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Subjective well-being and healthcare utilization: A mediation analysis

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ABSTRACT

Subjective well-being measures are gaining recognition as important determinants of health outcomes. This paper examines whether life satisfaction matters for healthcare usage in the older population and, if so, what might help explain this relationship. To that end, we develop a mediation framework and test whether lifestyle choices and social capital are pathways through which life satisfaction at baseline influences subsequent healthcare usage. Using Heckman's approach to correct for sample selection bias, we find that those high in life satisfaction may need less outpatient care. We also show that this effect is explained by increased physical activity.

1. Introduction

While in 2020 there were 727 million people aged 65 years or over, this number is projected to rise, reaching over 1.5 billion in 2050 (United Nations, 2020). As the elderly share of the population increases, maintaining health and well-being at advanced ages is becoming more important. Most countries have experienced economic growth over the past two decades, and this has contributed to increases in healthcare spending. Worldwide, the total spending on healthcare is substantial. It was US$ 7.8 trillion in 2017, which accounts for about 10% of GDP (WHO, 2019). These figures are expected to continue growing, so it is important to see what we can do to reduce healthcare spending.

A large body of literature shows that people's health status is related to their well-being. Low levels of well-being have been implicated in many common health problems, including early mortality, diabetes, and coronary heart disease (Steptoe, 2006). Meanwhile, a growing empirical literature is highlighting a new possibility. Positive psychological well-being may help to maintain physical health (see Diener et al., 2017, for a comprehensive review). Using data from The English Longitudinal Study of Ageing (ELSA), Steptoe et al. (2015) study the link between eudaimonic well-being and mortality and find a 30% reduction in the risk of death for the highest well-being quartile compared to the lowest. In a similar vein, Blanchflower and Oswald (2008) have shown that high well-being is associated with lower blood pressure across 16 European countries, and others have found high well-being to be predictive of fewer symptoms and chronic conditions (Ryff et al., 2015), stronger immune function (Barak, 2006), and better cardiovascular health (Yanek et al., 2013). The consensus from these studies is clear: positive well-being may have important implications for future health and survival.[1]

In this paper, we extend from the previous studies in two important ways. First, the earlier studies focus only on health outcomes. Using nationally representative panel data for Australia on individuals aged 50 and over, we shift the focus to healthcare usage. In this context, one issue we need to deal with is sample selection bias: healthcare usage is only observed if the respondent decides to see a doctor. Applying Heckman's approach to correct for this bias, we present new analysis evaluating the link between well-being and two measures of curative healthcare: outpatient and inpatient care.

Second, we provide additional evidence by conducting a mediation analysis using two forms of human capital investments – lifestyle choices and social capital – as possible mediators. Both forms of investments are worth investigating because they are critical inputs in health and relevant to health policies. Accordingly, we are able to quantify both the

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[1] There is more and more empirical evidence highlighting the role of well-being as the cause (rather than just a consequence) of various social and economic outcomes, including wages, unemployment, physical health, and longevity (e.g., Kesavayuth & Zikos, 2018; Mishra & Smyth, 2014; O'Connor, 2020; O'Connor & Graham, 2019).

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direct effects of well-being on healthcare usage as well as the indirect, mediational pathways through lifestyle choices and social capital.

In the current context, mediation assumes a specific process in which (i) subjective well-being impacts lifestyle choices and social capital, and (ii) lifestyle choices and social capital then impact healthcare usage. Discussing these requirements is important not least because they allow us to distinguish mediation from moderation. Regarding the second requirement, the role of healthy behaviors for health outcomes is well studied in the literature (e.g., Mokdad et al., 2005; Danaei et al., 2009). Healthy behaviors such as exercising and not smoking may slow down the process of health deterioration at an older age and thereby reduce healthcare usage (Bussolo et al., 2015). Increasing evidence also suggests that social capital, including social networks and social support, have beneficial effects on people's health (Goldsmith & Albrecht, 2011; Wright, 2016).

