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“Happiness and Medical Expenditures: Causal Evidence from Japanese Community Cohort - The Nagahama Study”

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Happiness and Medical Expenditures: Causal Evidence from Japanese Community Cohort - The Nagahama Study

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ABSTRACT

In Japan's era of population decline and fiscal strain, exploring alternative policy levers beyond conventional health-system reforms has become imperative. We examine whether higher subjective happiness keeps individual medical expenditures down, using the Nagahama Study, a community-based study conducted by the city of Nagahama in partnership with Kyoto University, which links municipal health checks with socioeconomic surveys in 2019 and 2020. An instrumental-variable two-part model, treating happiness as endogenous with perceived "mattering" and "trust" as instruments, shows that a one-point increase in subjective happiness lowers average monthly medical spending by about ¥248 in 2019 (non-IV: ¥102) and ¥326 in 2020 (non-IV: ¥157). This average effect can be decomposed into two components: the probability of any medical use (extensive margin) and out-of-pocket spending among individuals with positive spending (intensive margin). The extensive margin shows weak effects, while the intensive margin consistently drives the overall decline in both years. These findings imply that strengthening psychosocial well-being could complement conventional reforms as a feasible lever for cost containment in ageing societies.

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I. Introduction

Japan is ageing rapidly, and the sustainability of medical spending has become one of the country's most pressing policy challenges. In 2022, 29 percent of the population—36.2 million people—were aged 65 or older(Statistics Bureau of Japan, 2022). National medical care expenditure reached ¥46.7 trillion in the same year (Ministry of Health, Labour and Welfare, 2024), placing growing strain on universal coverage and public finance. Conventional reforms such as fee schedule revisions and promotion of generics have helped slow cost growth, but their reach remains limited (Ikegami, 2014). At the same time, interest is rising globally in well-being as an alternative policy lever: both researchers and governments, including Japan's Cabinet Office, have begun to integrate subjective well-being into policy frameworks—through annual surveys on satisfaction and quality of life and well-being KPIs (Cabinet Office, 2025) .

A robust international literature explores how higher subjective well-being is linked to healthier outcomes, reduced morbidity, and lower care utilization. Positive affect is theorized to broaden cognitive and behavioral repertoires, promoting preventive health actions (Fredrickson, 2004). Meta-analyses report that happier individuals experience lower cardiovascular risk and longer longevity (Chida & Steptoe, 2008; Boehm & Kubzansky, 2012). Longitudinal analyses show that people with lower happiness are more likely to become high-cost healthcare users (Goel et al., 2018). Instrumental-variable studies from Italy and Greece further provide causal evidence that happiness improves health outcomes, addressing reverse causality (Sabatini, 2014; Kyriopoulos et al., 2018). At the same time, social capital has been shown to shape both well-being and health behaviors (Helliwell & Putnam, 2004; Kim & Kawachi, 2017). Collectively, this body of research suggests that psychosocial well-being could serve as a policy-relevant strategy for reducing health risks and medical costs (Steptoe et al., 2015).

Although several Japanese studies have examined associations between subjective well-being, social relationships, and health outcomes, most remain correlational and do not address endogeneity. To date, no research using Japanese microdata has analyzed the causal link between happiness and individual medical expenditures. Even internationally, causal evidence on this topic is limited. Therefore, to address this gap, we draw on a unique community-based cohort dataset in Japan. In this study, we estimate the total causal effect of subjective happiness on individual out-of-pocket medical expenditures, capturing the combined influence of behavioral, psychological, biological, and social pathways.

The Nagahama Study is a community-based project launched in 2007 by the city of Nagahama in collaboration with Kyoto University, designed to collect medical information for about 10,000 adults to promote healthy community life. The Nagahama data integrates two sources — the Nagahama Prospective Cohort for Comprehensive Human Bioscience (the Nagahama Study), which provides longitudinal medical and clinical information, and the Nagahama Survey on Social Science (the Nagahama Socioeconomic Survey), which collects repeated data on socioeconomic and psychosocial conditions from the same participants. So far, four survey waves (2017, 2019, 2020, and 2023) have been conducted, achieving response rates of around 70 percent. Responses were linked to municipal health check records, allowing us to leverage rich, regional data that include psychosocial, socioeconomic, and clinical background (Setoh & Matsuda, 2022; Yano et al., 2022).

We estimate the causal impact of happiness on individual medical spending using an instrumental-variable two-part model with two-stage residual inclusion to handle endogeneity between happiness and medical spending in a non-linear setting. This approach handles both the high prevalence of zero expenditure and the skewed distribution of positive expenditures (Cragg, 1971; Mullahy, 1998; Terza et al., 2008). We also decompose effects into the extensive margin (any medical use) and the intensive margin (amount of out-of-pocket spending) following methods that address heavy-tail distribution issues (Deb & Norton, 2018; Karlsson et al., 2024). We perform this analysis separately for two cross-sections, 2019 and 2020, to test robustness across years, as these waves are highly comparable in questionnaire design and represent the pre-pandemic and pandemic periods, respectively.

The remainder of this paper is organized as follows. We begin by reviewing the relevant theoretical and empirical literature on happiness, health, and social capital (Section II). Section III describes the data sources and key variables, and Section IV outlines the empirical model and estimation strategy. Section V presents the main results, while Section VI discusses their interpretation, mechanisms, and policy implications. Section VII concludes with a summary of the findings and directions for future research.

II. Literature Review

Higher subjective well-being, captured as happiness and life satisfaction, may reduce medical spending through two primary pathways—biological resilience and health behavior—and within the broader context of social capital that shapes both. Moreover, positive feelings such as happiness may also support daily behavior in helpful ways, by making people slightly more open to different actions and responses (Fredrickson, 2004).

The biological resilience route posits that positive affect mitigates physiological stress responses, leading to reduced inflammation and improved immune functioning. Individuals with higher positive affect recover more quickly from stress, display lower levels of inflammatory biomarkers, and show reduced symptomatic infection in viral challenge experiments (Cohen et al., 2003). Meta-analyses confirm that positive psychological well-being is associated with lower morbidity and mortality (Chida & Steptoe, 2008; Diener & Chan, 2011). More recent reviews also document links between positive affect and favorable immune, autonomic, and endocrine profiles (Dockray & Steptoe, 2010; Pressman et al., 2019).

The health behavior route suggests that individuals with greater well-being engage more consistently in health-promoting behaviors—regular exercise, balanced nutrition, adequate sleep, and preventive medical care—which slow disease onset and progression. Longitudinal studies show that higher baseline well-being predicts improvements in physical activity and sleep quality over time (Stenlund et al., 2021). Declines in negative affect or increases in positive affect are also linked to favorable changes in health behaviors and outcomes (Diener et al., 2017). Over extended periods, these behavioral changes can reduce morbidity and thereby lower both utilization and spending.

