are summarised in Table A.1 and Table A.2

informative, accurate, and reliable since they are likely to contain less non-random measurement errors for consumption compared with other often used data sources.

Third, we study these issues within the context of Singapore, a well-developed country with a unique approach in financing health care. To our knowledge, most existing studies are in the context of low- and middle-income countries.[4] By conventional measures, Singapore has achieved excellent population health outcomes despite spending significantly less than most high-income countries. Much of its success has been attributed to its philosophy of individual responsibility in maintaining good health, and in paying for health care – most notably through a combination of individual medical savings accounts with a catastrophic health insurance scheme (see Section 2 for more details).

Although whether Singapore's success can be attributed to its health care financing system is a question that has been extensively discussed (Hsiao 1995; Barr 2001; Haseltine 2013; McKee and Busse 2013), there has been little rigorous empirical evidence on the performance of Singapore's health care system due in a large part to the lack of detailed individual or household level data on health spending. Particular mention should be made of the work by Chia and Tsui (2005) who examine the adequacy of medical savings accounts in Singapore by calibrating health care expenditures using semi-aggregated spending data.

Singaporeans have access to "self-insurance" in the form of a compulsory savings scheme called Medisave and private health insurance which is accessed mainly through their employers (more details about the Singaporean financing system is given in section 2). While it might appear at first blush that access to such extensive insurance protects Singaporeans from the financial impact of health shocks, this is an empirical question that we seek to address. In particular, our study is able to compare the end of year financial position of those who suffered a health shock with those that didn't. If indeed Singaporeans are fully protected against shocks, we would expect to see limited depletion in their assets. We find that across the board, health shocks are associated with a reduction in the end-of year cash balances. However, only those without private insurance suffer a depletion in their Medisave balances. The results suggest

[4] In these studies, the focus is on how individuals and households cope with the financial consequences of health shocks. While much of the evidence finds that ill health leads to a reduction in household income and consumption (e.g. Gertler and Gruber 2002; Sparrow et al. 2014; Wagstaff 2007), there are some studies of households being well insured against illness (Townsend 1994; Kochar 1995), even in the absence of health insurance (Liu 2016). A key question here is whether households can smooth food and non-food consumption in the presence of shocks. Access to formal (e.g. microcredit) and informal credit, as well as borrowing and gifts from family and friends (Wagstaff 2007), have shown to be important mechanisms through which households cope with shocks, without needing to sell assets such as livestocks (Mohanan 2011; Islam and Maitra 2012). See also Kruk et al. (2009) for a review of 40 countries.

that private insurance cushions the impact of shocks on Medisave balances but does not fully protect the overall financial position.

The findings in this paper provide concrete evidence on the extent to which individuals cope with health shocks in this context, which is useful for cross-country comparisons and drawing implications from Singapore's experiences.

Finally, our study of the short-term dynamics of medical expenditures complements a small body of work that examines the persistence of medical expenditures over time. Much of the existing studies are US-centric, and have used data from the biennial Health and Retirement Survey (HRS) (French et al. 2004), the Medical Expenditure Panel Survey (Monheit 2003) where households are surveyed five times over a two-year period, data of Medicare beneficiaries (Rettenmaier and Wang 2006; De Nardi et al. 2016) and claims data (Hirth et al. 2016). Recent work by Dobkin et al. (2018) use an event study approach to examine the economic consequences of hospital admissions using the data from the HRS, as well as data from credit reports (e.g. unpaid medical bills, bankruptcy). The richness in the Singapore Life Panel lies in the availability of detailed information every month on households' health expenditures, and health conditions of household members. The nature of the data allows us to obtain more accurate measures of income and expenditures and to uncover possible short-term volatility in these measures following a health shock.

Our paper is organised as follows. Section 2 describes the institutional context of Singapore's health system. Section 3 provides a background to the Singapore Life Panel. Section 4 discusses the data used in the analyses, and the econometric methods. The results from our analyses are discussed in Section 5, followed by a discussion of our findings in Section 6.

2. Institutional Context

Singapore is a high income country, with a GDP per capita of US$52,888 in 2015, similar to that of the US. In 2013, total expenditure on health as a percentage of GDP is 4.6 percent and health spending on a per capita basis amounted to USD$2,507 (World Health Organisation, 2015) The Government's share of total health expenditure is 40 percent. Private sources of funding accounted for the remaining 60 percent, and comprise of contributions by individuals in the form of out-of-pocket payments, private insurance and employer-provided benefits, as well as payments out of publicly managed health insurance programs and mandatory medical savings accounts (see elaboration below).

Health services are delivered through a combination of public and private providers. The public sector provides 80 percent of acute care through public hospitals financed via a mix of block grants and Diagnosis-Related Groups casemix payments by the government. The cost of hospitalisation in public hospitals are subsidised by the government, and the amount of subsidies vary from zero to up to 80 percent depending on the level of hospital amenities that patients choose to receive. Private hospitals account for the remaining 20 percent of acute care services and do not attract any government subsidy. The private sector dominates the primary care sector, with private medical clinics delivering 80 percent of primary care services. The government runs a network of clinics providing subsidised primary care, which also serves as a point of referral for specialist and hospital care in public hospitals.

Complementing government subsidies is a core set of three public programs that allow individuals to pay for their health care. The first program is a compulsory medical savings scheme Medisave which was introduced in 1984. Under Medisave, employed individuals contribute between 8 percent to 10.5 percent of their monthly wages, depending on their age, to a mandatory medical savings account. Contributions by self-employed individuals depend on the income reported in the preceding year. Individuals can withdraw funds from the Medisave accounts to pay for their own health care expenses, or those of their immediate family. There are limits on how much can be withdrawn from Medisave accounts and these vary depending on the types of expenditure and medical conditions. Expenses in excess of these limits are paid as out-of-pocket payments. Medisave can be used to pay for the cost of inpatient hospitalisation and approved day surgeries in both public and private hospitals, as well as outpatient treatments for certain chronic diseases (e.g. diabetes, hypertension), vaccinations and health screenings. There is a maximum that individuals can accumulate in their Medisave accounts and contributions in excess of this maximum are transferred to individuals' compulsory savings accounts that are earmarked for retirement purposes. Upon death, remaining funds are transferred to nominated beneficiary, or distributed according to intestacy laws.

A second program is Medishield, a publicly managed catastrophic health insurance scheme introduced in 1990 that covers large hospital expenses and certain expensive outpatient treatments (e.g. dialysis, chemotherapy). Premiums for Medishield can be paid using funds from individuals' medical savings accounts. In 2015 Medishield was replaced with Medishield Life and made compulsory. Medishield Life covers part of the costs of an inpatient hospital stay. It also covers some selected outpatient care (cancer therapy, dialysis, and immunosuppressants therapy for organ transplant). There is an annual maximum claim of $100,000, annual deductible (which depends on what class of ward the patient uses) and copayments between 3% and 10% depending on the size of the bill. For class C ward or day surgery, the deductible is $1,500 and for class B2 ward it is $2,000. While there are no deductibles for outpatient services covered by Medishield life, there are additional claim limits. For example, Medishield life will pay the lower of 90% or $3,000 for a cycle of chemotherapy. The proportion of the bill that the patient pays can come out of their (or family's) Medisave account or they can pay it in cash. A typical bill for heart attack would be $8,000 of which the patient would pay 30%.

An alternative to Medishield Life is the Integrated Shield Plan (IP) which bundles a Medishield Life plan with a private insurance plan approved by Government. Enrollees can use their Medisave accounts to pay the premium. The enrollee in an IP is essentially purchasing the Medishield Life plan from Government and an additional component provided by private insurers. IP plans presently in the market range from the basic plan to comprehensive. The most basic plan removes the upper limit on daily hospital charge so that patients can go to private or Class A wards if they wish. At the other end, there are IP plans which as well as covering higher price hospital stay, also cover a wider range of services such as pre- and post-hospitalisation treatment. All IP plans - however expensive - have 10% coinsurance, deductibles based on class of ward and annual limits. These deductibles and copayments means that even if patients have IP plans, they might choose to use lower class wards or public rather than private hospital in order to reduce their bill. IP premiums can be paid using Medisave balances, although there is a cap on how much can be paid.

The third program, Medifund, is an endowment fund established to assist poor and needy who are unable to afford their medical expenses. The scheme serves as a safety net for those who face financial difficulties in spite of government subsidies. Strict eligibility rules apply for Medifund assistance.

Outside the Government controlled 3M (and IP) system, individuals may purchase wholly private insurance. Premiums for private insurance are paid either from cash or as a fringe benefit provided by the employer. Private insurance can provide first dollar coverage (called "rider" coverage) which covers the patient's part of the bill from the IP plan (i.e. the deductible and the copayment). Private insurance plans can also include a wide range of services such as home care and step-down care. The popularity of so called rider-insurance has been a bone of contention with the Government. The concern is that by insulating patients against the full cost of care, these allow higher fees to be charged by doctors (Health Insurance Taskforce, 2016).

3. Background to the Singapore Life Panel

This study uses 19 monthly waves of data from the Singapore Life Panel. In 2014, the Centre for Research in the Economics of Ageing (CREA) was established at the Singapore Management University to study the economics of ageing in Singapore, and CREA commenced a major data collection program. This data set is the *Singapore Life Panel* (SLP), and is a population representative sample of Singapore citizens and residents aged 50 to 70 years. Similar to the RAND Life Panel and the Tilburg LISS, the survey is answered on-line on a monthly basis.

Recruitment for the Singapore Life Panel took place between May and July 2015, and 25,000 addresses were sent invitation letters. The addresses were provided to CREA by the Singapore Department of Statistics where it was believed that there was at least one person who was eligible (i.e. a citizen or resident and aged between 50 and 70). Additional documentation on the collection methods is available in Vaithianathan et al. (2017).

Canvassing occurred through both personal visit and telephone contact and 11,511 eligible households were recruited to the panel representing 15,212 respondents. This initial cohort corresponds to a response rate of 52% of all households invited to participate. Once recruited, the panel were invited to participate in monthly surveys. These surveys started with a pilot in August 2015, where only 1000 participants were asked to respond. The survey of all respondents recruited commenced from September 2015 onwards. Each month the survey asked respondents about their household spending, income, labour force status, health, household size, and subjective well-being. While these questions were repeated monthly, other questions were only asked quarterly or on an ad-hoc basis. For example, in January 2016 and 2017, two major asset survey modules were conducted where respondents were asked about their financial assets, annual income and intra-household transfers.

Given that the present paper utilises the household spending data, we need to establish whether the spending data being generated by the SLP accords with other published survey data that is population representative. Figure OA.1 in the online supplementary materials compares the monthly household expenditure reported by the SLP respondents with published data from Singapore Statistics. The data suggests that (at least for the first 4 waves of the SLP) the published statistics and SLP show very similar patterns – although the SLP suggests a slight rightward shift- which might be expected given that the period of coverage for SLP was 2016 and the average inflation rate in 2013 was 2.4% and in 2014 was 1%.

We also compared baseline demographic and economic features of the SLP respondents with published official statistics, and found them well matched. For example, 27% of the SLP sample had no formal schooling or only Primary compared to 29% of the comparable cohort from the 2010 Census of population. Additionally 31% of the SLP had post-secondary or tertiary education compared with 31% of the comparable Census cohort.

Table A.1 provides the sample size of respondents and households in each wave. Wave 0 is the baseline wave conducted at the time that a respondent agrees to be part of the panel during the recruitment period May and July 2015. We have 11,536 respondents from 8,723 households who were in the 50-70 age category and who completed the baseline survey. The baseline survey did not ask about detailed consumption questions but rather asked basic demographic information. Wave 1 was a "pilot wave" and only 1,000 households were invited which account for the smaller number of respondents.

Starting in August 2015 (wave 2), all panel members were invited to answer an approximately 15 minute survey which asked about their labour market status, health, subjective well-being and spending. Response rates have been remarkably stable for the first 19 months of the survey from wave 2 onwards, consistently eliciting around 7,500 age-eligible responses (Table A.1).[5]

4. Methods

4.1 Defining Health Shocks

We define a health shock as a *new* diagnosis of a chronic condition. In the baseline survey, respondents were asked the following question: *Has a doctor ever told you that you have any of the following conditions? Please check all that apply.* The conditions offered were Hypertension, Diabetes, Cancer, Heart problems, Stroke, Arthritis, Psychiatric problems and None of the above. Thereafter, at every monthly survey, the respondents were asked a two part question: *In [last month] (last calendar month), were you seen by a medical doctor?* If they replied yes to this question, they were further asked: *In [last month], did a doctor tell you that*

[5] The number of respondents in January 2016 (wave 6) is higher as respondents were paid more money to complete the additional annual asset module (Vaithianathan et al. 2017). A similar inducement was offered in January 2017 though there was no similar increase in completion rates.

you have any of the following condition? Please check all that apply. The same list of conditions were presented to them.

We define a condition being newly diagnosed in some month *t*, if the respondent did not have that diagnosis in the baseline, or in any month *t*-1 but in month *t* answered that they had visited the doctor and been told that they have that condition. Given the large set of conditions, for ease of interpretation, we define two subgroups: minor and major conditions. “Minor conditions” consist of Arthritis, Diabetes, Hypertension or Psychiatry, and “major conditions” are Cancer, Heart or Stroke.

The distribution of medical conditions at baseline and new diagnosis is shown in Table 1. The most prevalent minor condition is chronic hypertension with 3,320 (29%) reporting having hypertension in the baseline. An additional 895 respondents newly acquired the condition between the time they completed the baseline survey (between May and July 2015) and February 2017 (wave 19), corresponding to an incidence rate of 11%. The second highest most prevalent condition is diabetes (1,667 in the baseline) with only 414 reporting a new diagnosis after 19 waves. For arthritis, 1,193 report having this condition in the baseline, and 819 report a new diagnosis. A plausible reason for high incidence rate for arthritis may be the salience of the disease – a respondent might not recall ever being told about having arthritis at baseline, but might be able to recall being told about it at the last doctor’s visit.

Heart disease is the most common of all the major conditions we study, with 805 (7%) respondents reporting having been told they have the condition at baseline, and 480 acquired the condition after 19 waves, corresponding to an incidence rate of 4.5%. 372 respondents (3.2%) reported at baseline to have had cancer, and 168 (1.5%) had a stroke and the incidence rates after 19 waves are 1.3% and 0.8% respectively. The incidence rates of both major and minor conditions in the SLP are broadly comparable with those from the Health and Retirement Survey, where workers age between 50 to 60 years were found to have a 5% chance of suffering from a heart attack, stroke, or a new cancer diagnosis, and a 10% chance of being diagnosed with a new chronic medical condition over a two-year period (Coile 2004).

At each month of the survey, the respondents were asked the following question on the amount they spent on health care services: *Please provide your best estimate of how much in total [You and your spouse] spent in [last month]*. The five health spending categories are shown in Table A.2. Within each category they are also offered exemplars. Respondents are asked to provide information on out-of-pocket cost and funds paid from Medisave. We derive a measure of total monthly spending on health care services by summing over the five health spending categories.

The distribution of health expenditures by households for different categories of health spending and conditions are shown in Table 2. The mean total monthly spending (Panel A) on health care in the full sample is \$153, and is higher among respondents who reported to have a major condition (\$306) or a minor condition (\$198) at some point in the survey. Of all respondents who have had positive spending (Panel C) in any given month, the mean total monthly spending is \$319, and is highest for hospital services (\$854.3) followed by home nursing (\$422).

As noted in Panel B of Table 2, a substantial proportion of respondents in our sample reported to not have any monthly medical spending. This is largest for hospital and home nursing, where only 5.1% and 0.7% of respondents have positive expenditure. Overall 48% of the sample has positive total health spending. We accommodate this feature of the data in the econometric modelling using the two-part model, which we describe below.