Although the second requirement for mediation – how lifestyle choices and social capital impact healthcare usage – is intuitive, the first may not be so obvious and requires further investigation. A growing body of literature has linked well-being to health behaviors. Evidence suggests that positive well-being is associated with healthier behaviors. For example, individuals with higher levels of well-being tend to engage in more physical activity and less smoking relative to individuals with lower well-being levels (see Steptoe et al., 2006; Kim et al., 2017; and Boehm et al., 2012, for a review). Furthermore, individuals high in well-being have more friends and more social support (Lyubomirsky et al., 2005). Well-being may encourage healthier behaviors and social interactions because positive emotions broaden a person's awareness and promote novel thoughts and actions (Fredrickson, 2001). In turn, broader thought-action repertoires may encourage greater investments in positive lifestyle behaviors, leading to a larger stock of health capital, in line with Fredrickson's (1998) broaden-and-build theory.[2]

Taken together, the two requirements of the mediation process suggest that subjective well-being may impact healthcare usage via behavioral pathways. In this paper we aim to quantify those relationships and, in addition to the direct effect of well-being on healthcare usage, estimate the indirect effect through lifestyle choices and social capital. As well as being significant from an empirical point of view, our findings could also be useful in aiding the design or targeting of interventions that may help maintain people's health in later life.

2. Data

The data for this study come from the Household Income and Labour Dynamics of Australia (HILDA) Survey, which is a longitudinal panel study of a nationally representative sample of Australian households. Consistent with surveys on older adults, we focus our attention on individuals aged 50 or older. Our analytical sample corresponds to an unbalanced panel of 7455 individuals, and 14,607 observations (6815 males, 7792 females). The summary statistics and description of all the variables included in the analyses appear in Appendix Table A1.

Our main dependent variable, available in the 2009, 2013 and 2017 waves of HILDA, is healthcare usage. We distinguish between two types of curative healthcare: outpatient and inpatient care. Information on outpatient care is collected with the question: "Have you seen your family doctor or another general practitioner (GP) in the last 12 months?" Respondents were also asked whether during the last 12 months, they had ever been patient in a hospital overnight. If the respondents answered "yes" to any of those two questions, they were asked to state (i) how many times they had seen their family doctor or another GP, and/or (ii) how many nights they had been hospitalized. And from the responses to these two questions, we construct our continuous measures of inpatient and outpatient care.

Life satisfaction is one of the most used indicators of subjective well-being and has been recognized as a reliable and valid measure (Pavot & Diener, 1993). The life satisfaction question asks: "All things considered, how satisfied are you with your life?" Possible answers are reported on an 11-point scale where 0 indicates "totally dissatisfied" and 10 indicates "totally satisfied". Thus, our well-being measure is a cognitive/evaluative measure involving a reflective assessment of the respondent's life as a whole (Powdthavee, 2010, 2015).

3. Empirical model and strategy

To examine healthcare usage of older people in a mediation framework, we follow Diener et al. (2017) who have suggested using a cross-lagged design that focuses on the sequencing of events. Drawing on this perspective and following Ohrnberger et al. (2017) and Dour et al. (2014), well-being is measured at baseline; lifestyle choices and social capital are measured somewhat later; and healthcare usage is measured further in the future.

When analysing the effects of past levels of well-being on healthcare usage, we also need to deal with sample selection bias. A person's usage of outpatient healthcare is only observed if she decides to see her family doctor or another GP and is unobservable if she does not. (The same idea applies to the case of inpatient care.) Given that people who see their doctor are non-randomly selected from the population, the estimates obtained on this subpopulation are likely to be biased. To tackle this problem, we use Heckman's correction whereby the inverse Mills ratio is calculated and included in all regression analysis.[3] Hence, the estimation equation is given by:

$$\begin{aligned} HC_{it} &= \alpha_0 + \alpha_1 PH_{i,t=0} + \alpha_2 W_{i,t=0} + \alpha_3 Med_{i,t-1} + \alpha_4 X_{it} + \alpha_5 InverseMills_{it} \\ &\quad + \varepsilon_{it} \end{aligned} \tag{1}$$

where HC_{it} denotes inpatient or outpatient care of individual i at time t; $PH_{i,t=0}$ represents physical health at baseline[4]; $W_{i,t=0}$ is well-being at baseline; $Med_{i,t-1}$ is a vector of possible mediators, i.e., lifestyle choices (physical activity, smoking, and drinking alcohol) and social interactions at t-1; X_{it} is a vector of time-varying variables; and ε_{it} is an idiosyncratic error.