Social capital—including network density, social participation, and civic engagement—provides an environment that supports psychological resilience and encourages health-promoting behaviors. Systematic reviews show that indicators of social capital are positively related to mental and physical health outcomes (Helliwell & Putnam, 2004; Kim & Kawachi, 2017; Ehsan et al., 2019; Xue et al., 2020).

Fredrickson (2004) argues that positive emotion itself can temporarily broaden a person's attention and thinking. This short-term broadening is described as a shift that allows individuals to notice more options in everyday situations and to build psychological and social resources over time. The review also notes that greater positive emotion is linked to more active and constructive daily responses. These features suggest that well-being may support healthier and more adaptive patterns of behavior.Building on these pathways, previous research has explored how well-being relates to health outcomes. Evidence from longitudinal analyses indicates that lower life satisfaction is associated with a higher likelihood of becoming a "high-cost user" of healthcare in later years (Goel et al., 2018). A study of healthcare costs in Denmark found that higher mental well-being was associated with lower subsequent healthcare and sickness benefit expenditures, although the analysis did not employ instrumental variables and therefore does not establish causality (Santini et al., 2021). Instrumental-variable approaches applied in Italy and Greece further provide causal evidence that greater happiness improves self-rated health, helping to address concerns of reverse causality (Sabatini, 2014; Kyriopoulos et al., 2018). However, these studies have focused on subjective health outcomes rather than medical utilization or expenditures directly.

Taken together, the theoretical and empirical evidence supports the idea that subjective well-being may lower medical spending through resilience, behavior, and social capital. However, very few studies address monetary medical expenditures or adopt causal identification together with decomposition into the extensive margin and intensive margin. This research gap motivates our examination of the effect of happiness on medical spending in a Japanese cohort, using margin decomposition under strong controls and identification.

III. Data and Variables

3-1. Data

The Nagahama study is a community-based longitudinal study implemented by the city of Nagahama with technical and academic support from Kyoto University since 2007. It combines detailed medical and clinical information from periodic health examinations with repeated socioeconomic surveys, enabling linkage between health data and individual social and economic attributes. The cohort initially enrolled about 10,000 residents and has continued follow-up in successive examination cycles (Setoh & Matsuda, 2022; Yano et al., 2022).

The third examination cycle (2017–2022) included 6,362 participants, over 80 percent of whom attended their examinations between 2018 and 2021. Socioeconomic surveys were implemented in 2017, 2019, 2020, and 2023. We use the 2019 and 2020 waves because their questionnaires are highly comparable, include income and employment information relevant to health, and are closest to the third-cycle health examinations—allowing consistent linkage between health and lifestyle information from health examinations and socioeconomic survey results such as happiness, medical spending, income, working status, education, and social capital. The 2019 survey was conducted in January, whereas the 2020 survey took place in August, during the COVID-19 pandemic. Accordingly, the 2020 data may reflect behavioral and psychological changes associated with the pandemic.

After data cleaning and variable construction described in the next section, the analytic sample consists of 4,162 individuals in 2019 and 3,839 in 2020. The average age was 63.2 and 64.7 years, respectively, and women accounted for about two-thirds of participants. Because health examinations were conducted during weekdays and daytime, the sample tends to include more older adults and women—mainly retirees and housewives.

Table 1 Descriptive Statistics in 2019

	Total		Positive Medical Expenditure	
variable	mean	sd	mean	sd
medical expenditure (1,000 Yen)	1.82	6.35	7.66	11.18
happiness	7.43	1.92	7.40	1.98
mattering	5.63	2.08	5.72	2.01
trust	5.52	2.07	5.51	2.07
age	63.19	11.65	59.55	11.40
sex	1.67	0.47	1.58	0.49
aged 55 or below	0.27	0.44	0.38	0.49
aged 55 - 64	0.22	0.41	0.24	0.43
aged 65 - 74	0.32	0.47	0.27	0.45
aged 75 or older	0.19	0.40	0.11	0.32
not working	0.35	0.48	0.27	0.45
self employed	0.17	0.38	0.17	0.37
regular worker	0.17	0.38	0.25	0.44
non-regular worker	0.30	0.46	0.31	0.46
high school or below	0.55	0.50	0.46	0.50
professional school	0.25	0.43	0.27	0.45
university or higher	0.16	0.37	0.24	0.43
annu. house income (0 ~ 4mil.)	0.45	0.50	0.36	0.48
annu. house income (4 ~6mil.)	0.19	0.39	0.21	0.41
annu. house income (6 ~8mil.)	0.12	0.33	0.14	0.35
annu. house income (8 ~10mil.)	0.08	0.28	0.11	0.32
annu. house income (10mil. ~)	0.08	0.27	0.12	0.32
hypertension	0.36	0.48	0.33	0.47
hyperlipidemia	0.35	0.48	0.33	0.47
type1 diabetes	0.00	0.06	0.01	0.07
type2 diabetes	0.08	0.26	0.08	0.27
heart failure	0.01	0.11	0.02	0.13
gout	0.04	0.19	0.05	0.22
rheumatoid arthritis	0.02	0.14	0.02	0.12
reflux esophgitis	0.11	0.32	0.12	0.33
stroke	0.02	0.14	0.03	0.16
ischemic heart disease	0.04	0.19	0.04	0.20
cancer	0.10	0.29	0.10	0.30
exercise 30min_2day	0.34	0.47	0.28	0.45
daily activity 1h	0.49	0.50	0.43	0.50
brinkman index (=0)	0.71	0.45	0.65	0.48
brinkman index (1~400)	0.14	0.35	0.17	0.38
brinkman index (400~1200)	0.14	0.35	0.16	0.37
brinkman index (1200~)	0.01	0.09	0.01	0.11
weekly alcohol (<3)	0.70	0.46	0.65	0.48
weekly alcohol (3~8)	0.15	0.35	0.15	0.36
weekly alcohol (8~)	0.16	0.37	0.20	0.40
sleep time (<6h)	0.21	0.41	0.25	0.43
sleep time (6~8h)	0.66	0.48	0.61	0.49
sleep time (8h~)	0.14	0.34	0.14	0.34
meet friends	0.69	0.46	0.68	0.47
meet relatives	0.70	0.46	0.68	0.47
meet cowokers	0.35	0.48	0.40	0.49
local community participation	0.18	0.38	0.15	0.36
volunteer participation	0.48	0.50	0.49	0.50

Notes: Observations are drawn from 4,162 individuals in total, of whom 990 reported positive medical expenditure.