4.2 Econometric Strategy

Following Dobson et al. (2018), we adopt an event study approach to study the effects of health shocks on our outcomes of interest. Our model is based on the classical two-part model adapted to panel data. The first part of the econometric model examines whether an individual incurs medical expenses in a given month. The second part models the logarithm of monthly expenditure for those who report positive medical spending. Formally the model is written as

$$\boldsymbol{d_{iht} = \alpha_0 + \alpha_t \sum_{t=-2}^{12} S_{iht} + \gamma_{1t} + c_{1i} + v_{1iht}} \tag{1}$$

$$\boldsymbol{\log y_{iht} = \beta_0 + \beta_t \sum_{t=-2}^{12} S_{iht} + \gamma_{2t} + c_{2i} + v_{2iht}} \tag{2}$$

where $\boldsymbol{d_{iht}}$ takes the value of 1 if the *i*-th individual has non-zero expenditure for health service *h* (e.g. hospitalisation, prescription medications) in month *t*, and 0 if the individual has zero spending. $\boldsymbol{\log y_{iht}}$ is the logarithm of expenditure incurred by individual *i* for health service *h*, in month *t*. To quantify the monthly dynamics of the effects health shocks have on expenditures, we include as regressors a set of binary variables $\boldsymbol{S_{iht}}$ representing the forward, contemporaneous and lagged time periods $t_{-2}, \ldots t_0, \ldots t_{12}$ from the month of the shock. For example, $\boldsymbol{S_{ih0}}$ takes the value of 1 in the month (t_0) of the shock, and 0 otherwise. The binary variable for the last time period, S_{ih12}**,** is coded to capture the 12th month and all subsequent months thereafter. The coefficient estimates of α_t and β_t, for all t individually capture the effects of health shocks on health expenditure from time t_0, where the health shock occurred, for every subsequent month up to 12 months. c_i is an individual fixed-effect; γ_t is a set of monthly wave dummies and v_{iht} is an error term.

For the coefficient estimates of α_t and β_t to be interpreted as casual requires the identifying assumption that the occurrence, and timing, of the health shock is uncorrelated with the outcome, after conditioning on the individual and month effects. There are two key scenarios that could violate this assumption. The first scenario is if individuals with health conditions that are not severe, which require a lower intensity of medical care (and at lower costs), are less likely to see a doctor. This results in the classical sample selection problem. The second scenario is if adverse health outcomes are brought about by events such as job losses (e.g. Sullivan and Wachter 2009, Browning and Heinesen 2012), or if the health shock follows a period of deteriorating health.

To address these potential threats, we exploit *unanticipated* changes in health status through the diagnosis of *new* health conditions. We focus our attention on individuals with major health shocks – cancer, health disease and stroke – which are conditions that are likely to occur suddenly and are largely unexpected. The focus on major conditions that are severe in nature would minimise sample selection bias that arises if it is indeed the case that the probability of seeking treatment depends on the severity of individuals' conditions. The emphasis on new conditions would also reduce the possibility that individuals health status were deteriorating prior to the shock. For completeness, we also study individuals with minor health conditions, though these results will necessarily be qualified.

Our model specification allows us to directly test whether the health shocks we document are unanticipated. This involves testing if the coefficient estimates on the binary variables that represent the time periods one (t_{-1}) and two (t_{-2}) months prior to the onset of health shocks are statistically significant from zero. If the coefficient estimates on these forward time variables are significant, this would imply the presence of anticipatory health spending. As a further robustness check, we test if there exist an anticipation effect for a longer duration of time by estimating an alternative specification that includes 12 lead binary variables.

We estimate both equations using linear panel data models with individual fixed effects ("within" estimator) and allowing for heteroskedasticity-robust and clustered standard errors at the household level. For the logarithm of expenditures, we retransform predictions of log expenditures into its levels using the Duan smearing estimator in the calculation of the incremental effect of shocks on health expenditure in dollar terms. The wave dummies capture possible time-varying expenditure due to seasonality and macro-economic shocks.

5. Results

5.1 Health Shocks and the Dynamics of Health Expenditures

How does health shocks affect monthly health care expenditure? The key coefficient estimates are presented in Table 3, which shows the effect on total health expenditure in the period the shock occurs, denoted as period t_0, up to 12 months (t_1 to t_{12}) after the onset of illness. As discussed above, these estimates are obtained from the linear individual fixed effects model hence they are interpreted as the impact on health expenditure from within-individual variation in health shocks. Specifically, these coefficients capture how much an individual spends in each period on, and following, a health shock, over and above the amount they spent averaged over three months or more before occurrence of the shock.

The results in Table 3 show, perhaps unsurprisingly, that the contemporaneous effects of health shocks are the largest. Individuals with major and minor shocks are 17.3 and 20.4 percentage points more likely to report having positive total health expenditures (columns 1 and 2). With regard to the amount of spending, individuals with major shocks have significantly higher total health expenditures, with spending levels increasing by 79.3% compared to pre-shock levels. Individuals with minor shocks where total health expenditure increased on average by 19.5% (columns 3 and 4).

The availability of monthly data permits us to estimate the monthly dynamics of health care expenditure following a health shock. In Table 3, the coefficient estimates for periods 1 to 12 months after the shock indicates that while the impact on spending attenuates over time, it persists for up to 6 months following the occurrence of the shock. These temporal effects are summarised in Figure 1. Both major and minor shocks increase the probability of reporting positive expenditures by a similar quantum and with a similar temporal pattern (see top figure in Figure 1). In contrast, they show very different effects on the level of expenditures. For individuals with major conditions, heightened spending is observed up to 6 months after the shock, as well as at the 9th to 12th months (bottom figure in Figure 1). Minor conditions, however, have a smaller and transient impact, with the effect disappearing after one month.

We also find that while health shocks generally have a positive effect on health expenditures, the scale of impact affects different types of health expenditures differently (Tables OA.1 and OA.2 in the online supplementary materials). Individuals who have experienced a major health shock are more likely to have positive expenditures and have higher levels of spending for hospital services, as well prescription medications, compared with those with minor health shocks.

We included forward time variables to assess if health expenditures increase before shocks occur as an empirical test of the assumption that health shocks are not anticipatory in nature. These results are found at the top of Table 3. The coefficient estimates on these forward variables are not statistically significant for the major conditions we study, that is cancer, heart disease and stroke. For minor conditions, the coefficients of the temporal effects one month before onset is statistically significant. These results provide support that the major health shocks that we analyse are largely unanticipated, but not for minor shocks.

5.2 Health Shocks and Incremental Expenditures

We now turn to calculating the actual incremental spending on health that results from a health shock. We use the coefficient estimates from separate fixed effects models for each major condition, Heart, Cancer and Stroke, and for all minor conditions together. We transform log expenditures using the Duan smearing estimator (Duan 1983). Our estimates are interpreted as the average incremental effects of a shock on monthly health expenditures for each time period t_{-2} to t_0, and subsequently t_1, to t_{12}.

The incremental effect estimates are shown in Table 4, and summarised graphically in Figure 2. Total expenditure on health is highest for households where the respondent household member has cancer, followed by stroke and heart diseases. Across all conditions, health expenditures are generally highest in the first two months of illness. For example, for cancer sufferers, households spent \$1,226 and \$1,095, compared with \$602 and \$115 for stroke sufferers, and \$377 and \$227 for those with heart diseases. Cumulative household spending on health, over a 12 month duration from illness onset, is \$3,546 (US\$2555; €2283) for those with cancer, \$1,203 (US\$867; €775) for heart patients, and \$1,197 (US\$863; €771) for stroke patients.[6] Total health spending over 12 months for respondents diagnosed with any minor conditions (e.g. hypertension, arthritis) is considerably lower, at $130 (US$94; €84).

5.3 Health Expenditures and Private Health Insurance

We investigate how the availability of private health insurance influences households' total health expenditures in response to a health shock. We define that an individual has private health insurance if he or she is reported as having an Integrated Shield Plan or wholly private insurance, as described in Section 2. To mitigate potential biases arising from reverse causation, where for instance individuals take up private health insurance after experiencing a health shock, we use individuals' reported private health insurance status at baseline, and fix this over the entire sample period. Of course, this approach will not preclude other possible endogeneity issues arising from omitted variables such as individuals' underlying health conditions – individuals with worse health conditions are more likely to acquire more severe health shocks (associated with higher spending) and, at the same time, are more likely to be better insured. In the presence of such adverse selection, we may observe that private insured individuals spend more in response to a universally defined health shock.

The estimated incremental effect on households' total health expenditure in response to a major shock are shown in Figure 3; the corresponding parameter estimates are shown in Table OA.3. Overall, household spending on health is higher for individuals with private health insurance coverage, compared with those with only MediShield Life, the publicly provided catastrophic health insurance. This difference is most pronounced for those with cancer, where privately insured households spent $1,420 and $1,240 in the first two months of illness compared with those without private coverage ($659 and $663).

For privately insured households, the cumulative household spending on health, over a 12 month duration from illness onset, is $3,368 for those with cancer, $1,358 for heart patients, and $1945 for stroke patients. Cumulative spending is lower for household without private coverage, and are $2,749, $892 and $1,271 for cancer, heart and stroke sufferers respectively. That expenditure on health is higher for households with private health insurance is consistent with the function of private health insurance in Singapore – this covers health care services

[6] Cumulative household spending over a 12 month duration is calculated by adding the estimates of the incremental effects for each month t_0 to t_{12} that are statistically significant from zero. Statistical significance is based on the estimated standard errors of the set of binary shock variables $\boldsymbol{S_{iht}}$, from regression models that are estimated using linear fixed effects estimation.

from private hospitals and medical practitioners, and hospital services in public hospitals offering better amenities, both at a higher price.

5.4 Robustness Checks

Our empirical strategy hinges on the assumption that the health shocks we study are unanticipated. By including binary variables representing each of the two months prior to the onset of shocks, our test provides support that the major health shocks we study are unanticipated. To examine if there exists an anticipation effect for a longer duration of time prior to an onset of a shock, we estimate an alternative specification that includes 12 lead binary variables. To preserve degrees of freedom, we include only two post-shock binary variables to capture post-shock effects. The estimated coefficients are shown in Figures OA.2 - OA.5. Consistent with our baseline results, we do not find any evidence pointing to an anticipation effect for most outcomes analysed. An exception is the case of a minor shock on total health expenditures (Figure OA.5) where we find evidence of a small anticipatory effect (at time t-2), which is also observed in our baseline results.

We perform three additional checks. First, we aggregate our illness and expenditure data over a 3-month period instead of using monthly observations and rerun the regressions where shock variables are binary indicators representing quarters rather than months. This analysis takes into account the possibility that the onset of illness may not be that frequent, and serves to mitigate possible measurement errors that might arise (e.g. inability of respondents to recall the exact timing of shocks). These results are shown in Panel A in Table A.4. The estimated magnitude of the quarterly effects, and their temporal patterns, are consistent with those obtained from our analysis on monthly data.

Second, we use the aggregated quarterly sample to create a balanced panel to assess the effect of sample attrition on our estimates.[7] The results from the balanced sample are reported in Panel B of Table A.4 and is compared with those from the unbalanced sample in Panel A of the same table. For the extensive margin of health expenditures, we observe slightly larger coefficient estimates on the quarterly binary indicators in the balanced panel compared with the unbalanced panel. For the intensive margin, the estimated coefficients from the balanced sample are slightly smaller, and the effects less temporally persistent compared with the unbalanced sample results. The differences in the magnitude of the effects from the unbalanced

[7] We create a balanced panel using the aggregated quarterly sample rather than the monthly sample because doing the latter – a balanced panel comprising of respondents who responded to all 19 waves – would leave us with too few cases.

and balanced samples are small and indicate that potential biases from sample attrition is likely to be minimal.[8]

Third, we address potential biases that may occur if the onset of one type of health shock follows another. In the observation period, less than 3% of the respondents had reported suffering from both major and minor shocks in the observation period. To eliminate sequential effects, we restrict our sample to respondents who experienced only one type of shocks and re-run the analysis. The results are reported in Table A.5. The estimated magnitude of the effects, and the temporal patterns are very similar to our baseline results.

5.5 Health Shocks and Household Income

We estimate the expenditure regressions in Equation (2), where the outcome variable is the logarithm of household income, to examine how health shocks affect the amount of income households generate from work. Our regression estimates are presented in Table 5. We find that a major health shock leads to large and statistically significant reductions in household income when male household members fell ill. More specifically, for males, household income decreases by between 18% to 23% and these reduction occurs from 5 to 11 months after the onset of major illness. The effects for minor illnesses, and for when female household members fell ill, are not statistically significant from zero.

The effects on household income of major shocks, cancer, heart and stroke, are presented in Table OA.4. These estimates show that the reduction in household income is especially pronounced for males with stroke and cancer. Separating the analyses by major conditions, we observe that household income increases in the second and third months following the onset of cancer and stroke for females (Table OA.4).

5.6 The Effects of Health Shocks on Non-Health Expenditures.

What impact do health shocks have on households' non-health expenditures and its dynamics? To investigate this, we estimate the expenditure regressions in Equations (1) and (2) on a households' *total* non-health spending, and spending across 8 broad non-health categories: housing, utilities, food, transport, domestic services, leisure, home repairs and tobacco. The

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[8] A comprehensive investigation on the nature and consequence of attrition is beyond the scope of this paper. The consensus among studies that have examined this issue is that attrition does not lead to serious biases in the economic sense, even in the presence of statistical evidence of attrition bias, and large sample attrition. See Cheng and Trivedi (2015) and the references therein.

expenditure items within each spending category is detailed in Table A.3. We focus our discussion on major health shocks – cancer and heart– which we find to have the largest effects.[9]

Our main results are shown in Table 6 and summarised in Figure 4. Individuals with cancer reported a largest reduction in total non-health expenditure, from 14% to 29%. For these individuals, the drop in non-health spending persist for up to 5 months after onset, with spending levels reverting their pre-illness levels thereafter. The drop in non-health expenditure for individuals with a new heart diagnosis is small (~8%) in comparison to those with cancer. The results also indicate a significant drop in non-health spending for individuals with an onset of stroke.

What accounts for the drop in non-health spending among individuals with cancer and heart conditions? As shown in Figure 5a, for cancer sufferers, much of the reduction in non-health spending is driven by a decrease in spending on leisure. More specifically, the probability of reporting positive expenditure on leisure decreases by 6% to 16%, with the lower spending persisting for up to 11 months after onset (Table OA.5). By comparison, leisure spending by individuals with new heart conditions remain largely unchanged, and even increased slightly.

Individuals with a new cancer diagnosis also reported significant reductions in spending on tobacco which occur from the time of illness onset; lower spending levels persist for a number of months before increasing significantly (Figure 5b, Table OA.6). Our results also show that cancer suffers report large reductions in spending on home repairs (Tables OA.5, OA.6). Those with a new heart condition are more likely to increase spending on food (eating at home), and some reduction in transport spending (Tables OA.7, OA.8). Overall we find that health shocks affect household discretionary spending (e.g. leisure, home repairs) much more than they do on non-discretionary spending such as utilities and food.

6. Changes in Medical Savings and Cash Balances

How does the incidence of health shocks affect individuals' medical savings account and cash balances? As we discussed in Section 2, the funds for health expenditures can come from respondents' Medisave account or cash, or that of their spouses. The Medisave account is restricted in what it can pay and is principally used for hospital stays. If the respondent is

[9] For completeness, the results for stroke are shown in Tables OA.9 and OA.10. These are not discussed due to small sample sizes.

insured, this reduces their payment and also allows them to use a higher class of hospital ward. In Wave 6 and Wave 18 of the SLP survey, respondents were asked to provide information on their household asset balances. This included the amount of money they had in their Medisave accounts and the balances in their cash and checking account.

Table 7 shows the average change in Medisave balances and cash balances of respondents between Wave 6 and Wave 18. We compare respondents who had a major or minor shock between Wave 6 and 18, with those who had no shock. We further separate out those who were insured in the baseline with Integrated Plan and/or private insurance with those who did not. We restrict attention to those who answered at least 6 waves between wave 6 and 18.

Looking first at the impact of shocks on Medisave balances and cash balances, we observe that Medisave balances rose for all respondents, with and without shocks. However, major shocks are associated with a smaller increase in Medisave balances although the difference is not very large. Those experiencing no shock experienced an increase in their Medisave balances worth $243 more than those who experienced a major shock.

In the case of cash-balances, the impact of shocks seem more dramatic. Those who experienced a major shock depleted their cash by $8,119 compared to an increase of $3,425 of those who had no shock. When we disaggregate those who suffered major shocks into those who have private health insurance and those who do not, we see that a lot of the impact of major shocks on Medisave balances occur to those who are not insured, while the impact is on cash balances among those who were insured.

A reason for the larger effect of insurance on cash balances could be because individuals who use higher class wards cannot draw on their Medisave balances for much of the cost due to withdrawal limits. This means that when insured people use higher class wards, they are required to make higher out of pocket payments, leaving their cash-balances depleted as a consequence.