The use of lagged values for lifestyle choices and social interaction allows us to capture the fact that investments in health may take time to come into fruition (Grossman, 1972). More important, the baseline level of well-being is the earliest recorded information for each respondent. It may reflect genetic predispositions and parental investments in early life. Accordingly, this stock of well-being is orthogonal to the time-varying predictor variables included in the model.

To estimate the indirect effects of well-being through health investments in lifestyle choices and social interaction, we rewrite (1) using slightly different notation:

$$\begin{aligned} HC_{it} &= \alpha_0 + \alpha_1 PH_{i,t=0} + \alpha_2 W_{i,t=0} + \alpha_3 Med_{i,t-1}\left(W_{i,t=0}\right) + \alpha_4 X_{it} \\ &\quad + \alpha_5 InverseMills_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

Given that many of these health investments are closely related (e.g., smoking and alcohol consumption), we follow the practice of Lu et al.

[2] The broaden-and-build theory proposes an evolved function of positive emotions, which in turn tends to encourage greater investments in human capital. This theory has received substantial support by randomized controlled lab studies (Fredrickson, 2001) and experimental studies (Isen, 2000).

[3] We use Heckman's two-step estimation procedure. The inverse Mills ratio times its coefficient picks up the expected value of the error in the healthcare usage equation for inpatient (or outpatient) care conditional on seeing a doctor.

[4] The baseline level of physical health is included in our model to control for health endowments and early investments in one's health.

Table 1
Random effect regression models for physical activity, social interaction, smoking and drinking alcohol.

	Physical activity (t-1)	Social interaction (t-1)	Smoking (t-1)	Drinking (t-1)
	(1)	(2)	(3)	(4)
Life satisfaction baseline	0.0504***	0.0906***	−0.0329**	−0.00758
	(0.0109)	(0.0116)	(0.0136)	(0.0114)
Physical health baseline	0.00959***	0.00284***	−0.00220***	0.00539***
	(0.000502)	(0.000511)	(0.000553)	(0.000530)
Age (t-1)	0.0458	−0.249*	0.00311	0.0840
	(0.125)	(0.131)	(0.0747)	(0.0680)
Age squared (t-1)	−0.000236	0.00382*	−0.000374	−0.00106
	(0.00188)	(0.00197)	(0.00108)	(0.00102)
Age cubed (t-1)	−0.00000285	−0.0000195**	0.00000345	0.00000371
	(0.00000933)	(0.00000979)	(0.00000514)	(0.00000506)
Male (t-1)	0.145***	−0.137***	0.169***	0.371***
	(0.0204)	(0.0208)	(0.0234)	(0.0222)
Household size (t-1)	−0.0116	−0.0813***	−0.00549	−0.000704
	(0.0170)	(0.0200)	(0.0127)	(0.00941)
Real household income (t-1)	−0.0000344	0.000225	0.000263**	−0.00000828
	(0.000238)	(0.000248)	(0.000119)	(0.000121)
Married (t-1)	0.0586	−0.306***	−0.0688**	−0.0680**
	(0.0546)	(0.0632)	(0.0275)	(0.0339)
Higher education (t-1)	0.0827***	0.0468**	−0.126***	0.154***
	(0.0212)	(0.0216)	(0.0238)	(0.0225)
Unemployed (t-1)	0.201***	0.155*	0.0652	0.0341
	(0.0779)	(0.0873)	(0.0579)	(0.0469)
Not in the labor force (t-1)	0.0529*	0.117***	0.00154	−0.0251
	(0.0312)	(0.0334)	(0.0222)	(0.0182)
Observations	14,607	14,607	14,607	14,607

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are in parentheses. The models included a set of dummy variables for survey wave and Australian region of residence as control variables. The person-specific means of the time-varying predictors were additionally controlled for in each of the regressions.