Table 2 Descriptive Statistics in 2020

variable	Total mean	Total sd	Positive Medical Expenditure mean	Positive Medical Expenditure sd
medical expenditure (1,000 Yen)	1.39	5.04	9.50	9.81
happiness	7.40	1.88	7.22	1.87
mattering	5.71	2.00	5.81	1.93
trust	5.35	2.07	5.32	2.05
age	64.70	11.60	62.93	11.21
sex	1.67	0.47	1.58	0.49
aged 55 or below	0.23	0.42	0.27	0.44
aged 55 - 64	0.21	0.41	0.24	0.43
aged 65 - 74	0.34	0.47	0.34	0.47
aged 75 or older	0.22	0.42	0.16	0.36
not working	0.37	0.48	0.33	0.47
self employed	0.15	0.36	0.17	0.37
regular worker	0.16	0.37	0.22	0.41
non-regular worker	0.32	0.47	0.29	0.46
high school or below	0.59	0.49	0.50	0.50
professional school	0.24	0.43	0.26	0.44
university or higher	0.17	0.38	0.23	0.42
annu. house income (0 ~ 4mil.)	0.47	0.50	0.40	0.49
annu. house income (4 ~6mil.)	0.17	0.38	0.19	0.40
annu. house income (6 ~8mil.)	0.10	0.30	0.14	0.35
annu. house income (8 ~10mil.)	0.08	0.26	0.09	0.29
annu. house income (10mil. ~)	0.07	0.25	0.10	0.30
hypertension	0.35	0.48	0.37	0.48
hyperlipidemia	0.34	0.47	0.36	0.48
type1 diabetes	0.00	0.06	0.01	0.11
type2 diabetes	0.07	0.26	0.10	0.30
heart failure	0.01	0.10	0.01	0.10
gout	0.04	0.19	0.04	0.19
rheumatoid arthritis	0.02	0.15	0.03	0.18
reflux esophgitis	0.11	0.31	0.12	0.33
stroke	0.02	0.14	0.04	0.19
ischemic heart disease	0.04	0.19	0.05	0.21
cancer	0.09	0.29	0.12	0.32
exercise 30min_2day	0.34	0.48	0.32	0.47
daily activity 1h	0.51	0.50	0.49	0.50
brinkman index (=0)	0.71	0.45	0.65	0.48
brinkman index (1~400)	0.14	0.35	0.17	0.38
brinkman index (400~1200)	0.14	0.35	0.18	0.38
brinkman index (1200~)	0.01	0.08	0.00	0.06
weekly alcohol (<3)	0.70	0.46	0.67	0.47
weekly alcohol (3~8)	0.14	0.35	0.15	0.36
weekly alcohol (8~)	0.16	0.37	0.19	0.39
sleep time (<6h)	0.20	0.40	0.23	0.42
sleep time (6~8h)	0.66	0.47	0.64	0.48
sleep time (8h~)	0.14	0.35	0.13	0.34
meet friends	6.52	1.08	6.45	1.06
meet relatives	0.64	0.48	0.62	0.49
meet cowokers	0.65	0.48	0.66	0.47
local community participation	0.28	0.45	0.33	0.47
volunteer participation	0.39	0.49	0.44	0.50

Notes: Observations are drawn from 3,839 individuals in total, of whom 563 reported positive medical expenditure.

3-2. Variables

Happiness

We use a 10-point self-reported happiness indicator: *"How happy are you now?"* (1 = very unhappy, 10 = very happy). This captures hedonic well-being, the experience of satisfaction (Ryan & Deci, 2001). This indicator is widely adopted in population research linking subjective well-being to health, morbidity, and mortality outcomes (Sabatini, 2014; Steptoe et al., 2015; Kyriopoulos et al., 2018; Willroth et al., 2020). Because it is standard across many surveys, it supports comparability and serves as a credible baseline for exploring causal relationships between happiness and medical spending.

Medical Expenditure

Medical expenditure was obtained from the socioeconomic questionnaire asking: *"How much do you pay per month for medical services and prescription drugs? Exclude costs related to injuries."* Respondents reported their monthly out-of-pocket payments only, expressed in thousand yen. Individuals with not spending were coded as zero. This definition captures individual self-reported spending in the reference month. Importantly, the measure includes not only payments for visits to medical institutions but also pharmacy spending on over-the-counter medicines, vitamins, and other preventive products reported by respondents. In 2019, 76 percent of participants reported zero expenditure, and in 2020 the share was 85 percent. Such high proportions of zero values are consistent with the design of the cohort, where examinations were conducted on weekdays and required travel to local sites, attracting relatively healthier individuals. In the health econometrics literature, expenditure data are generally skewed and contain a substantial mass at zero (Deb & Norton, 2018), but the Nagahama study displays an even larger concentration of zeros for these reasons. The used medical expenditure variable is trimmed at the top one per cent to reduce the influence of outliers.

Instrumental Variables

Instrumental-variable estimation requires two key conditions: a relevance condition, where each instrument is strongly associated with the endogenous regressor, and an exclusion restriction, where the instruments affect the outcome only through that regressor.

In the Nagahama survey we use two ten-point questions as instruments for happiness: one asks whether respondents feel that *"what they are doing is valuable"*, and the other asks *"whether most people can be trusted or whether one must be careful"*. Similar mattering and trust items have been used as instruments in earlier causal studies of happiness and health (Sabatini, 2014; Kyriopoulos et al., 2018), although those papers examined self-rated health rather than medical expenditure.

To clarify the theoretical basis of the instruments, it is useful to distinguish the psychological dimensions of well-being that they represent. Hedonic well-being captures positive feelings such as happiness and life satisfaction, whereas eudaimonic well-being involves meaning, purpose, and social connection (Ryan & Deci, 2001; Ryff & Singer, 2008). Psychological research suggests that positive affect encourages health-promoting behaviors and thus serves as a behavioral driver of medical use (Pressman & Cohen, 2005; Diener et al., 2017; Pressman et al., 2019). Eudaimonic elements, in turn, provide a more stable foundation for well-being, and empirical work finds that hedonic and eudaimonic measures are strongly correlated and that higher subjective well-being is associated with better physical health and lower morbidity (Ryan & Deci, 2001; Diener & Chan, 2011; Diener et al., 2017). From this perspective, "mattering" and "trust" used here as instrumental variables can be viewed as reflecting eudaimonic aspects of well-being that plausibly influence happiness but are unlikely to exert any direct or causal effect on behavior of medical use, making them theoretically reasonable instruments for this analysis.

To empirically evaluate whether the instrumental variables satisfy the statistical requirements of "relevance" and "exclusion", we conduct standard diagnostic tests (Angrist et al., 1996; Staiger & Stock, 1997; Stock & Yogo, 2005). As shown in the Appendix Table A1, "mattering" and "trust" are strongly associated with happiness in the first stage (F-statistics exceed 20), indicating high relevance. Hansen's over-identification tests do not reject the null of valid instruments, supporting the exclusion restriction. These diagnostic results, together with the theoretical considerations above, justify the use of "mattering" and "trust" as instruments for happiness in our two-part model of medical spending.