7. Conclusions

This paper shows that while the dynamics of spending anything on health care is similar between a major and minor shock, the real difference lies in the amount of resources that is spent and the duration that spending lasts. Major shocks have large and persistent effects while minor shocks have small and mainly contemporaneous effects.

There is even considerable heterogeneity between the major diseases. The incremental spending in the 12 months following a cancer diagnosis is almost three times that following a heart diagnosis or stroke. To put the average 12-month incremental cancer spending of $3,546 into perspective, the median annual household income of those who experienced a cancer shock (as reported in wave 6) was $18,250 and the 75th percentile was $65,100. This suggests that the mean incremental costs of cancer in the first year following diagnosis is almost 20% of the median income. The documented level and volatility of spending induced by a health shock is crucial in determining the welfare of risk-averse individuals.

We find that insured respondents spend more following a major shock than do non-insured. This is most striking for cancer but also exists for heart and stroke. Overall, insured households report roughly 20-50 percent higher incremental spending in the 12 months following the onset of the disease compared with uninsured patients. These findings might suggest that insured individuals tend to seek more expensive medical care following the shock. Another plausible explanation is that there exists adverse selection in Singapore's private health insurance market where individuals more likely to acquire severe health shocks tend to be better insured.

We find that household income reduces following the onset of a major shock for male respondents only, but not for females. This may be because males are likely to be more attached to the labour force compared with females. Of respondents age 50 to 65 at the time of the baseline survey, males are more likely to report working for pay compared with females (63% versus 51%), and are also less likely to be working less than 35 hours per week (7% versus 23%).

We also find that non-health expenditure drops following a major shock with respondents with cancer reported a largest reduction in total non-health expenditure, from 14% to 29% driven largely by reduction in leisure spending. We also find considerably heterogeneity in the way that specific spending categories change with response to the health shock. For example, while a cancer shock leads to large and persistent reductions in leisure spending, heart disease does not exhibit this pattern and even shows some evidence of increased spending in some periods following the shock. This indicates that leisure consumption is complementary to some types of health and not others. Similarly, spending on smoking falls for some time after a cancer or heart shock, but jumps back after a year (with spending being even higher than prior to onset).

Our findings of the heterogeneity of health shock impacts on different non-health spending categories are interesting because they suggest that health shocks do affect marginal utility of consumption. This calls into question the standard assumptions that are used in modelling health shocks where the marginal rates of substitution between non-health consumption is assumed not to be affected by a health shock (Finkestein et al 2013). Our results suggest that not only do people allocate more of their budget toward health when they face a shock, they also redistribute their non-health spending categories. Additionally, this reallocation (reflecting changes in preferences) depends on the nature of the shock.

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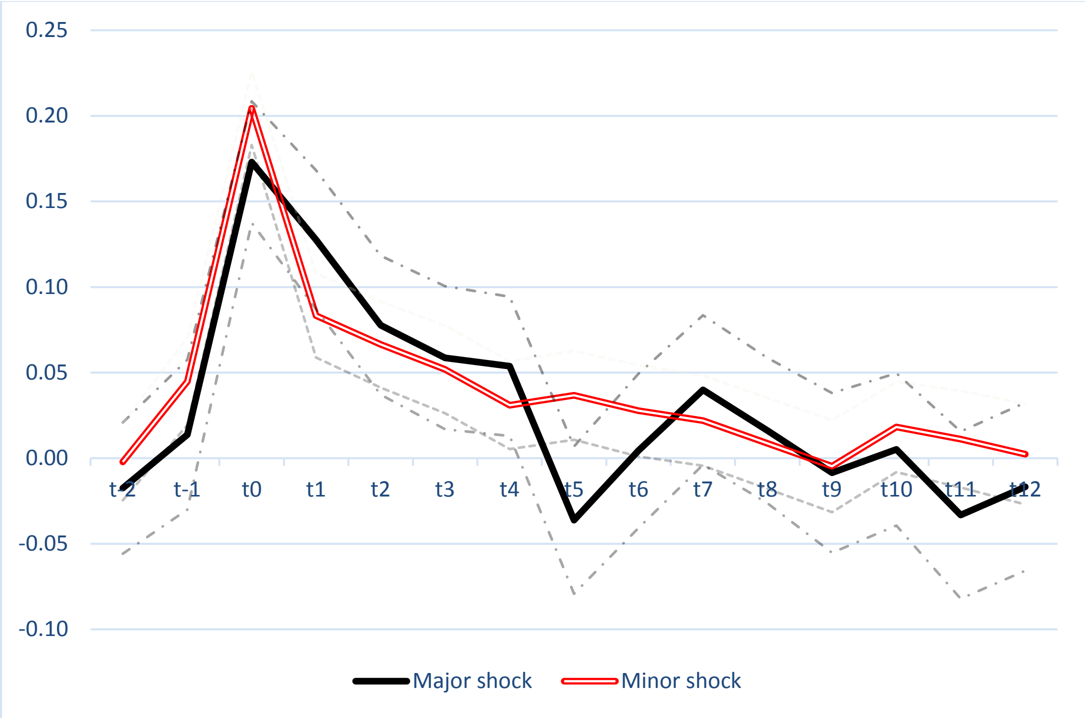

Figure 1: Effects of major and minor health shocks on whether report positive total health expenditure (top), and the logarithm of expenditures (bottom).

Notes: Dash and dotted lines show 95% confidence intervals.

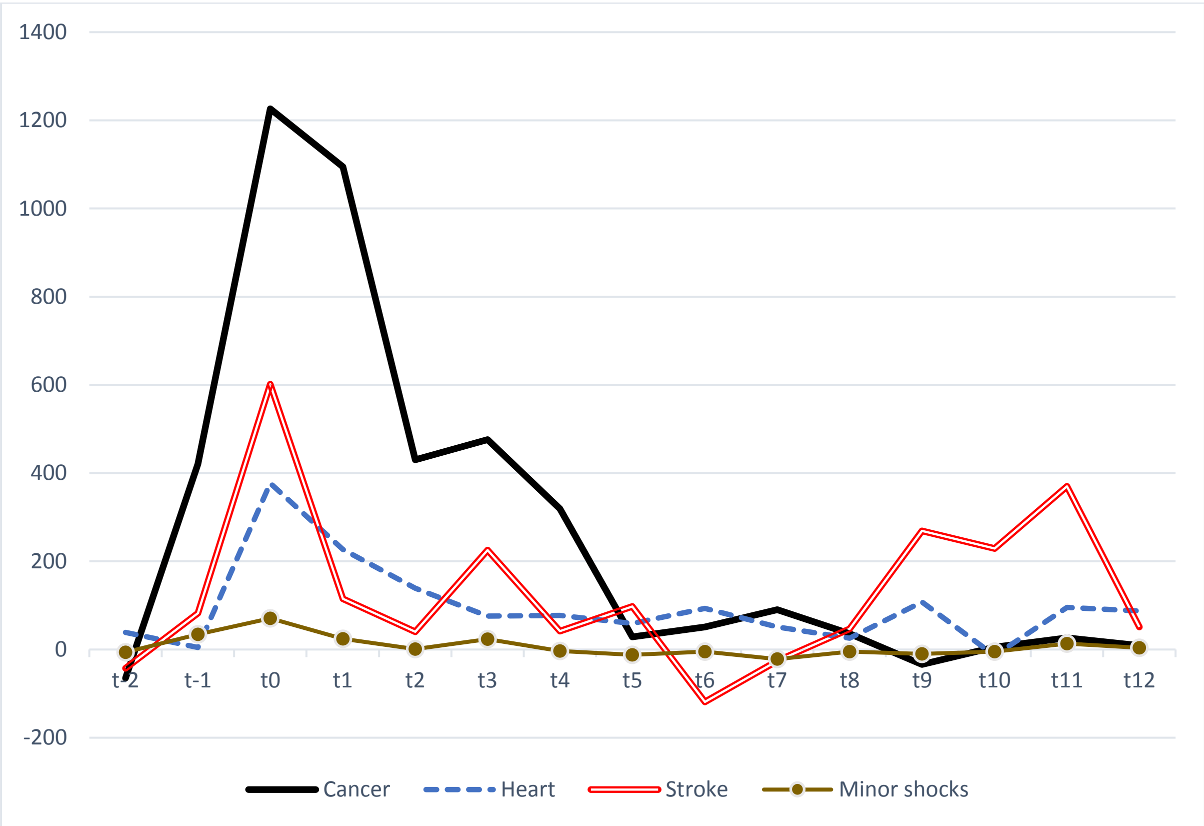

Figure 2: Incremental effects of health shocks on total expenditure for health care by conditions.

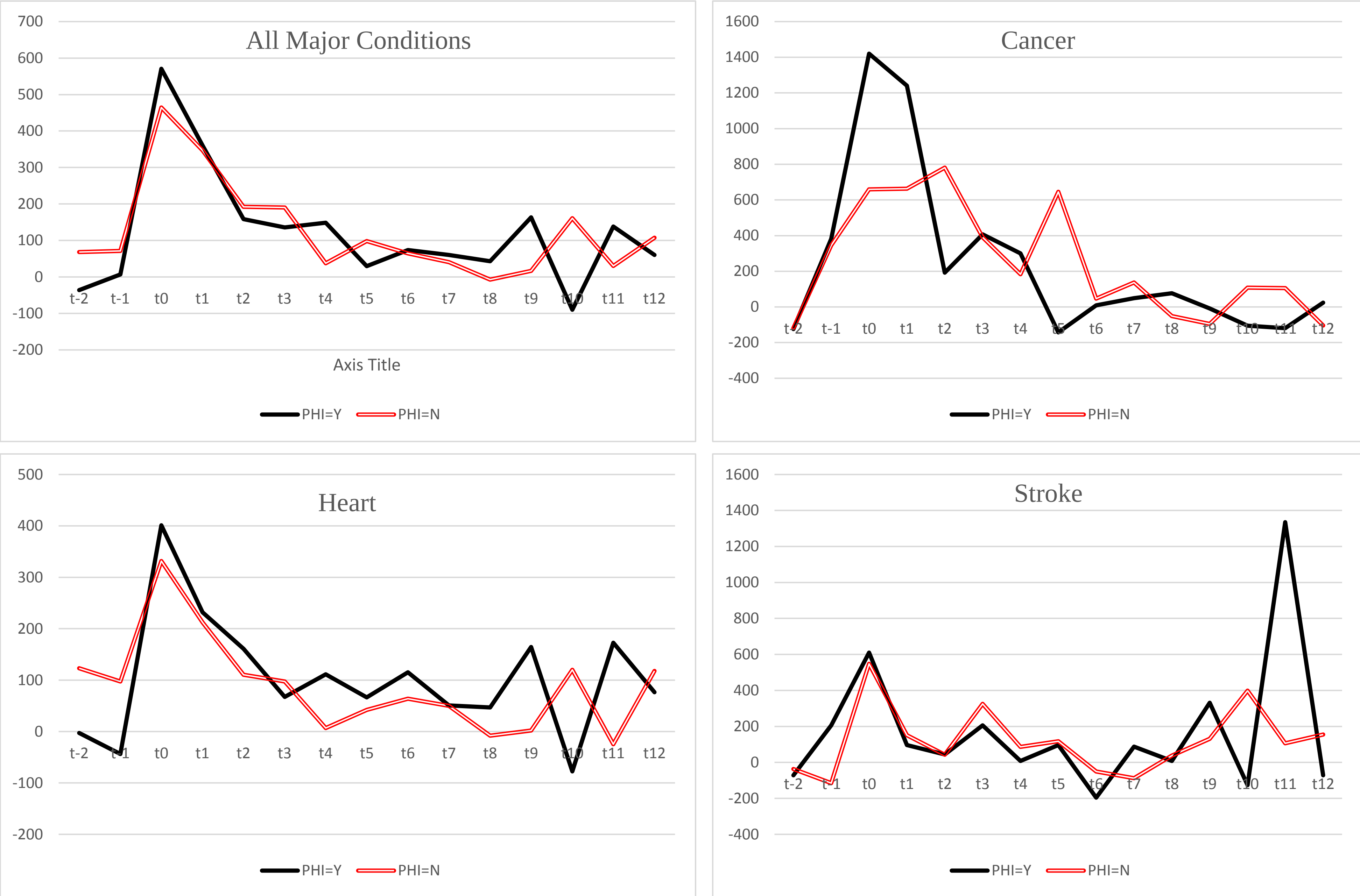

Figure 3: Incremental effects of health shocks on total expenditure for health care by conditions and private health insurance (PHI) status.

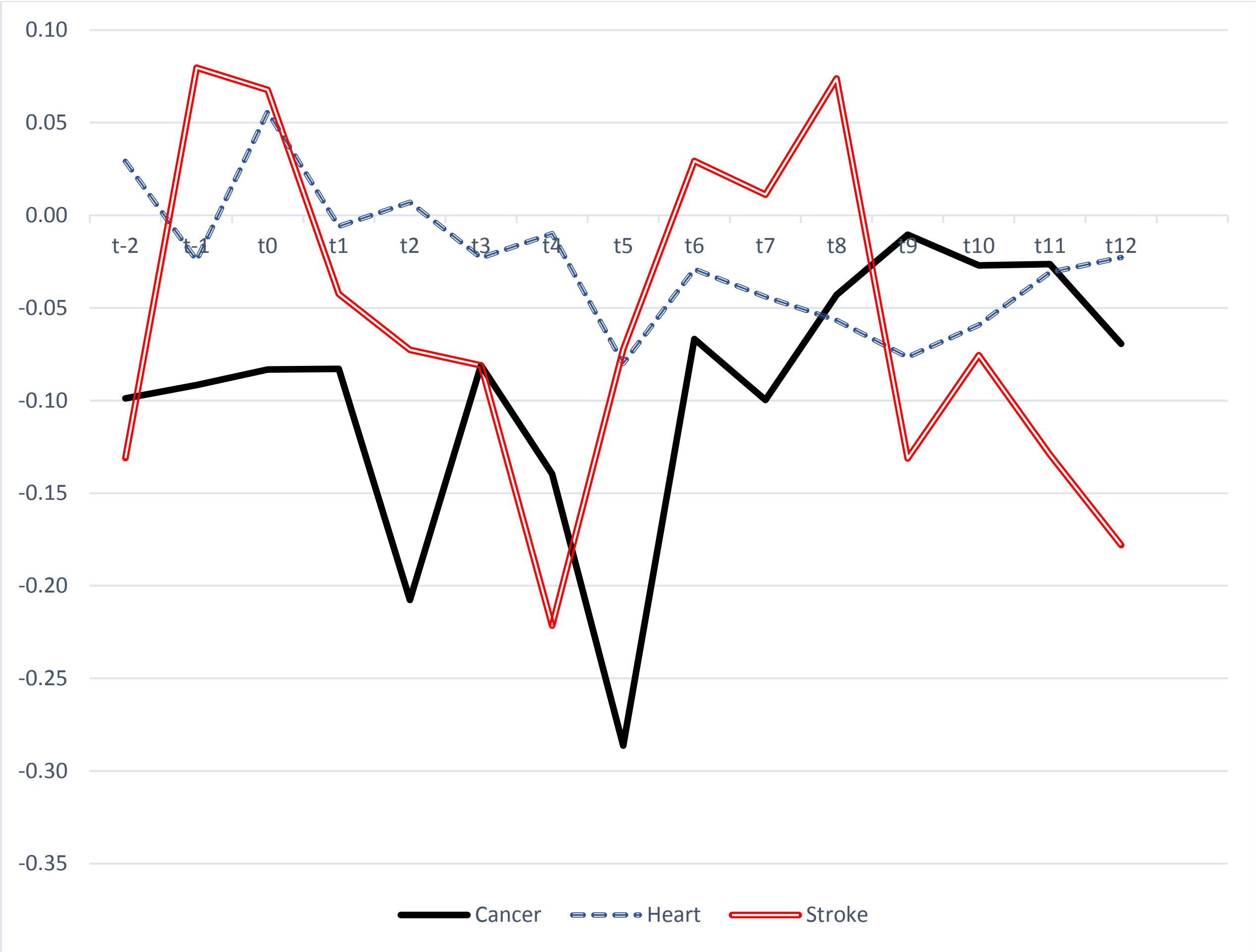

Figure 4: Effects of major health shocks on the logarithm of total non-health expenditures, by conditions.