(2020) and estimate (2) by including each of the four health investments separately.[5] Then we calculate the total derivative of (2) with respect to $W_{i,t=0}$ to disentangle the direct effect of well-being on healthcare usage from the indirect effect:

$$\frac{dHC}{dW} = \alpha_2 + \left(\frac{\partial HC}{\partial Med} \times \frac{dMed}{dW}\right) \tag{3}$$

The first term on the right-hand side of (3), α_2, represents the *direct effect* of baseline levels of well-being on healthcare usage. The other term in parenthesis is the *indirect effect* of well-being through a mediator variable (to ease notation subscripts have been omitted).

To identify the indirect, mediating effects we use equation (2) together with the following equation:

$$Med_{i,t-1} = \beta_0 + \beta_1 PH_{i,t=0} + \beta_2 W_{i,t=0} + \beta_3 X_{i,t-1} + v_{i,t-1} \tag{4}$$

The mediating effects are obtained by multiplying the coefficient β_2 in (4) with the coefficient α_3 in (2). This is in line with the product-of-coefficients method (Baron & Kenny, 1986; MacKinnon et al., 2007). We assume a composite error term of the form $\varepsilon_{it} = u_i + v_{it}$, where u_i is the person-specific error and v_{it} is the idiosyncratic error. To estimate the models, we use random effects instead of fixed effects. The use of random effects is permissible because the key independent variable is at baseline. We further augmented our specifications by including the person-specific means of the time-varying predictors as additional controls (Mundlak, 1978; Chamberlain, 1982). This minimizes the potential for time-invariant unobserved heterogeneity to bias the estimates. To aid the interpretation of our results, we standardized both our life satisfaction variable and the mediating variables to have a mean of 0 and a standard deviation of 1.

[5] We thus estimate equation (2) four times. This approach was first suggested in Baron and Kenny's (1986) seminal contribution on mediation analysis and has been widely utilized in psychological and economic studies.

4. Main results

We begin by examining whether life satisfaction at baseline is associated with the mediators at $t - 1$. Table 1 displays the results. Looking across the columns, we can see that life satisfaction is significantly related to the mediating variables, except for drinking. Those who are more satisfied with their life tend to participate more often in physical activity and social interactions, while smoking less frequently, consistent with previous findings in the literature (e.g., Boehm et al., 2012).

Our next step is to look at whether the mediators at $t - 1$ relate to healthcare usage at t, controlling for life satisfaction at baseline. Table 2 shows the results for outpatient care, and Table 3 shows analogous results for inpatient care. We find that drinking is associated with less outpatient care, while social interaction and smoking play no role. It should be noted that the variable on drinking does not capture the amount of alcohol consumed. Therefore, increasing the frequency of alcohol consumption may not necessarily be harmful for one's health if moderate amounts are being consumed (Ziebarth & Grabka, 2009; Kesavayuth et al., 2020). Nonetheless, the estimated coefficient on drinking is only marginally significant at the 10% level. Furthermore, physical activity is estimated to decrease outpatient care. Life satisfaction remains significant throughout, indicating that those high in life satisfaction may need less outpatient care. In contrast, life satisfaction does not seem to predict inpatient care, as also appears to be the case with each of the possible mediators (see Table 3).

Holding physical health at baseline constant, what explains why more satisfied people are less likely to become outpatients? The negative effect of life satisfaction on outpatient care could be explained by patient inertia. One potential cause of patient inertia is status quo bias, which suggests a strong preference for one's current state because the disadvantages of leaving it outweigh the advantages (Samuelson & Zeckhauser, 1988). What this implies is that individuals may perceive the process of choosing between doctors as slow, uncertain, and costly (Samuelson & Zeckhauser, 1988), or they may be prone to inaction inertia (Ritov & Baron, 1992). This may partly explain why life satisfaction appears to have a long-lasting and negative direct effect on outpatient care, holding baseline physical health constant. In addition,

Table 2
Random effect regression models for outpatient care.