Covariates

Our models adopt wide range of control variables across demographics, socioeconomic status, health conditions, lifestyle and social capital. Age was grouped into five-year bands, and a female indicator was used. Socioeconomic controls included employment status (regular employee, non-regular worker, self-employed, not working), highest educational attainment (high school or below, professional school, university or higher) and five brackets of household income. Health status dummies indicate whether the respondent is currently being treated for or has ever been diagnosed with hypertension, hyperlipidemia, type 1 diabetes, type 2 diabetes, heart failure, gout, rheumatoid arthritis, reflux esophagitis, stroke, ischemic heart disease, or cancer. Lifestyle variables comprise regular exercise (≥30 minutes of moderate-to-vigorous activity on two or more days per week), smoking intensity (Brinkman index), weekly alcohol consumption and average nightly sleep hours. Social capital is proxied by indicators for meeting friends, relatives and co-workers at least once a week and by participation in community or volunteer activities. Detailed definitions and corresponding questionnaire items are summarized in Appendix Table A4.

IV. Empirical Model

Health-care expenditure data often include many zero observations and are heavily skewed, so a single linear model is inappropriate. Following Cragg (1971) and subsequent work (Mullahy, 1998; Manning & Mullahy, 2001; Buntin & Zaslavsky, 2004), we adopt a two-part model that separates the decision whether to spend or not from the decision of how much to spend.

Let Y_i denote individual i's monthly out-of-pocket medical expenditure; H_i denote their self-reported happiness score on a 10-point scale; and X_i be a vector of control variables including age, sex, education, income, employment status, indicators for major chronic conditions, lifestyle factors (exercise, smoking intensity, alcohol use, sleep) and measures of social capital.

In the first part of the model, we analyse the binary outcome $D_i = 1\{Y_i > 0\}$ representing whether any medical expenditure occurs. The second part considers the level of $Y_i$conditional on $Y_i > 0$. Happiness may be endogenous because unobserved health status or socioeconomic factors can influence both happiness and spending. We therefore employ an instrumental-variable approach. The instruments are responses to questions about feeling that one's actions are valuable (mattering) and about whether most people can be trusted (trust). These variables correlate strongly with happiness but are not expected to affect medical use except through happiness, as discussed in the previous section.

We implement a two-stage residual inclusion estimator, which provides statistically consistent estimates in nonlinear models with endogenous regressors (Terza et al., 2008; Terza, 2017). In the first stage, happiness is regressed on the instruments and covariates:

$$(1) \quad H_i = \delta_0 + \mathrm{Z}_i\delta_1 + \mathrm{X}_i\delta_2 + u_i,$$

where $\mathrm{Z}_i$denotes the instrument vector and $u_i$is an error term. The residual $\hat{u}_i$is computed from this regression. The second stage includes $\hat{u}_i$to correct for endogeneity. For the extensive margin, we estimate a logistic model:

$$(2) \quad Pr(\, D_i = 1 \mid H_i, X_i\,) = \frac{\exp(\alpha_0 + \alpha_1 H_i + X_i\alpha_2 + \lambda\widehat{\mu_\iota})}{1 + \exp\big(\alpha_0 + \alpha_1 H_i + X_i\alpha_2 + \lambda\widehat{\mu_\iota}\big)}$$

For the intensive margin, we model positive expenditures using a log-link Gamma generalised linear model:

$$(3) \quad log\, \mathbb{E}\,(\,Y_i \mid D_i = 1, H_i, \mathrm{X}_i\,) = \beta_0 + \beta_1 H_i + \mathrm{X}_i\beta_2 + \eta\hat{u}_i.$$

These specifications allow the probability of any expenditure and the conditional mean to vary with happiness while controlling for covariates and endogeneity. Logistic and Gamma links are standard choices for two-part models of skewed cost data (Manning & Mullahy, 2001). The expected value of $Y_i$is $\mathbb{E}(Y_i \mid H_i, \mathrm{X}_i) = p_i\, \mu_i$, where $p_i = \Pr\,(D_i = 1 \mid H_i, \mathrm{X}_i)$ from the logistic model and $\mu_i = \exp\,(\beta_0 + \beta_1 H_i + \mathrm{X}_i\beta_2 + \eta\hat{u}_i)$ is the conditional mean expenditure among individuals with positive spending. To assess how happiness affects spending, we decompose the derivative of the unconditional mean:

$$(4) \quad \frac{\partial \mathbb{E}(Y_i)}{\partial H_i} = \mu_i \frac{\partial p_i}{\partial H_i} + p_i \frac{\partial \mu_i}{\partial H_i}.$$

For the logistic model, $\frac{\partial p_i}{\partial H_i} = \alpha_1 \, p_i(1 - p_i)$; for the log-link Gamma model, $\frac{\partial \mu_i}{\partial H_i} = \beta_1 \, \mu_i$. Substituting these expressions yields

$$(5) \quad \frac{\partial \mathbb{E}(Y_i)}{\partial H_i} = \alpha_1 \mu_i \, p_i(1 - p_i) \; + \; \beta_1 \mu_i \, p_i.$$

The first term ($\alpha_1 \mu_i \, p_i(1 - p_i)$) is the extensive effect, capturing how happiness influences the likelihood of any expenditure. The second term ($\beta_1 \mu_i \, p_i$) is the intensive effect, capturing how happiness affects the level of expenditure among those who use care. Evaluating these derivatives at sample means provides average marginal effects (Deb & Norton, 2018; Karlsson et al., 2024). Standard errors and confidence intervals are obtained via nonparametric bootstrapping with 1 000 replicates at the individual level (Efron & Tibshirani, 1994).

As discussed in the previous section, subjective happiness may affect medical use and spending—both directly and indirectly—through multiple biological, behavioral, and social pathways, including mechanisms that make people more open to a wider set of daily choices. Because these factors can also influence both happiness and spending as confounders, we control for a broad set of covariates. Our empirical strategy therefore aims to capture the total effect of happiness on individual medical expenditure.

V. Result

We analyze how happiness is related to monthly out-of-pocket medical expenditures using a two-part model with two-stage residual inclusion, comparing non-instrumented and IV estimates across two survey waves: 2019 (January, pre-pandemic) and 2020 (August, during COVID-19, when the Japanese government requested voluntary restraint in work and life activities).

In Table 3, the average marginal effects (AMEs) indicate a consistent negative association between happiness and medical spending. In the non-IV estimation, a one-point increase in happiness corresponds to a decrease of 0.102 (SE: 0.038) in 2019 and 0.157 (SE: 0.037) in 2020. After accounting for endogeneity through the IV specification, the estimated magnitudes become 0.248 (SE: 0.140) in 2019 and 0.326 (SE: 0.124) in 2020, while maintaining the same negative sign. The direction is stable across years, and the absolute size grows when instrumented. These results suggest that conventional models underestimate the true effect of happiness on medical costs, consistent with previous evidence(Sabatini, 2014; Kyriopoulos et al., 2018),who observed stronger causal effects of well-being and social capital after IV adjustment.