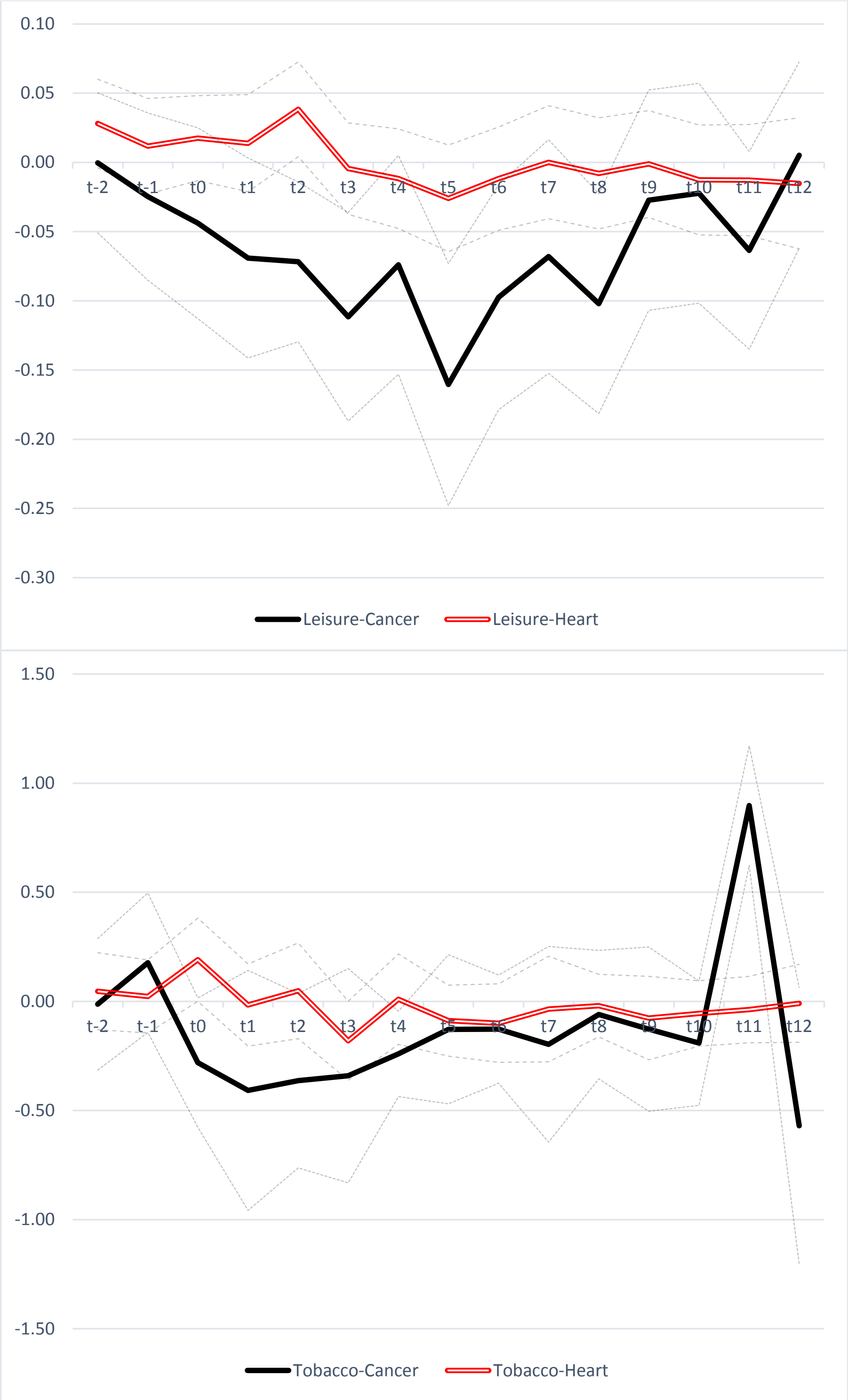

Figure 5. Effects of having cancer and heart conditions on (a) the probability of positive spending on leisure (top); and (b) the logarithm of spending on tobacco (bottom).

Table 1: Diagnosis (baseline and new diagnosis)

	Preprevalence		Conditional incidence		Postprevalence	
Types Chronic Conditions	# of cases in baseline	% of cases in baseline	# of new acquirers between baseline and Wave 19	% of new acquirers out of non-acquirers in baseline	# of cases after Wave 19	% of cases after Wave 19
Hypertension	3,320	28.8%	895	10.9%	4,215	36.5%
Diabetes	1,667	14.4%	414	4.2%	2,081	18.0%
Arthritis	1,193	8.1%	819	7.7%	1,750	15.2%
Psychiatric	131	1.1%	184	1.6%	315	2.7%
Heart Disease	805	7.0%	480	4.5%	1,285	11.1%
Cancer	372	3.2%	149	1.3%	521	4.5%
Stroke	168	1.5%	94	0.8%	262	2.3%

Table 2: Monthly household health expenditure by type of health care service

	Full Sample			Major Conditions			Minor Conditions		
Panel A: $ of Expenditure									
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Total health spending	153.2	667.9	133916	305.6	1202.7	9220	197.5	731.7	26335
Hospital services	43.2	447.7	132988	112.5	752.9	9136	56.1	475.2	26160
Outpatient services	40.0	120.2	133041	62.2	152.6	9141	48.7	121.9	26194
Prescription medications	35.8	97.9	133006	62.8	136.2	9136	51.2	115.6	26186
Other medications	21.2	63.6	133002	31.4	77.9	9138	27.2	68.7	26183
Home nursing	3.1	64.1	132958	5.0	73.2	9220	3.3	59.3	26147
Panel B: % with Non-zero Expenditure									
	Full Sample			Major Conditions			Minor Conditions		
Total health spending	48.0%			61.4%			59.8%		
Hospital services	5.1%			12.7%			7.7%		
Outpatient services	27.2%			37.5%			35.1%		
Prescription medications	27.0%			39.5%			37.1%		
Other medications	20.1%			27.9%			26.6%		
Home nursing	0.7%			1.4%			1.1%		
Panel C: $ of Expenditure Conditional on Non-zero Expenditure									
	Full Sample			Major Conditions			Minor Conditions		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Total health spending	319.4	936.4	64239	497.7	1503.5	5661	330.5	923.1	15737
Hospital services	854.3	1809.7	6719	964.9	2011.0	1065	733.6	1567.5	2000
Outpatient services	147.4	193.2	36139	165.7	211.9	3431	137.3	173.5	9190
Prescription medications	132.4	150.6	35924	159.0	177.9	3609	138.1	155.1	9713
Other medications	102.3	105.8	27623	112.6	112.5	2545	102.1	100.5	6967
Home nursing	421.6	622.0	970	352.7	509.3	129	302.4	486.4	287

Notes: The sample for the "Full sample" category refers to all respondents to the survey. Samples for "Major Conditions" and "Minor Conditions" refer to respondents who have had a new diagnosis of a chronic condition over the sample period for major and minor conditions which they did not have at baseline.

Table 3. Coefficient estimates of the effects of health shocks on the probability of reporting positive health expenditures and the logarithm of health expenditures

Variables	Probability of Positive Expenditure		Log Total Health Expenditure	
	Major Shock	Minor Shock	Major Shock	Minor Shock
	(1)	(2)	(3)	(4)
Period t_{-2}	-0.017	-0.002	0.009	-0.018
	(-0.89)	(-0.18)	(0.10)	(-0.40)
Period t_{-1}	0.014	0.045***	0.071	0.098**
	(0.62)	(3.44)	(0.91)	(2.22)
Period t_0	0.173***	0.204***	0.793***	0.195***
	(9.58)	(18.70)	(11.01)	(5.72)
Period t_1	0.128***	0.083***	0.574***	0.071*
	(6.18)	(6.65)	(7.44)	(1.84)
Period t_2	0.078***	0.066***	0.298***	0.003
	(3.75)	(5.17)	(3.98)	(0.06)
Period t_3	0.059***	0.052***	0.284***	0.068
	(2.75)	(3.97)	(3.68)	(1.63)
Period t_4	0.054***	0.031**	0.212***	-0.010
	(2.59)	(2.36)	(2.97)	(-0.22)
Period t_5	-0.036*	0.037***	0.108	-0.036
	(-1.65)	(2.78)	(1.36)	(-0.79)
Period t_6	0.004	0.028**	0.136*	-0.014
	(0.19)	(2.04)	(1.68)	(-0.33)
Period t_7	0.040*	0.022	0.106	-0.067
	(1.79)	(1.63)	(1.35)	(-1.45)
Period t_8	0.016	0.009	0.047	-0.014
	(0.75)	(0.64)	(0.57)	(-0.28)
Period t_9	-0.009	-0.005	0.210**	-0.030
	(-0.36)	(-0.34)	(2.24)	(-0.59)
Period t_{10}	0.005	0.018	-0.003	-0.015
	(0.23)	(1.36)	(-0.03)	(-0.32)
Period t_{11}	-0.033	0.011	0.187**	0.038
	(-1.33)	(0.78)	(2.15)	(0.81)
Period t_{12-max}	-0.017	0.002	0.143*	0.012
	(-0.67)	(0.16)	(1.85)	(0.23)
Constant	0.014	0.010	5.070***	4.916***
	(1.12)	(1.34)	(24.26)	(113.26)
N	678	1,969	638	1,853
*N*x*T*	10,029	28,673	5,661	15,737

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using ordinary least squares with individual fixed effects. The estimates show the effect on health expenditures for each time period t_{-2} to t_{12} prior to or after the shock. Model specification includes 18 wave dummies, whose coefficients are not shown above. Estimates in columns (1) and (2) denote the change in the probability of positive health care expenditures; estimates in columns (3) and (4) denote the estimates on the logarithm of total health expenditures.

Table 4. Conditional incremental effects of health shocks on total health expenditures (dollars)

Variables	Heart	Cancer	Stroke	Minor Shock
	(1)	(2)	(3)	(4)
Period t_{-2}	39.01	-64.86	-42.60	-6.08
Period t_{-1}	4.56	420.60***	82.46	34.46**
Period t_0	377.10***	1,226.23***	601.53***	70.76***
Period t_1	227.13***	1,094.62***	115.28	24.40*
Period t_2	138.98*	430.51**	39.91	0.83
Period t_3	76.18**	476.11**	225.29*	23.62
Period t_4	77.16	318.76**	41.76	-3.24
Period t_5	58.98	28.82	97.36	-11.84
Period t_6	93.40**	51.01	-118.78	-4.71
Period t_7	51.16	90.36	-25.80	-21.80
Period t_8	25.54	36.00	46.68	-4.62
Period t_9	107.46**	-33.83	269.27	-9.78
Period t_{10}	-13.70	5.67	228.81	-4.89
Period t_{11}	95.58**	26.20	370.12*	13.05
Period t_{12-max}	87.13**	8.70	51.08	3.93

Notes: *** p<0.01, ** p<0.05, * p<0.1. Reported statistical significance is based on the estimated standard errors of the set of binary shock variables $\boldsymbol{S_{iht}}$, from regression models that are estimated using linear fixed effects estimation. Standard errors are clustered at the level of the household. Incremental effects are interpreted as the average change in total health expenditures from a 0 to 1 in the health shock explanatory variable $\boldsymbol{S_{ijt}}$ for each time period t_{-2} to t_{12}. Predictions of log expenditures are transformed into level expenditures using the Duan smearing estimator.

Table 5. Health shocks on the logarithm of total household income from work, by gender of respondent

	Major		Minor	
	Male	Female	Male	Female
Period t_{-2}	-0.054	-0.042	-0.081	0.030
	(-0.56)	(-0.30)	(-1.23)	(0.38)
Period t_{-1}	-0.021	0.033	-0.193**	0.035
	(-0.22)	(0.33)	(-2.45)	(0.62)
Period t_0	-0.083	-0.013	0.051	0.027
	(-0.84)	(-0.16)	(0.76)	(0.50)
Period t_1	-0.090	-0.099	-0.018	0.011
	(-1.20)	(-0.89)	(-0.30)	(0.18)
Period t_2	-0.040	-0.067	-0.004	-0.008
	(-0.43)	(-0.70)	(-0.06)	(-0.13)
Period t_3	-0.130	0.120	-0.048	0.040
	(-1.20)	(1.35)	(-0.72)	(0.56)
Period t_4	-0.039	-0.040	-0.075	0.005
	(-0.38)	(-0.37)	(-1.42)	(0.09)
Period t_5	-0.175*	-0.101	-0.014	0.062
	(-1.75)	(-0.91)	(-0.20)	(1.07)
Period t_6	-0.096	-0.014	-0.036	0.018
	(-0.95)	(-0.18)	(-0.58)	(0.36)
Period t_7	-0.113	-0.095	0.024	-0.020
	(-1.18)	(-1.02)	(0.46)	(-0.34)
Period t_8	-0.229***	-0.156	0.006	-0.050
	(-2.62)	(-1.55)	(0.09)	(-0.95)
Period t_9	-0.189*	0.057	0.032	0.060
	(-1.72)	(0.46)	(0.52)	(1.04)
Period t_{10}	-0.197*	-0.101	-0.070	-0.072
	(-1.74)	(-0.97)	(-1.09)	(-1.39)
Period t_{11}	-0.185	-0.175	0.070	-0.008
	(-1.63)	(-1.17)	(1.00)	(-0.15)
Period t_{12-max}	-0.079	-0.016	-0.093**	-0.018
	(-0.72)	(-0.18)	(-1.97)	(-0.32)
Constant	7.291***	6.958***	7.204***	7.033***
	(70.92)	(52.44)	(98.87)	(94.00)
N	216	196	507	596
*N*x*T*	1,572	1,347	3,256	3,867

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using linear fixed effects estimation on the logarithm of total household income from work for each time period t_{-2} to t_{12} prior to or after the shock.

Table 6. Coefficient estimates of the effects of health shocks on the logarithm of total non-health expenditures

	Cancer	Heart	Stroke
	(1)	(2)	(3)
Period t_{-2}	-0.100	0.029	-0.131
	(-1.43)	(0.82)	(-1.13)
Period t_{-1}	-0.092	-0.024	0.080
	(-1.38)	(-0.67)	(0.80)
Period t_0	-0.083	0.056	0.068
	(-1.31)	(1.61)	(0.81)
Period t_1	-0.083	-0.006	-0.043
	(-1.36)	(-0.18)	(-0.46)
Period t_2	-0.208***	0.007	-0.073
	(-3.41)	(0.20)	(-0.77)
Period t_3	-0.081	-0.023	-0.081
	(-1.19)	(-0.64)	(-0.74)
Period t_4	-0.140**	-0.010	-0.222**
	(-2.00)	(-0.24)	(-2.19)
Period t_5	-0.286***	-0.080**	-0.072
	(-3.91)	(-2.14)	(-0.70)
Period t_6	-0.067	-0.029	0.029
	(-1.17)	(-0.75)	(0.32)
Period t_7	-0.100	-0.044	0.011
	(-1.51)	(-1.11)	(0.11)
Period t_8	-0.043	-0.057	0.074
	(-0.62)	(-1.30)	(0.63)
Period t_9	-0.011	-0.077**	-0.131
	(-0.13)	(-1.98)	(-0.99)
Period t_{10}	-0.027	-0.059	-0.076
	(-0.41)	(-1.47)	(-0.76)
Period t_{11}	-0.026	-0.031	-0.129
	(-0.38)	(-0.71)	(-1.00)
Period t_{12-max}	-0.069	-0.023	-0.178
	(-0.84)	(-0.50)	(-1.52)
Constant	7.779***	7.937***	7.572***
	(93.31)	(83.49)	(76.91)
N	146	477	93
*N*x*T*	1,961	6,385	1,247

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on the logarithm of non-health expenditures in a given month. Total non-health expenditures are calculated as a sum of expenditure across spending categories such as housing cost, food, utilities, transport, domestic, home repairs, tobacco and leisure. Estimates denote the change in the logarithm of total health expenditures in month in t_0 which the shock occurs, and $t \pm m$ for *m* months prior to or after the shock.