	Outpatient care			
	(1)	(2)	(3)	(4)
Life satisfaction baseline	−0.183**	−0.206**	−0.223**	−0.229**
	(0.0908)	(0.0904)	(0.0919)	(0.0905)
Physical health baseline	−0.0851***	−0.0922***	−0.0916***	−0.0879***
	(0.00597)	(0.00611)	(0.00629)	(0.00618)
Age	−0.365	−0.393	−0.399	−0.342
	(1.037)	(1.044)	(1.038)	(1.036)
Age squared	0.00790	0.00818	0.00801	0.00737
	(0.0156)	(0.0157)	(0.0156)	(0.0156)
Age cubed	−0.0000295	−0.0000292	−0.0000275	−0.0000253
	(0.0000775)	(0.0000778)	(0.0000775)	(0.0000773)
Male	−0.0388	−0.181	−0.129	0.133
	(0.192)	(0.196)	(0.197)	(0.200)
Household size	−0.298**	−0.289**	−0.278**	−0.277**
	(0.127)	(0.126)	(0.127)	(0.127)
Real household income	0.00238	0.00241	0.00219	0.00210
	(0.00149)	(0.00150)	(0.00152)	(0.00151)
Married	0.350	0.308	0.333	0.358
	(0.453)	(0.459)	(0.462)	(0.463)
Higher education	−0.139	−0.190	−0.204	−0.0984
	(0.154)	(0.155)	(0.154)	(0.155)
Unemployed	0.604	0.560	0.570	0.551
	(0.612)	(0.606)	(0.613)	(0.609)
Not in the labor force	0.672***	0.655***	0.628***	0.613***
	(0.228)	(0.229)	(0.231)	(0.231)
Mediator (t-1)	−0.396***	−0.00677	−0.248	−0.362*
	(0.129)	(0.110)	(0.207)	(0.199)
Inverse Mills ratio	3.501	3.557	2.723	2.513
	(2.716)	(2.833)	(2.953)	(2.932)
Observations	13,456	13,456	13,456	13,456

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Robust standard errors are in parentheses. The models included a set of dummy variables for survey wave and Australian region of residence as control variables. In the model (1), the frequency of physical activity is the mediator; in the model (2), the frequency of social interaction is the mediator; in the model (3), the frequency of smoking is the mediator; and in the model (4), the frequency of drinking alcohol is the mediator. The person-specific means of the time-varying predictors were additionally controlled for in each of the regressions.

further analysis reveals that life satisfaction at baseline has a significant beneficial effect on physical health at *t*, which could also be a reason why more satisfied people are less likely to become outpatients.

The findings reported thus far raise the possibility that the frequency of physical activity is a mediational pathway linking baseline life satisfaction to subsequent usage of outpatient care. Table 4 summarizes the results. Sobel-Goodman mediation tests are conducted to assess whether the possible mediating effect is significant. As expected, we find that life satisfaction has a significant direct and indirect impact on outpatient care.[6] The direct effect is negative, indicating that those who report higher levels of life satisfaction may need less outpatient care. The indirect effect is explained by physical activity. The results show that about 10% of the overall link between baseline life satisfaction and outpatient care is accounted for by physical activity (panel A).[7] This indirect effect is generated by the positive association of life satisfaction with physical activity. Those high in life satisfaction tend to participate more often in physical activity, which in turn leads to less frequent visits to their family doctor or GP.

Table 3
Random effect regression models for inpatient care.