Decomposition in Table 3 shows that the major pathway is the intensive margin. The extensive margin coefficients, capturing the probability of incurring any medical expenditure, show relatively small and statistically weak increase: 0.134 (SE: 0.068) in 2019 and 0.031 (SE: 0.081) in 2020. In contrast, the intensive margin—representing the conditional spending level among individuals with positive spending—shows large and significant decrease: 0.382 (SE: 0.121) in 2019 and 0.357 (SE: 0.097) in 2020. Hence, the overall decline in medical expenditure driven by happiness primarily results from reduced spending among individuals, not from lower probability of health care use. The magnitude of both intensive margins is stable across two different years and represents the central empirical finding of this study.

Examining covariates from both the logit and GLM stages (Appendix A2 and A3), we find several patterns. In the logit model relevant to extensive margin, chronic-disease dummies—hypertension, hyperlipidemia, diabetes, and cancer—show positive and significant coefficients, suggesting that these health conditions mainly influence the decision to use medical services. Older age (55–64, 65–74, 75+) also raises the probability of medical utilization, while exercise frequency and sleep time are weakly negative. In the GLM model relevant to intensive margin, age, female gender, and the same chronic conditions remain positive and significant, indicating higher out-of-pocket spending once services are used. Regular exercise and longer sleep duration are negatively associated with expenditures. These results confirm that preventive behaviors reduce the conditional cost of care.

Regarding social capital, variables reflecting social participation and interpersonal networks, meeting friends or relatives, participation in local community or volunteer activities, do not display strong direct effects on either margin. Yet, several of these indicators are positively associated with happiness (Appendix A1), implying that social capital contributes indirectly through higher well-being rather than directly altering expenditure patterns. This observation is consistent with recent empirical evidence linking social capital to better health (Xue et al., 2020).

Table 3. Marginal Effects of Happiness on Medical Expenditures

	2019	2020
Non-IV Two Part Estimation		
Average Marginal Effects	-0.102***	-0.157***
	(0.038)	(0.037)
Extensive Margin	0.005	-0.062***
	(0.021)	(0.024)
Intensive Margin	-0.106***	-0.095***
	(0.034)	(0.029)
IV Two Part Estimation		
Average Marginal Effects	-0.248*	-0.326*
	(0.140)	(0.124)
Extensive Margin	0.134**	0.031
	(0.068)	(0.081)
Intensive Margin	-0.382***	-0.357***
	(0.121)	(0.097)

Notes: Own calculations based on the Nagahama Cohort Survey. Standard errors in parentheses are bootstrapped (1,000 replications). Coefficients can be interpreted as the change in monthly out-of-pocket medical expenditures (1,000 ¥) associated with a one-point increase in happiness multiplied by 1,000 for monetary interpretation. "Extensive Margin" reports marginal effects for the probability of any positive medical spending, and "Intensive Margin" reports marginal effects on expenditure conditional on positive spending. "Average Marginal Effects" represent the sum of both components. *Asterisks indicate significance at the 10%(*), 5%(**), and 1%(***) levels, respectively.*

VI. Discussion

To help interpret the results, we first evaluate the estimated average marginal effects (AMEs) and their monetary meaning. Our analysis provides causal evidence that higher happiness keeps individual medical expenditures down. In the IV estimation, a one-point increase in happiness lowers average monthly out-of-pocket spending by ¥248 (SE = ¥140) in 2019 and ¥326 (SE = ¥129) in 2020, whereas the corresponding non-IV decreases are ¥102 (SE = ¥38) and ¥157 (SE = ¥37). The decomposition shows that this overall decrease is almost entirely driven by the intensive margin, representing the spending level among individuals with positive spending. The estimated intensive-margin effects amount to ¥382 (SE = ¥121) for 2019 and ¥357 (SE = ¥97) for 2020, corresponding to roughly 4–5 percent of the average monthly expenditure among individuals with positive spending. The extensive margin—capturing the probability of any medical spending—shows relatively small and statistically weak change.

These results indicate that happier individuals spend less once they want to use care, implying that happiness primarily stabilizes medical consumption on the intensive side rather than reducing the likelihood of seeking care. This magnitude is economically meaningful, given that people aged 65 years and older account for ¥28.1 trillion (60.2 percent) of Japan's national medical expenditure (Ministry of Health, Labour and Welfare, 2024)

The IV estimates in Appendix A2 and A3 reveal a consistent but asymmetric pattern between the two margins. In the logit model, the coefficient on happiness is small and statistically weak—positive in sign but only marginally different from zero—suggesting that happiness has little net effect on the probability of any medical use. This modest association likely reflects the wide definition of medical utilization in our data, which includes routine checkups, minor treatments, and prescription refills. In contrast, the GLM results show a large and highly significant decrease in conditional spending among individuals with positive spending. Together, these findings indicate that happiness may increase preventive or low-intensity care while reducing costly or avoidable spending once care is sought. This dual pattern aligns with the behavioral interpretation that hedonic well-being acts as a motivational trigger for early health actions and self-regulation in healthcare use. The same direction and relative magnitudes appear in both 2019 and 2020, implying that the mechanism linking happiness and medical spending remained stable even under the external constraints of the COVID-19 pandemic.

Covariate patterns are aligned with economic intuition and support the behavioral interpretation. Chronic conditions (hypertension, hyperlipidemia, type-2 diabetes) predict higher probabilities and levels of spending; preventive behaviors (regular exercise, sufficient sleep) are related to lower conditional costs. Age and gender gradients match Japan's known cost distribution, in which older women with multiple chronic conditions face the highest out-of-pocket burden.

A concise synthesis of Japanese multilevel evidence indicates that community social capital improves psychological well-being and shapes healthcare behavior through trust, reciprocity, and social participation (Mizuochi, 2016; Kim & Kawachi, 2017; Haseda et al., 2018). Taken together, these studies show that communities with active participation and mutual trust tend to support mental health, promote preventive use, and discourage unnecessary care. Our findings fit these studies well: happiness appears to be the psychological path through which socially embedded participation is translated into more efficient medical spending. This reading is also consistent with the direction of Japan's community-based integrated care system, which emphasizes locally grounded participation and cooperative networks as pillars for sustaining population health and economic efficiency (Tsutsui, 2012; Otaga, 2024).

VII. Conclusion

This study aimed to identify whether higher happiness causally keeps individual medical expenditures down. While previous studies have often discussed happiness and health behaviors in correlational terms, few have provided causal evidence. Using an econometric framework, this research approached the issue from a social science perspective, demonstrating how subjective well-being relates to healthcare economics in an aging population.

The study addressed theoretical and empirical challenges by applying an instrumental-variable two-part model that separates the probability of medical use from the conditional level of expenditure. This modeling framework enabled us to estimate the causal effects of happiness while accounting for endogeneity. The analysis was conducted using micro-level data from the Nagahama cohort for 2019 and 2020, which include detailed information on health status, lifestyle, and medical expenditures.