Table 7. Changes in Medisave and cash balances

	Medisave		Cash	
	Balances in Wave 6 (Median)	Average Change in Balances (w18-w6)	Balances in Wave 6 (Median)	Average Change in Balances (w18-w6)
No shock (n=5905)	$20,000	$1,488	$ 45,969	$3,425
Minor Shock (n=669)	$10,000	$1,335	$45,000	$4,332
Major Shock (n=252)	$12,000	$1,245	$44,877	$-8,119
Major Shock and Uninsured (n=86)	$ 5,000	$-869	$38,873	$-5,356
Major Shock and Insured (n=166)	$20,000	$2,340	$48,000	$-9,551

APPENDIX

Table A.1: Sample size and waves (Respondents aged 50-70 and corresponding households)

Wave	Respondents	Households
0	11,536	8,725
1	873	620
2	7,317	5,449
3	7,205	5,342
4	7,462	5,481
5	7,878	5,781
6	8,680	6,476
7	7,253	5,310
8	7,265	5,287
9	7,526	5,506
10	7,482	5,457
11	7,531	5,499
12	7,790	5,703
13	7,457	5,431
14	7,435	5,415
15	7,486	5,440
16	7,196	5,205
17	7,608	5,523
18	7,782	5,689
19	7,400	5,385

Notes: Wave 0 is the baseline survey which was in the field from May to July 2015. Wave 1 is a pilot survey where only 1,000 panel members were invited to participate.

Table A.2: Health Spending Categories

	Exemplars/details offered to respondents in the SLP Survey
Hospital Services	Out-of-pocket cost and costs paid from Medisave for hospital and nursing home care
Outpatient Services	Out-of-pocket cost and costs paid from Medisave of visits to doctors, traditional physicians (e.g. traditional Chinese physicians), physiotherapists, and psychologists; eye care and dental service fees; lab tests.
Prescription Medications	Prescription medications: out-of-pocket cost and anything paid from Medisave for prescription
Other Medications	out-of-pocket cost and anything paid from Medisave for traditional medicines (e.g. Chinese medicine, Ayurvedic, etc.), over-the-counter medications, other medical products (e.g. wheelchair,| crutches) and therapeutic equipment
Home Nursing	Home nursing: hiring costs of a helper due to health problems (do not include domestic services by a maid here)
Health Insurance	None.

Table A.3: Non-health Spending Categories

Broad Category	Expenditure categories
Housing	Mortgage; Property tax, Home and content insurance; Rent.
Utilities	Utilities and other fuels; Communication
Food	Food and beverages
Transport	Road use fees; Vehicle insurance; Petrol; Vehicle Repair and maintenance; Public transport
Domestic Services	Domestic and housekeeping
Leisure	Dining and/or drinking out; Entertainment; Sports; Hobbies and leisure equipment; package tours and vacation.
Home Repairs	Home repairs and maintenance
Tobacco	Tobacco

Table A.4. Robustness check using a sample where monthly observations are aggregated over a 3-month period

Variables	Probability of Positive Expenditure		Log Total Health Expenditure	
	Major Shock	Minor Shock	Major Shock	Minor Shock
	(1)	(2)	(3)	(4)
Panel A: Unbalanced Sample				
Period $t_{\min(-9)-(-7)}$	-0.023	0.001	-0.013	-0.029
	(-1.34)	(0.10)	(-0.23)	(-0.93)
Period $t_{(-6)-(-4)}$	-0.018	0.003	0.046	-0.120**
	(-0.95)	(0.29)	(0.70)	(-2.57)
Period $t_{(-3)-(-1)}$	-0.005	0.012	0.050	-0.030
	(-0.25)	(1.15)	(0.75)	(-0.77)
Period t_{0-2}	0.124***	0.127***	0.610***	0.060*
	(7.00)	(12.13)	(9.31)	(1.72)
Period t_{3-5}	0.023	0.043***	0.241***	-0.029
	(1.28)	(3.87)	(3.64)	(-0.76)
Period t_{6-8}	0.017	0.023**	0.131*	-0.066*
	(0.96)	(2.05)	(1.92)	(-1.72)
Period t_{9-max}	0.003	0.009	0.174**	-0.007
	(0.16)	(0.79)	(2.41)	(-0.17)
Panel B: Balanced Sample				
Period $t_{\min(-9)-(-7)}$	0.017	-0.002	-0.209*	0.027
	(0.54)	(-0.14)	(-1.91)	(0.45)
Period $t_{(-6)-(-4)}$	0.010	-0.010	-0.187	-0.232**
	(0.23)	(-0.42)	(-0.97)	(-2.19)
Period $t_{(-3)-(-1)}$	0.035	0.010	-0.236	-0.095
	(0.70)	(0.37)	(-1.20)	(-0.96)
Period t_{0-2}	0.169***	0.135***	0.451**	-0.008
	(3.11)	(4.56)	(2.12)	(-0.08)
Period t_{3-5}	0.076	0.063**	0.075	-0.090
	(1.43)	(2.03)	(0.40)	(-0.91)
Period t_{6-8}	0.067	0.021	-0.052	-0.088
	(1.46)	(0.74)	(-0.32)	(-0.98)
Period t_{9-max}	0.007	0.003	0.232	-0.113
	(0.16)	(0.11)	(1.50)	(-1.30)

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using ordinary least squares with individual fixed effects. The estimates show the effect on health expenditures for each time period t_{-2} to t_{12} prior to or after the shock. Estimates in columns (1) and (2) denote the change in the probability of positive health care expenditures; estimates in columns (3) and (4) denote the estimates on the logarithm of total health expenditures.

Table A.5. Robustness check: sample of respondents with only one health shock.

Variables	Probability of Positive Expenditure		Log Total Health Expenditure	
	Major Shock	Minor Shock	Major Shock	Minor Shock
	(1)	(2)	(3)	(4)
Period t_{-2}	-0.007	0.002	-0.118	-0.023
	(-0.27)	(0.14)	(-1.03)	(-0.48)
Period t_{-1}	0.045	0.050***	0.137	0.070
	(1.57)	(3.63)	(1.30)	(1.50)
Period t_0	0.186***	0.210***	0.878***	0.200***
	(7.86)	(17.72)	(8.78)	(5.51)
Period t_1	0.148***	0.088***	0.670***	0.061
	(5.32)	(6.38)	(6.08)	(1.47)
Period t_2	0.092***	0.072***	0.340***	0.002
	(3.25)	(5.19)	(3.37)	(0.04)
Period t_3	0.070**	0.053***	0.235**	0.046
	(2.48)	(3.72)	(2.25)	(1.05)
Period t_4	0.079***	0.037***	0.191**	-0.012
	(2.85)	(2.59)	(1.97)	(-0.26)
Period t_5	-0.025	0.045***	0.120	-0.041
	(-0.85)	(3.13)	(1.06)	(-0.85)
Period t_6	0.004	0.028*	0.053	-0.038
	(0.13)	(1.85)	(0.48)	(-0.82)
Period t_7	0.038	0.024	0.025	-0.100**
	(1.24)	(1.59)	(0.24)	(-1.99)
Period t_8	0.022	0.011	-0.029	-0.046
	(0.73)	(0.76)	(-0.24)	(-0.90)
Period t_9	-0.013	-0.0004	0.164	-0.090*
	(-0.38)	(-0.02)	(1.30)	(-1.75)
Period t_{10}	0.024	0.015	0.061	-0.008
	(0.77)	(1.04)	(0.56)	(-0.17)
Period t_{11}	-0.044	0.009	0.214*	0.044
	(-1.26)	(0.55)	(1.69)	(0.85)
Period t_{12-max}	-0.046	-0.001	0.171	-0.009
	(-1.34)	(-0.05)	(1.47)	(-0.16)
Constant	0.009	0.009	4.991***	4.858***
	(0.56)	(1.07)	(20.27)	(105.32)
N	387	1,678	364	1,579
*N*x*T*	5,621	24,265	3,122	13,198

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using ordinary least squares with individual fixed effects. The estimates show the effect on health expenditures for each time period t_{-2} to t_{12} prior to or after the shock. Model specification includes 18 wave dummies, whose coefficients are not shown above. Estimates in columns (1) and (2) denote the change in the probability of positive health care expenditures; estimates in columns (3) and (4) denote the estimates on the logarithm of total health expenditures.

ONLINE APPENDICES

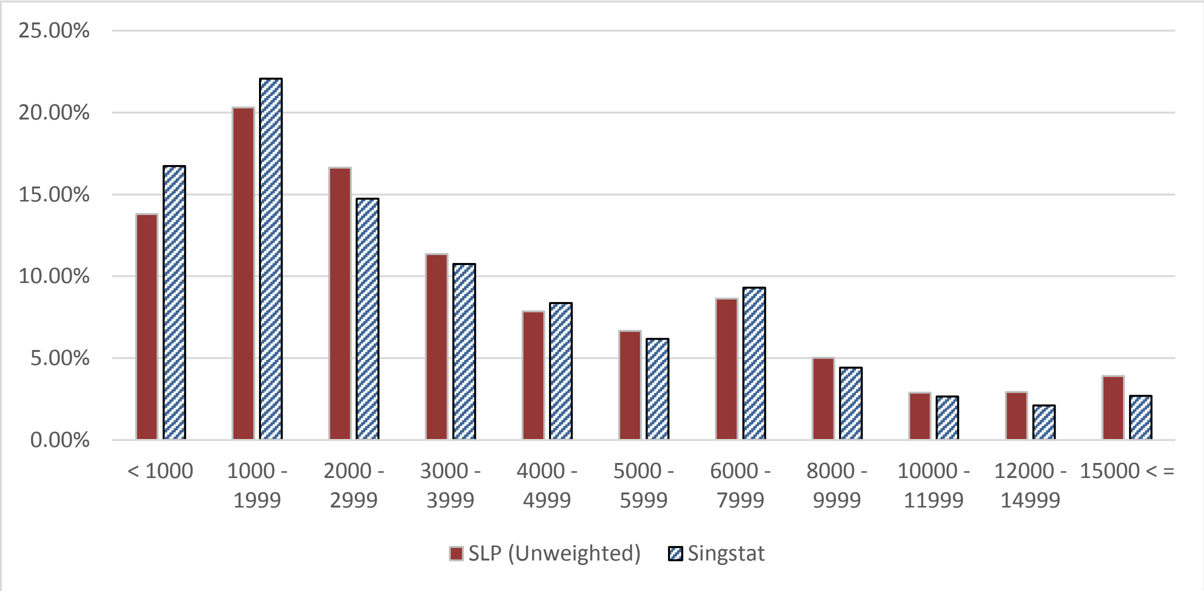

Figure OA.1: Monthly Household Expenditure Amongst Employed Residents aged 50 – 70 (: Wave 1- 4 of SLP and Singapore Household and Expenditure Survey)

Notes: Singstat data taken from the Report on the Household Expenditure Survey from 2012/13, Table 5 "Households by Monthly Household Income and Working Status/ Occupation of Main Income Earner (excluding imputed rental of owner-occupied accommodation)". Employed persons is defined as work for one hour or more either for pay, profit or family gains; or (ii) have a job or business to return to but are temporarily absent because of illness, injury, breakdown of machinery at workplace, labour management dispute or other reasons.) SLP: Employed defined as answering the question "What is your current employment situation?" with Working for pay or Self-employed. Spending variables were winsorised at the 99th percentile. Source: Vaithianathan et al. (2017).

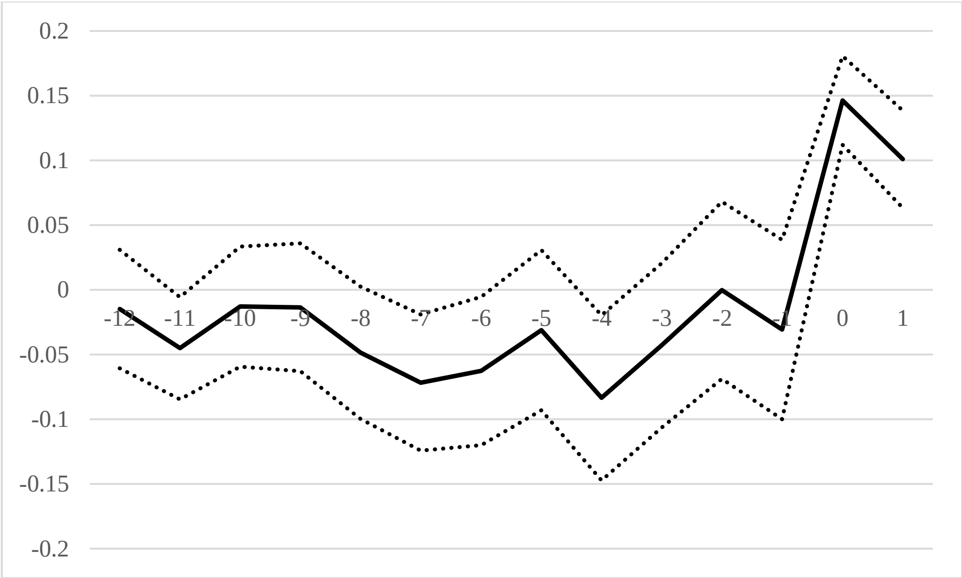

Figure OA.2: Test of pre-trends in the probability of reporting positive total health expenditure for major shocks

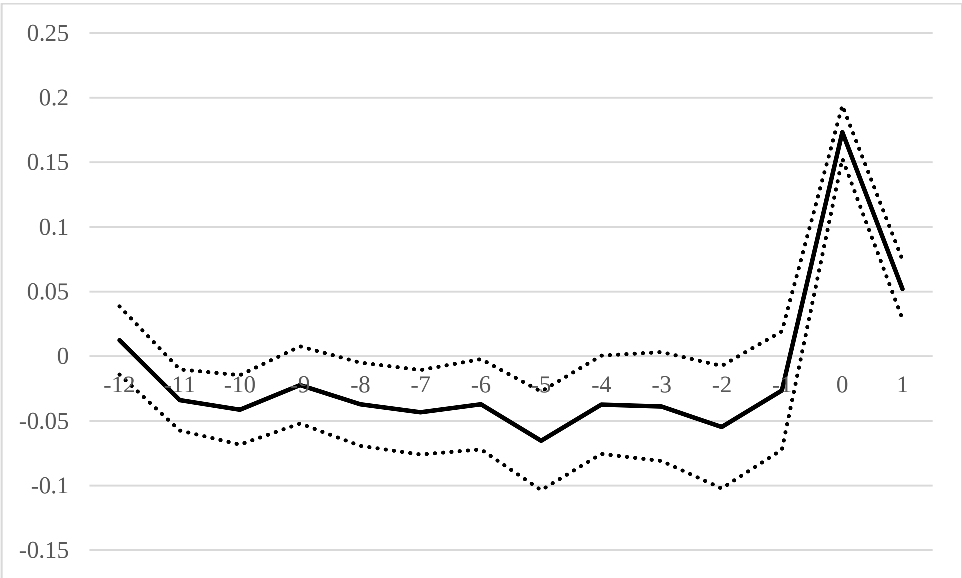

Figure OA.3: Test of pre-trends in the probability of reporting positive total health expenditure for major shocks

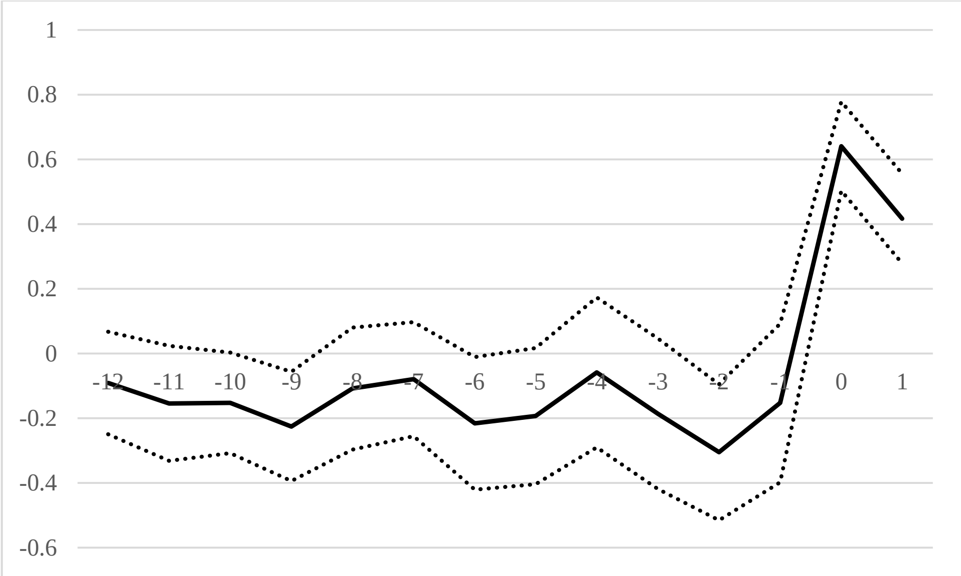

Figure OA.4: Test of pre-trends in log total health expenditure for major shocks

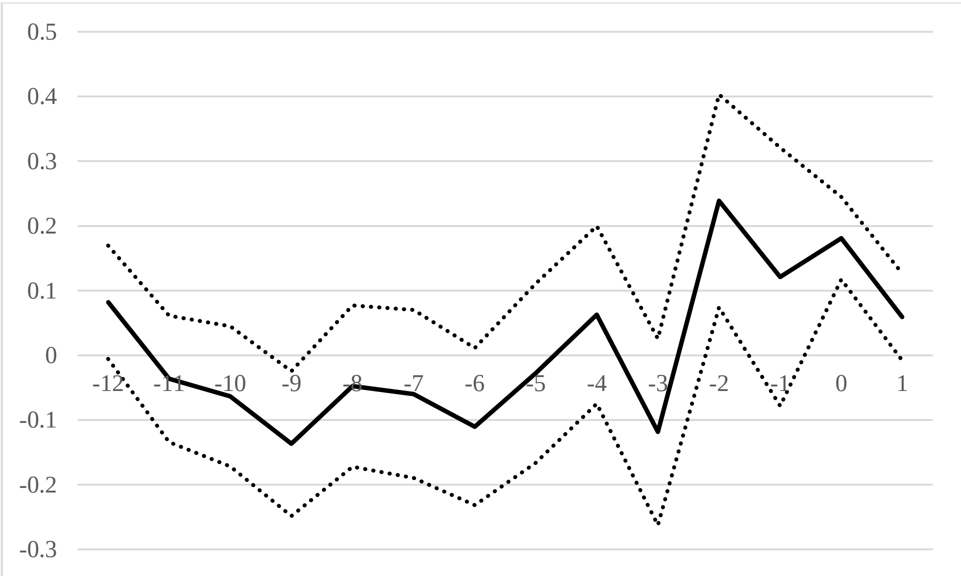

Figure OA.5: Test of pre-trends in log total health expenditure for minor shocks

Table OA.1 Coefficient estimates of the effects of health shocks on the probability of reporting positive health expenditures, by types of health care

	Major Conditions					Minor Conditions				
	Hospital	Outpatient	Prescription	Other Meds	Home Nursing	Hospital	Outpatient	Prescription	Other Meds	Home Nursing
Period t_{-2}	0.0000	0.023	-0.004	-0.012	-0.003	0.007	0.005	-0.014	0.007	0.005
	(0.00)	(1.19)	(-0.19)	(-0.70)	(-0.56)	(0.93)	(0.41)	(-1.23)	(0.64)	(1.64)
Period t_{-1}	0.038***	0.003	0.036	-0.007	-0.002	0.009	0.041***	0.006	0.018	-0.006***
	(2.59)	(0.16)	(1.54)	(-0.34)	(-0.42)	(1.13)	(3.04)	(0.50)	(1.45)	(-2.82)
Period t_0	0.200***	0.141***	0.154***	0.028	0.005	0.043***	0.160***	0.148***	0.067***	0.002
	(10.92)	(6.95)	(7.77)	(1.50)	(0.91)	(5.29)	(13.33)	(12.56)	(6.12)	(0.72)
Period t_1	0.124***	0.117***	0.073***	0.035*	0.005	0.012	0.076***	0.065***	0.028**	0.0002
	(6.39)	(5.35)	(3.40)	(1.81)	(0.85)	(1.58)	(5.94)	(5.18)	(2.33)	(0.08)
Period t_2	0.078***	0.056***	0.074***	0.032*	0.006	0.003	0.059***	0.036***	0.014	-0.002
	(4.75)	(2.67)	(3.55)	(1.71)	(1.13)	(0.34)	(4.62)	(2.86)	(1.22)	(-0.68)
Period t_3	0.051***	0.075***	0.034	-0.018	0.005	0.004	0.041***	0.027**	0.005	0.001
	(3.26)	(3.34)	(1.59)	(-0.97)	(0.80)	(0.47)	(3.17)	(2.19)	(0.43)	(0.20)
Period t_4	0.060***	0.065***	-0.003	0.005	0.001	-0.011	0.029**	0.022*	0.011	-0.002
	(3.62)	(2.89)	(-0.16)	(0.25)	(0.20)	(-1.55)	(2.30)	(1.67)	(0.95)	(-0.63)
Period t_5	0.032**	-0.012	0.001	-0.042**	-0.003	-0.004	0.039***	0.017	0.008	-0.001
	(2.05)	(-0.53)	(0.06)	(-2.33)	(-0.65)	(-0.43)	(3.05)	(1.33)	(0.65)	(-0.34)
Period t_6	0.040***	0.006	0.047**	-0.004	0.007	0.004	0.017	0.013	0.003	-0.001
	(2.62)	(0.24)	(2.12)	(-0.25)	(1.02)	(0.46)	(1.29)	(0.99)	(0.20)	(-0.28)
Period t_7	0.037**	0.017	0.060***	0.010	0.001	-0.003	0.015	0.018	0.010	0.004
	(2.24)	(0.72)	(2.61)	(0.50)	(0.19)	(-0.34)	(1.12)	(1.35)	(0.82)	(1.29)
Period t_8	0.021	0.011	0.026	-0.027	-0.003	-0.006	0.008	0.016	0.009	-0.0002
	(1.29)	(0.47)	(1.11)	(-1.35)	(-0.43)	(-0.68)	(0.59)	(1.22)	(0.74)	(-0.05)
Period t_9	-0.004	0.043*	-0.011	0.043**	0.005	-0.004	-0.009	-0.016	0.020	0.002
	(-0.22)	(1.77)	(-0.46)	(1.97)	(0.63)	(-0.45)	(-0.62)	(-1.24)	(1.61)	(0.45)
Period t_{10}	0.009	0.028	-0.011	0.044*	0.004	-0.006	0.017	0.010	0.028**	-0.001
	(0.53)	(1.20)	(-0.47)	(1.87)	(0.61)	(-0.66)	(1.17)	(0.70)	(2.09)	(-0.33)
Period t_{11}	0.021	0.029	-0.005	-0.023	0.008	-0.012	-0.007	0.002	0.017	0.002
	(1.23)	(1.04)	(-0.19)	(-1.02)	(0.95)	(-1.37)	(-0.46)	(0.16)	(1.29)	(0.54)
Period t_{12-max}	0.017	0.031	0.015	0.012	0.007	-0.003	-0.001	-0.006	0.011	0.001
	(1.07)	(1.16)	(0.62)	(0.50)	(1.00)	(-0.36)	(-0.09)	(-0.39)	(0.82)	(0.30)
Constant	0.0002	0.006	0.003	0.005	0.001	-0.003	0.010	0.001	0.003	-0.001
	(0.03)	(0.56)	(0.28)	(0.44)	(0.58)	(-0.92)	(1.44)	(0.16)	(0.39)	(-0.59)
N	678	678	678	678	678	1,969	1,969	1,969	1,969	1,969
NxT	10,029	10,029	10,029	10,029	10,029	28,673	28,673	28,673	28,673	28,673

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using fixed effects linear probability model. Model specification includes 18 wave dummies.

Table OA.2 Coefficient estimates of the effects of health shocks on the logarithm of health expenditures, by types of health care

	Major Conditions					Minor Conditions				
	Hospital	Outpatient	Prescription	Other Meds	Home Nursing	Hospital	Outpatient	Prescription	Other Meds	Home Nursing
Period t_{-2}	-0.268	0.107	-0.006	-0.006	0.471	0.101	-0.070	-0.005	-0.042	0.314
	(-0.75)	(1.17)	(-0.07)	(-0.07)	(0.75)	(0.50)	(-1.32)	(-0.10)	(-0.79)	(0.84)
Period t_{-1}	0.106	0.145	0.029	-0.064	0.398	0.256	0.088	0.041	-0.050	-0.461**
	(0.47)	(1.63)	(0.41)	(-0.79)	(0.61)	(1.41)	(1.60)	(0.96)	(-1.05)	(-2.38)
Period t_0	0.885***	0.351***	0.203***	0.022	0.162	-0.104	0.101***	0.039	0.052	-0.319
	(4.82)	(5.02)	(3.48)	(0.29)	(0.25)	(-0.68)	(2.76)	(1.20)	(1.29)	(-0.98)
Period t_1	0.657***	0.273***	0.227***	0.048	0.448	-0.369**	0.040	-0.016	-0.013	-0.463
	(3.05)	(3.68)	(3.55)	(0.65)	(0.81)	(-2.29)	(0.97)	(-0.44)	(-0.27)	(-1.12)
Period t_2	0.281	0.115	0.177**	0.059	-0.154	-0.199	0.010	-0.009	-0.060	0.137
	(1.17)	(1.49)	(2.46)	(0.78)	(-0.27)	(-0.99)	(0.23)	(-0.22)	(-1.27)	(0.33)
Period t_3	0.399	0.263***	0.035	0.037	-0.018	-0.218	0.145***	0.009	-0.083*	0.089
	(1.63)	(3.11)	(0.50)	(0.42)	(-0.03)	(-1.19)	(2.91)	(0.22)	(-1.68)	(0.31)
Period t_4	0.133	0.087	0.099	0.020	-0.576	-0.239	-0.021	0.025	-0.030	0.141
	(0.61)	(1.08)	(1.22)	(0.26)	(-1.35)	(-1.08)	(-0.40)	(0.60)	(-0.65)	(0.43)
Period t_5	-0.122	0.055	0.036	-0.117	-0.486	-0.037	-0.029	-0.071*	-0.052	0.722***
	(-0.61)	(0.58)	(0.47)	(-1.35)	(-0.87)	(-0.17)	(-0.55)	(-1.65)	(-1.07)	(2.65)
Period t_6	-0.306	0.114	0.022	0.001	0.259	-0.215	-0.016	0.008	-0.018	-0.150
	(-1.18)	(1.34)	(0.31)	(0.01)	(0.46)	(-1.05)	(-0.30)	(0.19)	(-0.35)	(-0.43)
Period t_7	0.271	0.063	0.024	-0.060	0.803	-0.277	-0.036	-0.013	-0.068	-0.078
	(1.16)	(0.72)	(0.32)	(-0.69)	(1.21)	(-1.42)	(-0.68)	(-0.29)	(-1.24)	(-0.19)
Period t_8	0.281	0.026	0.031	-0.072	0.788	-0.030	-0.023	0.022	-0.091*	0.252
	(1.09)	(0.32)	(0.42)	(-0.82)	(1.27)	(-0.13)	(-0.44)	(0.46)	(-1.72)	(0.65)
Period t_9	0.172	0.051	0.154*	0.016	0.434	-0.442**	0.095	0.034	-0.012	0.760
	(0.52)	(0.53)	(1.82)	(0.18)	(0.72)	(-1.97)	(1.60)	(0.70)	(-0.25)	(1.61)
Period t_{10}	-0.153	-0.005	0.020	-0.019	0.041	-0.280	-0.048	-0.019	-0.079	0.473
	(-0.55)	(-0.06)	(0.25)	(-0.22)	(0.07)	(-1.33)	(-0.86)	(-0.40)	(-1.42)	(1.23)
Period t_{11}	-0.217	0.041	0.004	-0.099	0.260	0.115	0.091*	0.058	-0.002	0.563
	(-0.72)	(0.45)	(0.05)	(-1.08)	(0.85)	(0.58)	(1.70)	(1.21)	(-0.04)	(1.49)
Period t_{12-max}	0.023	0.055	0.256***	-0.025	-0.407	0.059	0.121*	-0.015	-0.072	0.497
	(0.10)	(0.62)	(3.00)	(-0.28)	(-1.35)	(0.30)	(1.94)	(-0.30)	(-1.22)	(1.17)
Constant	5.518***	4.430***	4.335***	4.342***	5.704***	5.615***	4.458***	4.667***	4.177***	4.966***
	(22.35)	(64.83)	(64.53)	(60.49)	(12.65)	(11.98)	(38.53)	(44.96)	(91.07)	(8.44)
N	392	578	586	513	62	831	1,626	1,679	1,452	128
*N*x*T*	1,065	3,431	3,609	2,545	129	2,000	9,190	9,713	6,967	287

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using fixed effects ordinary least squares model. Model specification includes 18 wave dummies.

Table OA.3. Conditional incremental effects of major health shocks on total health expenditures by private health insurance status

Variables	Heart		Cancer		Stroke	
	Private Health Insurance = Yes	Private Health Insurance = No	Private Health Insurance = Yes	Private Health Insurance = No	Private Health Insurance = Yes	Private Health Insurance = No
	(1)	(2)	(3)	(4)	(5)	(6)
Period t_{-2}	-2.64	123.08	-124.33	-118.21	-72.38	-36.50
Period t_{-1}	-43.68	97.39	381.40**	345.66	206.16	-115.23
Period t_0	401.17***	331.58***	1420.13***	659.01***	610.18***	547.72***
Period t_1	232.14***	212.20***	1240.36***	662.71**	96.37	151.12
Period t_2	160.83***	110.58**	192.48	781.13**	43.54	42.92
Period t_3	67.11	97.51	407.09*	390.72	205.50	325.47*
Period t_4	111.43**	6.91	300.23*	183.12	7.45	86.34
Period t_5	66.44	42.21	-142.69	645.90**	96.31	117.53
Period t_6	115.02*	63.97	9.36	46.19	-195.98	-51.16
Period t_7	50.95	49.98	49.57	137.28	86.97	-87.43
Period t_8	46.63	-8.06	77.04	-51.61	8.03	38.06
Period t_9	164.27**	1.87	-8.86	-95.57	331.28	130.48
Period t_{10}	-77.52	119.84**	-105.18	108.59	-126.16	397.99*
Period t_{11}	172.88***	-24.65	-118.64	105.85	1334.86***	106.58
Period t_{12-max}	76.42	117.71*	23.61	-103.43	-71.40	154.80

Notes: *** p<0.01, ** p<0.05, * p<0.1. Reported statistical significance is based on the estimated standard errors of the set of binary shock variables S_{iht} , from regression models that are estimated using linear fixed effects estimation. Standard errors are clustered at the level of the household. Incremental effects are interpreted as the average change in total health expenditures from a 0 to 1 in the health shock explanatory variable $\boldsymbol{S_{iht}}$ for each time period t_{-2} to t_{12}. Predictions of log expenditures are transformed into level expenditures using the Duan smearing estimator. Private health insurance is defined as the availability of Integrated Plans or wholly private health insurance; individuals without private health insurance are covered under Medishield Life, the public catastrophic health insurance program.

Table OA.4. Effect of having major shocks on the logarithm of household income from work, by gender of respondent.