The results show that happiness significantly keeps conditional out-of-pocket spending down by approximately 4-5% of average monthly medical expenditures among individuals with positive spending, while slightly increasing the probability of medical use. These findings indicate that happiness promotes appropriate access to care but restrains excessive spending. This dual pattern, observed both before and during the COVID-19 pandemic, suggests that the relationship between happiness and medical spending is stable even under external constraints. Happiness thus appears to serve as a behavioral foundation for efficient medical consumption.

Our findings also fit within Japan's broader policy context. The observed pattern is consistent with the direction of the community-based integrated care system, which emphasizes local participation and cooperation as essential elements for achieving both sustainable health and economic outcomes (Tsutsui, 2012; Otaga, 2024).

Although the analysis focuses primarily on older adults, this study highlights the academic value of integrating economic and social science approaches to healthcare research. Future work should connect subjective well-being with more objective medical data—ranging from electronic medical records to insurance claims data—to improve the accuracy of expenditure evaluation. In this regard, Japan's ongoing Medical DX (Digital Transformation) initiative provides an important opportunity to establish integrated data systems for more precise and timely health policy evaluation (Ministry of Health, Labour and Welfare, 2023).

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Ethics approval and consent to participate

The Nagahama Study protocols were approved by the Ethics Committee of Kyoto University Graduate School of Medicine (approval number: G278) and by the Nagahama Municipal Review Board. Written informed consent was obtained from all participants. All data were anonymized prior to analysis.

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Declaration of competing interest

The author declares no conflicts of interest.

Data availability

The data that support the findings of this study are not publicly available due to ethical restrictions imposed by the Nagahama Study Executive Committee.

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Table A1 Two-stage Residual Inclusion Estimation

Variable	2019 Coef.		2019 SE	2020 Coef.		2020 SE
mattering	0.26	***	(0.02)	0.27	***	(0.02)
trust	0.10	***	(0.01)	0.09	***	(0.02)
aged 55 - 64	0.12		(0.08)	0.17	*	(0.09)
aged 65 - 74	0.01		(0.10)	0.02		(0.10)
aged 75 or older	0.03		(0.12)	0.12		(0.12)
sex	0.27	**	(0.09)	0.16	*	(0.10)
self employed	-0.03		(0.09)	-0.12		(0.09)
regular worker	-0.11		(0.11)	-0.03		(0.12)
non-regular worker	-0.11		(0.08)	-0.01		(0.08)
professional school	-0.11		(0.07)	0.08		(0.07)
university or higher	0.00		(0.08)	0.18	**	(0.08)
annu. house income (0 ~ 4mil.)	-0.28	***	(0.09)	-0.23	***	(0.08)
annu. house income (4 ~6mil.)	-0.14		(0.10)	0.01		(0.09)
annu. house income (6 ~8mil.)	-0.07		(0.11)	-0.17		(0.11)
annu. house income (8 ~10mil.)	0.10		(0.12)	0.08		(0.13)
hypertension	-0.14	**	(0.06)	-0.11	*	(0.07)
hyperlipidemia	0.00		(0.06)	0.03		(0.06)
type1 diabetes	0.72	*	(0.44)	0.49		(0.33)
type2 diabetes	-0.18		(0.11)	-0.09		(0.12)
heart failure	-0.01		(0.25)	-0.06		(0.30)
gout	0.07		(0.16)	-0.11		(0.16)
rheumatoid arthritis	-0.08		(0.22)	-0.12		(0.21)
reflux esophgitis	0.07		(0.08)	0.02		(0.09)
stroke	0.18		(0.20)	-0.04		(0.23)
ischemic heart disease	0.31	**	(0.12)	0.07		(0.14)
cancer	0.08		(0.09)	-0.13	*	(0.10)
exercise 30min_2day	0.04		(0.06)	0.02		(0.07)
daily activity 1h	0.00		(0.06)	0.07		(0.06)
brinkman index (1~400)	-0.08		(0.09)	-0.05		(0.10)
brinkman index (400~1200)	-0.11		(0.10)	-0.06		(0.11)
brinkman index (1200~)	-0.78	**	(0.35)	-0.01		(0.31)
weekly alcohol (3~8)	0.01		(0.08)	0.02		(0.09)
weekly alcohol (8~)	0.04		(0.09)	0.00		(0.09)
sleep time (<6h)	-0.22	***	(0.07)	-0.29	***	(0.07)
sleep time (8h~)	0.18	**	(0.08)	0.19	**	(0.09)
meet_friends	0.20	***	(0.07)	0.10	*	(0.06)
meet_relatives	0.13	**	(0.07)	0.20	***	(0.06)
meet_cowokers	0.09		(0.07)	0.00		(0.07)
local community participation	0.16	**	(0.08)	0.04		(0.09)
volunteer participation	0.00		(0.06)	0.14	**	(0.06)

Notes: Ordinary least squares estimates from the first-stage regressions of the two-stage residual inclusion (2SRI) procedure. The dependent variable is subjective happiness. The fitted residuals from these regressions are used in the subsequent two-part models of monthly medical expenditures to correct for the endogeneity of happiness.The joint F-statistics from the first-stage regressions indicate that both instruments (mattering and trust) are strongly correlated with happiness (2019: F = 175.1, $p < 0.001$, partial R^2 = 0.096; 2020: F = 154.3, $p < 0.001$, partial R^2 = 0.094), confirming instrument relevance. The Hansen J-tests of over-identifying restrictions show no evidence of violation of the exclusion condition (2019: $\chi^2(1) = 1.47$, p = 0.23; 2020: $\chi^2(1) = 0.12$, p = 0.73). Asterisks indicate significance at the 10%(*), 5%(**), and 1%(***) levels, respectively.

Table A2 - IV and Non-IV Two-Part Logistic Model

	Non-IV Estimation				IV Estimation			
	2019		2020		2019		2020	
Variable	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
happiness	0.01	(0.02)	-0.07 ***	(0.02)	0.14 **	(0.07)	0.03	(0.08)
residuals from 2SRI					-0.15 **	(0.07)	-0.10	(0.09)
aged 55 - 64	-0.37 ***	(0.11)	0.00	(0.14)	-0.40 ***	(0.11)	-0.02	(0.14)
aged 65 - 74	-0.63 ***	(0.13)	-0.22	(0.16)	-0.65 ***	(0.13)	-0.24	(0.16)
aged 75 or older	-1.20 ***	(0.17)	-0.72 ***	(0.20)	-1.24 ***	(0.17)	-0.75 ***	(0.21)
sex	-0.59 ***	(0.12)	-0.39 ***	(0.15)	-0.63 ***	(0.12)	-0.41 ***	(0.15)
self employed	-0.15	(0.12)	-0.06	(0.16)	-0.16	(0.12)	-0.06	(0.16)
regular worker	0.04	(0.14)	-0.10	(0.18)	0.05	(0.14)	-0.10	(0.18)
non-regular worker	0.05	(0.11)	-0.23 *	(0.13)	0.07	(0.11)	-0.23 *	(0.13)
professional school	0.17 *	(0.10)	0.28 **	(0.12)	0.17 *	(0.10)	0.27 **	(0.12)
university or higher	0.44 ***	(0.10)	0.38 ***	(0.13)	0.42 ***	(0.10)	0.36 ***	(0.13)
annu. house income (0 ~ 4mil.)	-0.20 *	(0.12)	-0.15	(0.14)	-0.16	(0.12)	-0.12	(0.14)
annu. house income (4 ~6mil.)	-0.05	(0.13)	0.08	(0.15)	-0.03	(0.13)	0.09	(0.15)
annu. house income (6 ~8mil.)	-0.05	(0.14)	0.31 *	(0.17)	-0.04	(0.14)	0.32 *	(0.17)
annu. house income (8 ~10mil.)	0.06	(0.15)	0.09	(0.20)	0.04	(0.15)	0.08	(0.20)
hypertension	0.06	(0.09)	0.12	(0.11)	0.08	(0.09)	0.13	(0.11)
hyperlipidemia	0.04	(0.09)	0.14	(0.10)	0.04	(0.09)	0.13	(0.10)
type1 diabetes	0.28	(0.57)	1.40 **	(0.56)	0.19	(0.58)	1.36 **	(0.56)
type2 diabetes	0.13	(0.15)	0.35 **	(0.17)	0.15	(0.15)	0.35 **	(0.17)
heart failure	0.55 *	(0.31)	-0.17	(0.45)	0.56 *	(0.31)	-0.16	(0.45)
gout	-0.04	(0.19)	-0.33	(0.26)	-0.06	(0.19)	-0.31	(0.26)
rheumatoid arthritis	-0.25	(0.30)	0.62 **	(0.28)	-0.24	(0.30)	0.63 **	(0.28)
reflux esophgitis	0.09	(0.12)	0.07	(0.14)	0.08	(0.12)	0.07	(0.15)
stroke	0.54 **	(0.24)	0.84 ***	(0.28)	0.52 **	(0.24)	0.85 ***	(0.28)
ischemic heart disease	0.16	(0.21)	0.42 *	(0.24)	0.11	(0.21)	0.41 *	(0.24)
cancer	0.22 *	(0.13)	0.45 ***	(0.15)	0.21 *	(0.13)	0.46 ***	(0.15)
exercise 30min_2day	-0.09	(0.09)	-0.05	(0.11)	-0.10	(0.09)	-0.05	(0.11)
daily activity 1h	-0.18 **	(0.08)	0.01	(0.10)	-0.19 **	(0.08)	0.00	(0.10)
brinkman index (1~400)	0.02	(0.12)	0.11	(0.15)	0.04	(0.12)	0.12	(0.15)
brinkman index (400~1200)	-0.03	(0.13)	0.05	(0.16)	0.00	(0.13)	0.06	(0.17)
brinkman index (1200~)	0.39	(0.38)	-0.90	(0.70)	0.50	(0.38)	-0.89	(0.70)
weekly alcohol (3~8)	-0.03	(0.11)	-0.05	(0.15)	-0.04	(0.11)	-0.05	(0.15)
weekly alcohol (8~)	0.07	(0.11)	-0.03	(0.14)	0.06	(0.11)	-0.03	(0.15)
sleep time (<6h)	0.27 ***	(0.09)	0.12	(0.11)	0.31 ***	(0.09)	0.15	(0.12)
sleep time (8h~)	0.18	(0.12)	0.06	(0.15)	0.16	(0.12)	0.04	(0.15)
meet_friends	0.13	(0.09)	-0.07	(0.11)	0.09	(0.12)	-0.09	(0.11)
meet_relatives	0.00	(0.09)	0.17	(0.11)	-0.02	(0.12)	0.15	(0.11)
meet_cowokers	-0.09	(0.09)	0.21 *	(0.11)	-0.12	(0.09)	0.20	(0.11)
local community participation	-0.19 *	(0.11)	-0.08	(0.15)	-0.22 *	(0.12)	-0.09	(0.15)
volunteer participation	0.16 *	(0.08)	0.27 ***	(0.10)	0.14 *	(0.08)	0.25 **	(0.11)

Notes: Logistic regressions for the extensive margin of the two-part model. The dependent variable is a binary indicator equal to one if monthly medical expenditures are positive and zero otherwise. Residuals from the first-stage 2SRI regressions are included to correct for potential endogeneity of happiness. All models include the same demographic, socioeconomic, health, and behavioral covariates as in the baseline specifications. Asterisks indicate significance at the 10%(*), 5%(**), and 1%(***) levels, respectively.