	Cancer		Heart		Stroke	
	Male	Female	Male	Female	Male	Female
Period t_{-2}	0.272	0.177	-0.101	-0.080	0.066	-0.268
	(1.04)	(0.57)	(-0.97)	(-0.47)	(0.41)	(-1.00)
Period t_{-1}	-0.253	0.226	0.061	-0.042	0.193	0.211**
	(-1.12)	(1.42)	(0.66)	(-0.33)	(0.66)	(2.10)
Period t_0	-0.290	-0.041	-0.120	-0.010	0.357	-0.037
	(-1.42)	(-0.22)	(-1.52)	(-0.10)	(0.72)	(-0.15)
Period t_1	-0.092	-0.069	-0.025	-0.130	0.142	0.078
	(-0.37)	(-0.36)	(-0.29)	(-0.89)	(0.65)	(0.39)
Period t_2	-0.087	0.546**	-0.014	-0.199*	-0.417*	0.021
	(-0.41)	(2.20)	(-0.13)	(-1.78)	(-1.67)	(0.11)
Period t_3	-0.037	0.136	-0.113	0.102	-0.569	0.281**
	(-0.13)	(1.17)	(-1.07)	(0.81)	(-1.35)	(2.16)
Period t_4	-0.268	0.319	0.082	-0.124	-0.278	0.108
	(-1.58)	(1.65)	(0.70)	(-0.87)	(-0.68)	(0.45)
Period t_5	-0.172	0.123	-0.119	-0.156	-0.152	0.014
	(-0.69)	(0.66)	(-1.24)	(-1.10)	(-0.34)	(0.07)
Period t_6	-0.152	0.159	-0.035	-0.047	-0.045	0.008
	(-0.64)	(1.17)	(-0.38)	(-0.52)	(-0.07)	(0.04)
Period t_7	-0.104	-0.014	-0.035	-0.154	-0.341	0.390
	(-0.44)	(-0.11)	(-0.35)	(-1.29)	(-1.56)	(1.64)
Period t_8	-0.146	-0.010	-0.198*	-0.237*	-0.072	0.192
	(-1.06)	(-0.10)	(-1.91)	(-1.65)	(-0.30)	(0.55)
Period t_9	-0.295*	0.018	-0.107	0.094	0.217	0.034
	(-1.67)	(0.18)	(-0.84)	(0.59)	(0.73)	(0.23)
Period t_{10}	-0.068	0.124	-0.166	-0.161	-0.463**	0.058
	(-0.59)	(1.23)	(-1.24)	(-1.09)	(-2.42)	(0.44)
Period t_{11}	-0.237	-0.403	-0.144	-0.076	0.223	-0.109
	(-1.04)	(-0.75)	(-1.18)	(-0.67)	(0.71)	(-0.55)
Period t_{12-max}	-0.233	0.035	0.013	-0.002	-0.741**	-0.042
	(-1.24)	(0.28)	(0.10)	(-0.01)	(-2.11)	(-0.27)
Constant	7.261***	6.959***	7.292***	6.963***	7.280***	6.947***
	(69.63)	(48.54)	(70.19)	(53.62)	(68.51)	(47.91)
N	216	196	216	196	216	196
*N*x*T*	1,572	1,347	1,572	1,347	1,572	1,347

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis, with standard errors clustered at the level of the household. Models are estimated using fixed effects ordinary least squares model. Model specification includes 18 wave dummies.

Table OA.5. Effect of having cancer on the probability of positive non-health expenditure by spending categories

	Total non-health	Housing	Utilities	Food	Transport	Domestic services	Leisure	Home repairs	Tobacco
Period t_{-2}	0.0004	-0.068*	0.002	-0.028	0.038	-0.002	-0.0003	-0.006	0.005
	(0.03)	(-1.95)	(0.09)	(-0.92)	(1.47)	(-0.07)	(-0.01)	(-0.18)	(0.29)
Period t_{-1}	0.003	-0.014	-0.001	-0.011	0.011	0.040	-0.025	0.017	0.014
	(0.15)	(-0.37)	(-0.05)	(-0.35)	(0.39)	(1.07)	(-0.81)	(0.39)	(0.63)
Period t_{0}	-0.012	-0.025	-0.057**	-0.010	-0.006	-0.014	-0.044	0.021	-0.002
	(-0.68)	(-0.76)	(-2.08)	(-0.39)	(-0.21)	(-0.54)	(-1.26)	(0.55)	(-0.14)
Period t_{1}	-0.017	-0.040	-0.061*	-0.027	0.006	-0.010	-0.069*	0.027	0.016
	(-0.86)	(-1.35)	(-1.84)	(-0.94)	(0.20)	(-0.29)	(-1.89)	(0.70)	(0.93)
Period t_{2}	0.016	0.001	0.022	-0.052*	0.005	-0.006	-0.072**	0.030	-0.004
	(1.06)	(0.03)	(0.86)	(-1.74)	(0.15)	(-0.22)	(-2.46)	(0.73)	(-0.23)
Period t_{3}	-0.027	-0.004	-0.015	-0.058*	-0.021	-0.019	-0.112***	0.019	0.037*
	(-1.27)	(-0.13)	(-0.58)	(-1.70)	(-0.55)	(-0.58)	(-2.93)	(0.52)	(1.69)
Period t_{4}	-0.011	-0.021	-0.053**	-0.037	0.018	-0.028	-0.074*	-0.066**	-0.003
	(-0.50)	(-0.73)	(-1.99)	(-1.14)	(0.46)	(-1.03)	(-1.85)	(-2.00)	(-0.19)
Period t_{5}	-0.039	-0.081**	-0.089***	-0.091**	-0.034	-0.031	-0.160***	-0.047	0.006
	(-1.62)	(-2.24)	(-2.62)	(-2.10)	(-0.76)	(-0.90)	(-3.63)	(-1.38)	(0.42)
Period t_{6}	-0.039	-0.001	-0.017	-0.031	0.005	-0.053*	-0.097**	0.009	-0.010
	(-1.61)	(-0.01)	(-0.61)	(-0.97)	(0.14)	(-1.66)	(-2.37)	(0.23)	(-0.61)
Period t_{7}	-0.046*	-0.036	-0.074**	-0.060	0.015	0.037	-0.068	-0.075*	0.014
	(-1.79)	(-1.23)	(-2.14)	(-1.64)	(0.36)	(0.99)	(-1.59)	(-1.93)	(0.69)
Period t_{8}	-0.044*	-0.035	-0.062*	-0.023	0.034	-0.009	-0.102**	-0.028	-0.019
	(-1.92)	(-0.85)	(-1.88)	(-0.67)	(0.89)	(-0.25)	(-2.54)	(-0.63)	(-1.20)
Period t_{9}	-0.033*	-0.007	-0.015	-0.017	0.003	0.012	-0.027	-0.078*	-0.003
	(-1.86)	(-0.22)	(-0.76)	(-0.66)	(0.10)	(0.36)	(-0.68)	(-1.82)	(-0.12)
Period t_{10}	-0.039	0.016	-0.030	-0.030	0.007	-0.032	-0.022	-0.047	-0.006
	(-1.43)	(0.43)	(-1.03)	(-0.82)	(0.16)	(-0.77)	(-0.55)	(-1.11)	(-0.36)
Period t_{11}	-0.038	-0.013	-0.038	-0.010	0.007	-0.031	-0.064*	-0.008	-0.014
	(-1.44)	(-0.33)	(-1.26)	(-0.27)	(0.18)	(-0.76)	(-1.76)	(-0.18)	(-0.99)
Period t_{12-max}	-0.002	-0.004	0.025	-0.028	0.033	0.005	0.005	0.025	-0.003
	(-0.16)	(0.84)	(0.84)	(-0.76)	(1.07)	(0.11)	(0.15)	(0.54)	(-0.21)
Constant	0.018	0.028	0.020	0.025	0.013	-0.001	0.021	0.007	-0.015
	(1.57)	(0.84)	(1.12)	(1.61)	(0.69)	(-0.04)	(0.88)	(0.31)	(-0.79)
N	149	149	149	149	149	149	149	149	149
*N*x*T*	2,181	2,181	2,181	2,181	2,181	2,181	2,181	2,181	2,181

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on whether individuals have positive non-health expenditure for each time period t_{-2} to t_{12} prior to or after the shock. Expenditure items in broad categories include: **Leisure** – dining and/or drinking out, entertainment, sports, hobbies and leisure equipment, package tours and vacation. **Housing** cost – mortgage, property tax, home and content insurance, rent. **Utilities** – utilities and other fuels, communication. **Transport** – road use fees, vehicle insurance, petrol, vehicle repair and maintenance, public transport. **Domestic services** – domestic and housekeeping. **Home repairs** – home repairs and maintenance.

Table OA.6. Effect of having cancer on the logarithm of non-health expenditure by spending categories

	Total non-health	Housing	Utilities	Food	Transport	Domestic services	Leisure	Home repairs	Tobacco
Period t_{-2}	-0.099	-0.292*	0.010	-0.087	-0.177	-0.004	0.010	-0.039	-0.013
	(-1.43)	(-1.81)	(0.19)	(-1.12)	(-1.54)	(-0.03)	(0.19)	(-0.20)	(-0.09)
Period t_{-1}	-0.092	-0.250*	-0.014	-0.158**	-0.0202	0.005	-0.014	-0.067	0.177
	(-1.38)	(-1.74)	(-0.31)	(-2.05)	(-0.22)	(0.03)	(-0.31)	(-0.27)	(1.14)
Period t_0	-0.083	-0.010	0.008	0.002	-0.0612	-0.047	0.008	-0.479**	-0.281*
	(-1.31)	(-0.07)	(0.23)	(0.02)	(-0.71)	(-0.36)	(0.23)	(-2.07)	(-1.95)
Period t_1	-0.083	-0.185	0.001	-0.141*	-0.0738	-0.192	0.001	-0.269	-0.408
	(-1.36)	(-1.25)	(0.03)	(-1.94)	(-0.81)	(-1.63)	(0.03)	(-1.33)	(-1.53)
Period t_2	-0.208***	-0.049	-0.002	-0.018	-0.0761	0.004	-0.002	-0.456**	-0.363*
	(-3.41)	(-0.36)	(-0.04)	(-0.26)	(-0.83)	(0.03)	(-0.04)	(-2.04)	(-1.87)
Period t_3	-0.081	-0.007	0.013	-0.078	-0.1195	0.010	0.013	-0.397**	-0.341
	(-1.19)	(-0.05)	(0.29)	(-1.08)	(-1.36)	(0.10)	(0.29)	(-2.03)	(-1.43)
Period t_4	-0.140**	-0.001	0.016	0.052	-0.1367	0.035	0.016	-0.024	-0.241**
	(-2.00)	(-0.00)	(0.35)	(0.77)	(-1.23)	(0.39)	(0.35)	(-0.09)	(-2.53)
Period t_5	-0.286***	0.320*	-0.080	-0.065	-0.1305	0.089	-0.080	-0.619**	-0.128
	(-3.91)	(1.87)	(-1.40)	(-0.96)	(-1.56)	(0.97)	(-1.40)	(-2.17)	(-0.77)
Period t_6	-0.067	0.149	0.072	-0.075	-0.0588	-0.051	0.072	-0.549*	-0.127
	(-1.17)	(1.03)	(1.51)	(-0.93)	(-0.74)	(-0.34)	(1.51)	(-1.74)	(-1.05)
Period t_7	-0.100	0.027	0.032	-0.077	-0.0047	0.038	0.032	-0.243	-0.196
	(-1.51)	(0.20)	(0.72)	(-0.96)	(-0.06)	(0.36)	(0.72)	(-0.80)	(-0.90)
Period t_8	-0.043	0.116	0.020	-0.010	0.1417	-0.379*	0.020	-0.518*	-0.060
	(-0.62)	(0.69)	(0.46)	(-0.18)	(1.63)	(-1.68)	(0.46)	(-1.77)	(-0.42)
Period t_9	-0.011	-0.148	0.025	-0.049	-0.0192	0.020	0.025	-0.230	-0.128
	(-0.13)	(-0.92)	(0.47)	(-0.64)	(-0.24)	(0.10)	(0.47)	(-0.67)	(-0.70)
Period t_{10}	-0.027	-0.033	0.009	-0.129	0.0561	0.001	0.009	-0.423	-0.191
	(-0.41)	(-0.19)	(0.19)	(-1.58)	(0.71)	(0.01)	(0.19)	(-1.26)	(-1.38)
Period t_{11}	-0.026	0.138	-0.008	-0.109*	0.0925	0.055	-0.008	-0.361	0.897***
	(-0.38)	(1.36)	(-0.20)	(-1.71)	(1.14)	(0.60)	(-0.20)	(-1.03)	(6.75)
Period t_{12-max}	-0.069	-0.017	-0.022	-0.122*	-0.0889	-0.152***	-0.022	0.386	-0.570*
	(-0.84)	(-0.13)	(-0.59)	(-1.68)	(-1.04)	(-2.99)	(-0.59)	(1.23)	(-1.85)
Constant	7.779***	5.162***	5.853***	5.773***	5.270***	5.484***	5.489***	4.864***	4.951***
	(93.31)	(34.13)	(161.76)	(89.69)	(45.47)	(21.83)	(47.57)	(25.74)	(23.45)
N	146	121	143	146	143	74	142	101	26
*N*x*T*	1,961	1,068	1,833	1,841	1,762	468	1,833	509	148

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on the logarithm of non-health expenditure for each time period t_{-2} to t_{12} prior to or after the shock. Expenditure items in broad categories include: **Leisure** – dining and/or drinking out, entertainment, sports, hobbies and leisure equipment, package tours and vacation. **Housing** cost – mortgage, property tax, home and content insurance, rent. **Utilities** – utilities and other fuels, communication. **Transport** – road use fees, vehicle insurance, petrol, vehicle repair and maintenance, public transport. **Domestic services** – domestic and housekeeping. **Home repairs** – home repairs and maintenance.

Table OA.7. Effect of having heart disease on the probability of positive non-health expenditure by spending categories

	Total non-health	Housing	Utilities	Food	Transport	Domestic services	Leisure	Home repairs	Tobacco
Period t_{-2}	0.011	-0.017	0.017	0.024*	0.013	-0.021	0.028*	0.019	0.004
	(1.20)	(-0.85)	(1.54)	(1.68)	(0.97)	(-1.34)	(1.73)	(0.86)	(0.37)
Period t_{-1}	0.008	0.025	-0.002	0.030**	-0.007	-0.008	0.012	-0.009	-0.012
	(0.78)	(1.12)	(-0.14)	(2.16)	(-0.45)	(-0.45)	(0.67)	(-0.41)	(-1.35)
Period t_0	0.018*	0.020	0.021	0.035**	0.019	0.0011	0.018	0.008	-0.003
	(1.87)	(1.03)	(1.55)	(2.37)	(1.37)	(0.06)	(1.13)	(0.41)	(-0.26)
Period t_1	0.003	0.010	0.0002	0.024	-0.002	-0.012	0.014	0.0311	-0.012
	(0.27)	(0.49)	(0.01)	(1.48)	(-0.11)	(-0.74)	(0.78)	(1.37)	(-1.32)
Period t_2	0.018*	0.021	0.026*	0.031*	0.019	-0.007	0.038**	0.006	-0.0000
	(1.70)	(1.05)	(1.89)	(1.84)	(1.32)	(-0.50)	(2.20)	(0.26)	(-0.00)
Period t_3	0.014	0.039*	0.004	0.028*	-0.013	0.006	-0.004	-0.024	-0.008
	(1.37)	(1.82)	(0.32)	(1.78)	(-0.78)	(0.38)	(-0.26)	(-1.04)	(-0.85)
Period t_4	0.0003	-0.003	-0.008	0.004	-0.011	-0.009	-0.012	-0.0100	-0.015**
	(0.03)	(-0.14)	(-0.55)	(0.21)	(-0.70)	(-0.53)	(-0.64)	(-0.46)	(-2.38)
Period t_5	0.0039	0.008	0.005	0.007	0.005	-0.041**	-0.0260	-0.010	-0.012
	(0.37)	(0.39)	(0.35)	(0.50)	(0.30)	(-2.41)	(-1.32)	(-0.39)	(-1.60)
Period t_6	0.008	0.015	0.011	0.012	0.017	-0.013	-0.0117	0.008	0.002
	(0.80)	(0.68)	(0.84)	(0.67)	(1.09)	(-0.74)	(-0.62)	(0.33)	(0.21)
Period t_7	0.010	-0.009	0.016	0.026	0.007	-0.032	0.0001	-0.016	-0.012
	(1.01)	(-0.45)	(1.08)	(1.43)	(0.42)	(-1.64)	(0.01)	(-0.62)	(-1.11)
Period t_8	0.016**	0.004	0.012	0.028	-0.004	-0.027	-0.0080	-0.016	-0.014**
	(2.05)	(0.19)	(0.78)	(1.54)	(-0.23)	(-1.47)	(-0.39)	(-0.62)	(-2.21)
Period t_9	0.008	-0.012	0.021	-0.004	0.001	-0.012	-0.0011	-0.011	-0.020***
	(0.78)	(-0.60)	(1.37)	(-0.18)	(0.04)	(-0.62)	(-0.06)	(-0.42)	(-3.09)
Period t_{10}	0.016**	-0.007	0.007	0.058***	-0.006	0.005	-0.0126	0.009	-0.013**
	(1.97)	(-0.36)	(0.45)	(3.53)	(-0.29)	(0.28)	(-0.63)	(0.34)	(-2.34)
Period t_{11}	0.003	0.011	-0.014	0.010	-0.035*	0.006	-0.0128	0.050*	-0.014**
	(0.33)	(0.48)	(-0.73)	(0.47)	(-1.70)	(0.26)	(-0.63)	(1.84)	(-2.46)
Period t_{12-max}	0.009	0.020	-0.005	-0.004	0.025	0.005	-0.0151	0.034	-0.007
	(0.77)	(0.91)	(-0.29)	(-0.20)	(1.41)	(0.25)	(-0.63)	(1.21)	(-1.09)
Constant	0.009	0.006	0.010	0.010	0.014	0.004	0.0126	0.001	-0.006
	(1.28)	(0.35)	(1.01)	(1.11)	(1.35)	(0.24)	(0.98)	(0.07)	(-0.56)
N	480	480	480	480	480	480	480	480	480
*N*x*T*	7,145	7,145	7,145	7,145	7,145	7,145	7,145	7,145	7,145

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on whether individuals have positive non-health expenditure for each time period t_{-2} to t_{12} prior to or after the shock. Expenditure items in broad categories include: **Leisure** – dining and/or drinking out, entertainment, sports, hobbies and leisure equipment, package tours and vacation. **Housing** cost – mortgage, property tax, home and content insurance, rent. **Utilities** – utilities and other fuels, communication. **Transport** – road use fees, vehicle insurance, petrol, vehicle repair and maintenance, public transport. **Domestic services** – domestic and housekeeping. **Home repairs** – home repairs and maintenance.