Table A3 IV and Non-IV Two Part Log-Link Gamma Generalised Liniear Model

	Non-IV Estimation				IV Estimation			
	2019		2020		2019		2020	
Variable	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
happiness	-0.09 ***	(0.02)	-0.09 ***	(0.02)	-0.30 ***	(0.09)	-0.32 ***	(0.07)
residuals from 2SRI					0.25 ***	(0.09)	0.26 ***	(0.07)
aged 55 - 64	0.16	(0.13)	0.33 **	(0.14)	0.19	(0.13)	0.38 ***	(0.13)
aged 65 - 74	0.72 ***	(0.15)	0.74 ***	(0.16)	0.76 ***	(0.15)	0.76 ***	(0.16)
aged 75 or older	1.01 ***	(0.18)	0.69 ***	(0.20)	1.06 ***	(0.18)	0.76 ***	(0.20)
sex	0.17	(0.15)	-0.01	(0.12)	0.22	(0.15)	0.04	(0.12)
self employed	-0.13	(0.15)	0.06	(0.14)	-0.12	(0.16)	0.05	(0.14)
regular worker	0.04	(0.17)	0.04	(0.19)	0.02	(0.18)	0.00	(0.19)
non-regular worker	-0.02	(0.14)	-0.12	(0.13)	-0.07	(0.13)	-0.15	(0.13)
professional school	-0.13	(0.12)	0.00	(0.12)	-0.11	(0.12)	0.01	(0.12)
university or higher	0.21	(0.13)	-0.19 *	(0.11)	0.26 *	(0.14)	-0.13	(0.11)
annu. house income (0 ~ 4mil.)	0.07	(0.13)	-0.16	(0.12)	-0.03	(0.14)	-0.27 **	(0.12)
annu. house income (4 ~6mil.)	0.14	(0.16)	-0.05	(0.14)	0.11	(0.16)	-0.07	(0.14)
annu. house income (6 ~8mil.)	-0.19	(0.17)	-0.09	(0.16)	-0.20	(0.18)	-0.16	(0.15)
annu. house income (8 ~10mil.)	-0.22	(0.19)	0.02	(0.18)	-0.14	(0.20)	0.04	(0.18)
hypertension	0.48 ***	(0.10)	0.13	(0.09)	0.45 ***	(0.10)	0.11	(0.09)
hyperlipidemia	0.35 ***	(0.09)	0.15 *	(0.09)	0.35 ***	(0.09)	0.14 *	(0.09)
type1 diabetes	-0.07	(0.24)	-0.04	(0.17)	0.12	(0.25)	0.14	(0.18)
type2 diabetes	0.43 ***	(0.13)	0.23 *	(0.12)	0.35 ***	(0.12)	0.24 **	(0.12)
heart failure	0.01	(0.21)	-0.28	(0.27)	0.07	(0.21)	-0.29	(0.28)
gout	-0.11	(0.15)	-0.28 *	(0.17)	-0.09	(0.15)	-0.36 **	(0.17)
rheumatoid arthritis	1.67 ***	(0.26)	0.43 **	(0.18)	1.63 ***	(0.25)	0.33 *	(0.17)
reflux esophgitis	0.31 **	(0.14)	0.10	(0.11)	0.31 **	(0.14)	0.13	(0.11)
stroke	0.22	(0.28)	0.26 *	(0.16)	0.31	(0.28)	0.26 *	(0.15)
ischemic heart disease	0.47 **	(0.21)	0.27	(0.19)	0.53 **	(0.20)	0.31 *	(0.18)
cancer	0.37 ***	(0.14)	0.28 **	(0.12)	0.33 **	(0.13)	0.23 **	(0.12)
exercise 30min_2day	0.02	(0.11)	0.02	(0.10)	0.03	(0.11)	0.03	(0.10)
daily activity 1h	0.08	(0.10)	0.17 *	(0.09)	0.08	(0.10)	0.23 **	(0.09)
brinkman index (1~400)	0.33 **	(0.15)	-0.08	(0.12)	0.29 *	(0.15)	-0.07	(0.11)
brinkman index (400~1200)	0.20	(0.15)	0.05	(0.12)	0.18	(0.15)	0.02	(0.12)
brinkman index (1200~)	0.09	(0.37)	1.06 *	(0.60)	-0.10	(0.36)	1.00 *	(0.56)
weekly alcohol (3~8)	0.07	(0.14)	-0.09	(0.12)	0.07	(0.14)	-0.09	(0.12)
weekly alcohol (8~)	-0.12	(0.15)	0.06	(0.11)	-0.13	(0.14)	0.06	(0.11)
sleep time (<6h)	-0.02	(0.11)	0.17	(0.12)	-0.05	(0.11)	0.10	(0.11)
sleep time (8h~)	0.09	(0.14)	0.21 *	(0.13)	0.13	(0.14)	0.26 **	(0.13)
meet_friends	-0.03	(0.12)	0.04	(0.09)	0.04	(0.12)	0.09	(0.09)
meet_relatives	-0.05	(0.11)	-0.04	(0.10)	0.03	(0.11)	0.02	(0.10)
meet_cowokers	0.03	(0.12)	-0.02	(0.11)	0.07	(0.11)	0.04	(0.10)
local community participation	-0.11	(0.12)	0.14	(0.12)	0.14	(0.12)	0.19	(0.12)
volunteer participation	0.18 *	(0.10)	0.12	(0.09)	0.22 **	(0.10)	0.16 *	(0.09)

Notes: Logistic regressions for the extensive margin of the two-part model. The dependent variable is a binary indicator equal to one if monthly medical expenditures are positive and zero otherwise. Residuals from the first-stage 2SRI regressions are included to correct for potential endogeneity of happiness. All models include the same demographic, socioeconomic, health, and behavioral covariates as in the baseline specifications. Asterisks indicate significance at the 10%(*), 5%(**), and 1%(***) levels, respectively.

Table A4 Variable Definitions

variable	questionnaire	definition/ coding rule
medical expenditure (1,000 Yen)	"how much do you pay per month for medical services and prescription drugs? Exclude costs related to injuries"	Monthly out-of-pocket medical spending in units of ¥ 1,000
happiness	"How happy are you now? (1 = very unhappy – 10 = very happy)"	Ten-point scale.
mattering	"I feel that what I am doing is valuable." (1 = strongly agree – 10 = strongly disagree)	Reverse-coded ten-point scale
trust	"Most people can be trusted or one should be careful." (1 = most people can be trusted – 10 = one must be careful)	Reverse-coded ten-point scale
age	Registered birth year	Grouped into dummy bands; aged 55 or below (used as referece), 55–64, 65–74, and 75 or older
sex	Registered sex	1 = female, 0 = male.
employment status	"Which of the following describes your working status" and "for those who ansewered as employee, what is your employment type"	Dummies (not-working, self employed (self-emloyed, freelance, family worker etc.), regular worker (regular work, executive), non-regular worker (contract, part-time, dispatched, reemployed)
educational attainment	"What is the highest level of education you completed?"	Dummies (high school or below (used as reference), professional school, university or higher)
annual household income	"What is your household's total annual income (before tax) including all sources?"	Five income categories: (1) 0–4 million ¥, (2) 4–6 million ¥, (3) 6–8 million ¥, (4) 8–10 million ¥, (5) 10 million ¥ or more (used as reference).
hypertension / hyperlipidemia / type1 diabetes / type2 diabetes / heart failure / gout / rheumatoid arthritis / reflux esophagitis / stroke / ischemic heart disease / cancer	Health-check records (self-report of physician diagnosis or current treatment).	1 = currently treated or ever diagnosed; 0 otherwise.
exercise 30min_2day	"Do you engage in ≥ 30 minutes of moderate-to-vigorous activity on ≥ 2 days per week?"	Dummy = 1 if yes.
daily activity 1h	"Do you engage in walking or physical activity of similar intensity for at least one hour per day in your daily life?"	Dummy = 1 if yes.
brinkman index	"How many cigarettes do you smoke per day and for how many years?"	Dummy variables for each category; 0 = reference
weekly alcohol	Derived from questions on drinking frequency (days per week) and amount per occasion (one unit = 180 ml of sake).	Dummy variables for each category; <3 unit = reference
sleep time	Computed from reported bed time and wake time	Dummy variables for each category; 6h-8h = reference
meet friends / meet relatives / meet coworkers	"How often do you meet friends, relatives, and coworkers?"	Dummy = 1 if meeting ≥ once per week
local community participation	"Do you participate in community activities (e.g., neighborhood association, senior club) and how often?"	Dummy = 1 if participating ≥ once per month
volunteer participation	"Do you participate in volunteer / NPO / civic activities and how often?"	Dummy = 1 if participating ≥ once per month