Table OA.8. Effect of having heart disease on the logarithm of non-health expenditure by spending categories

	Total non-health	Leisure	Housing	Utilities	Food	Transport	Domestic services	Home repairs	Tobacco
Period t_{-2}	0.029	0.109*	-0.004	-0.002	-0.014	-0.042	-0.028	-0.075	0.047
	(0.82)	(1.74)	(-0.05)	(-0.08)	(-0.37)	(-0.93)	(-0.32)	(-0.62)	(0.53)
Period t_{-1}	-0.024	-0.068	0.001	-0.042*	-0.030	-0.056	-0.126	-0.132	0.023
	(-0.67)	(-1.16)	(0.01)	(-1.78)	(-0.80)	(-1.34)	(-1.46)	(-1.21)	(0.27)
Period t_0	0.056	0.024	0.037	0.022	-0.006	-0.034	-0.004	-0.136	0.191**
	(1.61)	(0.49)	(0.53)	(1.04)	(-0.18)	(-0.76)	(-0.06)	(-1.43)	(1.99)
Period t_1	-0.006	-0.018	0.002	-0.041*	0.027	-0.012	-0.014	-0.160	-0.017
	(-0.18)	(-0.28)	(0.03)	(-1.70)	(0.74)	(-0.29)	(-0.21)	(-1.52)	(-0.18)
Period t_2	0.007	0.056	-0.040	0.012	-0.004	-0.022	-0.114	-0.142	0.049
	(0.20)	(1.09)	(-0.64)	(0.56)	(-0.11)	(-0.50)	(-1.62)	(-1.31)	(0.44)
Period t_3	-0.023	-0.004	-0.079	0.003	0.007	-0.030	0.007	-0.150	-0.180*
	(-0.64)	(-0.07)	(-1.29)	(0.13)	(0.21)	(-0.66)	(0.09)	(-1.29)	(-1.98)
Period t_4	-0.010	-0.006	-0.099	-0.001	0.002	-0.105**	0.084	-0.287**	0.010
	(-0.24)	(-0.11)	(-1.35)	(-0.04)	(0.06)	(-2.13)	(1.28)	(-2.53)	(0.10)
Period t_5	-0.080**	-0.030	-0.130**	-0.041	-0.048	-0.095**	0.085	-0.143	-0.089
	(-2.14)	(-0.49)	(-2.08)	(-1.59)	(-1.12)	(-2.09)	(1.33)	(-1.00)	(-1.08)
Period t_6	-0.029	-0.015	-0.056	-0.013	0.002	-0.052	0.184**	0.013	-0.100
	(-0.75)	(-0.23)	(-0.82)	(-0.57)	(0.04)	(-1.07)	(2.12)	(0.09)	(-1.10)
Period t_7	-0.044	0.055	-0.018	0.009	0.016	-0.048	0.120	-0.022	-0.035
	(-1.11)	(0.93)	(-0.26)	(0.45)	(0.39)	(-0.94)	(1.61)	(-0.18)	(-0.29)
Period t_8	-0.057	0.027	-0.031	-0.024	-0.007	-0.088	0.053	0.036	-0.019
	(-1.30)	(0.42)	(-0.44)	(-1.02)	(-0.16)	(-1.55)	(0.64)	(0.29)	(-0.27)
Period t_9	-0.077**	-0.001	0.028	-0.040	-0.072*	-0.103**	0.042	-0.217	-0.076
	(-1.98)	(-0.02)	(0.38)	(-1.21)	(-1.65)	(-1.97)	(0.39)	(-1.30)	(-0.79)
Period t_{10}	-0.059	-0.019	-0.117*	-0.027	0.029	-0.080	0.087	-0.125	-0.055
	(-1.47)	(-0.30)	(-1.68)	(-0.99)	(0.73)	(-1.51)	(0.90)	(-0.81)	(-0.73)
Period t_{11}	-0.031	0.097	-0.097	-0.050*	0.017	-0.097**	0.078	0.045	-0.037
	(-0.71)	(1.46)	(-1.15)	(-1.73)	(0.40)	(-2.04)	(0.83)	(0.28)	(-0.49)
Period t_{12-max}	-0.023	0.033	-0.042	-0.001	-0.012	-0.050	-0.041	-0.122	-0.090
	(-0.50)	(0.48)	(-0.78)	(-0.04)	(-0.27)	(-0.95)	(-0.59)	(-0.90)	(-0.10)
Constant	7.937***	5.847***	6.055***	5.835***	5.899***	5.469***	5.377***	4.839***	5.311***
	(83.49)	(29.55)	(21.73)	(86.73)	(54.19)	(36.29)	(68.28)	(46.34)	(30.68)
N	477	463	403	468	475	468	238	346	81
*N*x*T*	6,385	5,490	3,344	6,015	5,962	5,924	1,527	1,761	554

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on the logarithm of non-health expenditure for each time period t_{-2} to t_{12} prior to or after the shock. Expenditure items in broad categories include: **Leisure** – dining and/or drinking out, entertainment, sports, hobbies and leisure equipment, package tours and vacation. **Housing** cost – mortgage, property tax, home and content insurance, rent. **Utilities** – utilities and other fuels, communication. **Transport** – road use fees, vehicle insurance, petrol, vehicle repair and maintenance, public transport. **Domestic services** – domestic and housekeeping. **Home repairs** – home repairs and maintenance.

Table OA.9. Effect of having stroke on the probability of positive non-health expenditure by spending categories (Unreferenced)

	Total non-health	Leisure	Housing	Utilities	Food	Transport	Domestic services	Home repairs	Tobacco
Period t_{-2}	-0.0206	0.0237	-0.0392	-0.0380	-0.0736*	-0.0030	-0.0478	-0.0313	-0.0144
	(-0.64)	(0.49)	(-0.82)	(-1.07)	(-1.68)	(-0.08)	(-1.48)	(-0.66)	(-0.63)
Period t_{-1}	0.0032	0.0314	0.0348	0.0186	0.0074	0.0278	0.0244	0.0505	0.0005
	(0.15)	(0.73)	(0.72)	(0.67)	(0.21)	(0.76)	(0.77)	(1.27)	(0.02)
Period t_0	0.0077	0.0034	0.0410	0.0384	0.0432	0.0311	-0.0231	0.0722	-0.0047
	(0.32)	(0.08)	(1.00)	(1.59)	(1.33)	(1.11)	(-0.71)	(1.55)	(-0.22)
Period t_1	0.0216**	0.0010	-0.0184	0.0230	0.0206	0.0336	0.0209	-0.0114	-0.0031
	(2.20)	(0.02)	(-0.47)	(0.83)	(0.66)	(1.38)	(0.66)	(-0.30)	(-0.22)
Period t_2	0.0374*	0.0586	0.0644	-0.0355	0.0672	0.0532*	0.0199	-0.0163	0.0234
	(1.85)	(1.20)	(1.21)	(-0.86)	(1.57)	(1.73)	(0.51)	(-0.42)	(1.00)
Period t_3	0.0107	0.0321	0.0717	0.0200	-0.0248	-0.0508	0.0026	0.0787	0.0119
	(0.36)	(0.56)	(1.46)	(0.52)	(-0.49)	(-1.05)	(0.06)	(1.45)	(0.49)
Period t_4	0.0322	0.0725	-0.0627	-0.0148	0.0344	0.0011	-0.0194	0.0601	-0.0043
	(0.97)	(1.36)	(-1.33)	(-0.38)	(0.83)	(0.03)	(-0.53)	(1.18)	(-0.20)
Period t_5	0.0298	0.0378	-0.0240	-0.0175	0.0308	-0.0497	-0.0311	0.0487	-0.0116
	(0.91)	(0.68)	(-0.47)	(-0.49)	(0.90)	(-1.15)	(-0.82)	(0.97)	(-0.90)
Period t_6	0.0060	0.0189	-0.0078	-0.0126	0.0133	0.0136	-0.0298	0.0483	0.0406
	(0.26)	(0.38)	(-0.18)	(-0.31)	(0.31)	(0.46)	(-0.82)	(0.93)	(1.48)
Period t_7	-0.0446	0.0074	0.0224	0.0228	0.0193	-0.0969*	-0.0481	-0.0157	-0.0223
	(-1.28)	(0.13)	(0.46)	(0.59)	(0.47)	(-1.73)	(-1.09)	(-0.28)	(-1.32)
Period t_8	-0.0222	-0.0593	-0.0018	0.0489	-0.0873	-0.0257	-0.0158	0.0375	0.0402
	(-0.60)	(-1.11)	(-0.03)	(1.44)	(-1.32)	(-0.66)	(-0.43)	(0.81)	(1.50)
Period t_9	-0.0038	-0.1014	-0.0169	-0.0158	-0.0406	-0.0216	0.0092	0.0081	-0.0163
	(-0.16)	(-1.43)	(-0.42)	(-0.40)	(-0.70)	(-0.43)	(0.17)	(0.16)	(-1.05)
Period t_{10}	-0.0376	-0.0028	-0.0337	0.0190	-0.0089	-0.0093	0.0130	-0.0094	-0.0259
	(-1.06)	(-0.05)	(-0.83)	(0.44)	(-0.15)	(-0.23)	(0.21)	(-0.18)	(-1.60)
Period t_{11}	-0.0106	-0.0415	0.0008	-0.0189	-0.1035*	-0.0424	-0.0236	-0.0007	-0.0245
	(-0.45)	(-0.84)	(0.02)	(-0.47)	(-1.68)	(-0.86)	(-0.74)	(-0.01)	(-1.21)
Period t_{12-max}	-0.0157	-0.0290	-0.0772	-0.0086	-0.1404*	-0.0043	-0.0572	-0.0309	-0.0396
	(-0.56)	(-0.42)	(-1.65)	(-0.25)	(-1.86)	(-0.12)	(-1.33)	(-0.52)	(-1.31)
Constant	0.0087	0.0073	0.0016	0.0115	0.0183	0.0060	0.0075	-0.0032	-0.0127
	(0.57)	(0.23)	(0.04)	(0.43)	(0.73)	(0.22)	(0.26)	(-0.12)	(-0.44)
N	94	94	94	94	94	94	94	94	94
*N*x*T*	1404	1404	1404	1404	1404	1404	1404	1404	1404

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on whether individuals have positive non-health expenditure for each time period t_{-2} to t_{12} prior to or after the shock. Expenditure items in broad categories include: **Leisure** – dining and/or drinking out, entertainment, sports, hobbies and leisure equipment, package tours and vacation. **Housing** cost – mortgage, property tax, home and content insurance, rent. **Utilities** – utilities and other fuels, communication. **Transport** – road use fees, vehicle insurance, petrol, vehicle repair and maintenance, public transport. **Domestic services** – domestic and housekeeping. **Home repairs** – home repairs and maintenance.

Table OA.10. Effect of having stroke on the logarithm of non-health expenditure by spending categories (Unreferenced)

	Total non-health	Leisure	Housing	Utilities	Domestic services	Home repairs	Tobacco
Period t_{-2}	-0.131	0.165	-0.023	0.032	-0.030	-0.044	0.023
	(-1.13)	(0.78)	(-0.17)	(0.54)	(-0.16)	(-0.52)	(0.05)
Period t_{-1}	0.080	-0.037	-0.083	0.010	-0.089	0.040	-0.197
	(0.80)	(-0.28)	(-0.65)	(0.18)	(-0.74)	(0.49)	(-0.68)
Period t_0	0.068	-0.101	0.003	-0.020	0.200	-0.044	0.212
	(0.81)	(-0.97)	(0.03)	(-0.45)	(0.89)	(-0.61)	(1.01)
Period t_1	-0.043	-0.112	0.043	-0.060	-0.040	0.030	-0.110
	(-0.46)	(-0.96)	(0.29)	(-1.10)	(-0.20)	(0.41)	(-0.42)
Period t_2	-0.073	-0.128	-0.004	-0.038	0.065	-0.011	-0.126
	(-0.77)	(-0.92)	(-0.02)	(-0.66)	(0.34)	(-0.12)	(-0.44)
Period t_3	-0.081	-0.305**	0.140	0.001	-0.237	-0.094	-0.550
	(-0.74)	(-2.35)	(0.70)	(0.02)	(-0.92)	(-0.95)	(-1.54)
Period t_4	-0.222**	-0.012	0.073	-0.017	0.022	-0.141	0.146
	(-2.19)	(-0.08)	(0.51)	(-0.31)	(0.10)	(-1.57)	(0.72)
Period t_5	-0.072	0.002	-0.078	-0.117**	-0.399	-0.032	-0.303
	(-0.70)	(0.01)	(-0.50)	(-2.00)	(-1.65)	(-0.34)	(-0.95)
Period t_6	0.029	-0.107	0.017	0.042	0.104	-0.057	-0.037
	(0.32)	(-0.61)	(0.10)	(0.85)	(0.41)	(-0.64)	(-0.15)
Period t_7	0.011	-0.126	-0.154	-0.038	-0.265	-0.068	0.294
	(0.11)	(-0.60)	(-0.80)	(-0.70)	(-0.87)	(-0.59)	(0.96)
Period t_8	0.074	0.139	-0.027	-0.101	-0.025	0.048	-0.052
	(0.63)	(0.64)	(-0.16)	(-1.36)	(-0.13)	(0.41)	(-0.13)
Period t_9	-0.131	-0.086	0.021	-0.112*	-0.102	-0.138	0.018
	(-0.99)	(-0.57)	(0.14)	(-1.76)	(-0.41)	(-0.98)	(0.07)
Period t_{10}	-0.076	-0.206	0.141	-0.122	-0.058	-0.054	0.117
	(-0.76)	(-1.20)	(1.20)	(-1.38)	(-0.21)	(-0.79)	(0.23)
Period t_{11}	-0.129	-0.622***	0.057	-0.097	-0.354	-0.003	-0.619**
	(-1.00)	(-3.56)	(0.36)	(-1.54)	(-1.31)	(-0.03)	(-2.28)
Period t_{12-max}	-0.178	-0.247	-0.135	-0.057	0.009	0.115	0.138
	(-1.52)	(-1.32)	(-0.69)	(-0.74)	(0.04)	(1.26)	(0.28)
Constant	7.572***	5.468***	6.281***	5.804***	4.911***	5.861***	3.519***
	(76.91)	(42.87)	(9.34)	(103.81)	(36.07)	(65.65)	(26.77)
N	93	93	70	91	19	93	61
*N*x*T*	1,247	941	524	1,135	138	1,108	252

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics in parenthesis. Models are estimated using linear fixed effects estimation on the logarithm of non-health expenditure for each time period t_{-2} to t_{12} prior to or after the shock. Expenditure items in broad categories include: **Leisure** – dining and/or drinking out, entertainment, sports, hobbies and leisure equipment, package tours and vacation. **Housing** cost – mortgage, property tax, home and content insurance, rent. **Utilities** – utilities and other fuels, communication. **Domestic services** – domestic and housekeeping. **Home repairs** – home repairs and maintenance. Food and Transport are excluded due to small sample sizes.