	Inpatient care			
	(1)	(2)	(3)	(4)
Life satisfaction baseline	−1.233	−0.698	−1.036	−1.120
	(1.331)	(1.566)	(1.420)	(1.373)
Physical health baseline	0.179	0.134	0.181	0.198
	(0.192)	(0.261)	(0.248)	(0.244)
Age	−6.685	−3.462	−5.825	−6.854
	(10.18)	(11.20)	(10.98)	(11.23)
Age squared	0.0818	0.0409	0.0702	0.0844
	(0.132)	(0.144)	(0.141)	(0.145)
Age cubed	−0.000387	−0.000193	−0.000335	−0.000407
	(0.000650)	(0.000720)	(0.000704)	(0.000723)
Male	−4.253	−3.216	−3.593	−4.221
	(3.071)	(2.931)	(2.805)	(3.218)
Household size	−1.484	−1.280	−1.530	−1.603
	(1.001)	(1.182)	(1.164)	(1.155)
Real household income	−0.0151	−0.00929	−0.0135	−0.0149
	(0.0178)	(0.0212)	(0.0203)	(0.0205)
Married	3.258	2.515	3.035	3.486
	(3.224)	(4.176)	(3.712)	(3.881)
Higher education	−1.756	−1.197	−1.569	−1.753
	(1.456)	(1.466)	(1.435)	(1.450)
Unemployed	5.084	2.928	5.034	5.209
	(6.965)	(8.404)	(8.266)	(7.846)
Not in the labor force	−2.066	−1.363	−1.615	−1.836
	(2.324)	(2.644)	(2.461)	(2.504)
Mediator (t-1)	2.376	0.285	−1.955	1.387
	(2.691)	(0.919)	(1.711)	(2.767)
Inverse Mills ratio	−35.13	−25.59	−32.34	−35.26
	(31.40)	(37.54)	(35.48)	(35.41)
Observations	2,354	2,354	2,354	2,354

Note: See Table 2.

Table 4
Sobel-Goodman mediation tests between life satisfaction and outpatient care.

	Coefficient	Standard error
Panel A: The mediating effect of physical activity		
Indirect effect	−0.020**	(0.008)
Direct effect	−0.183**	(0.091)
Sobel-Goodman mediation test	−2.557**	
Panel B: The mediating effect of social interaction		
Indirect effect	−0.001	(0.010)
Direct effect	−0.206**	(0.090)
Sobel-Goodman mediation test	−0.062	
Panel C: The mediating effect of smoking		
Indirect effect	0.008	(0.008)
Direct effect	−0.223**	(0.092)
Sobel-Goodman mediation test	1.074	
Panel D: The mediating effect of drinking		
Indirect effect	0.003	(0.004)
Direct effect	−0.229**	(0.091)
Sobel-Goodman mediation test	0.625	

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

As MacKinnon et al. (2020) and Vanderweele (2015: p. 45–46) highlighted, the indirect effect could vary depending on the level of the exposure (here, life satisfaction), which is often referred to as XM interaction or exposure-mediator interaction. To that end, we conducted a sensitivity analysis to assess whether the mediated effect is equal across all levels of exposure. We thus estimated equation (2) four more

[6] A potential concern is that our results are driven by attrition bias that would arise if, for example, those with very low levels of life satisfaction are more likely to drop out from the panel survey over time. To mitigate this concern, we reconducted our analysis by including a dummy variable that switches from 0 to 1 if the respondent leaves the survey in the next wave. The results were qualitatively similar with or without the indicator variable for attrition (see Table A2).

[7] It is worth noting that including or excluding the inverse Mills ratio makes little difference for the estimated effects of baseline life satisfaction and does not alter any of our conclusions.

times, each time including the corresponding exposure-mediator interaction term.

Table A3 displays the results. Looking across the columns, we can see that in three out of four cases the XM interaction is not statistically significant. The only significant interaction is for drinking. But because the effect of baseline levels of life satisfaction on drinking was not significantly different from zero (see Table 1), the indirect effect of life satisfaction on outpatient care through drinking is not significant as well. It turns out that the estimates obtained with or without XM interaction are consistent, thus lending further support for our empirical approach.

5. Conclusion

We developed a mediation framework and tested whether lifestyle choices and social capital are pathways through which life satisfaction at baseline influences subsequent healthcare usage. Using nationally representative panel data for Australia on individuals aged 50 and over, we showed that those high in life satisfaction may need less outpatient care, and this effect is explained by increased physical activity. The estimates were not significant for inpatient care. These results remain after correcting for sample selection bias, as well as controlling for various confounding factors, including age, education, and initial health status.

Our findings are especially important for older adults in their own planning, and for policy makers. Older adults would benefit from participating in regular physical activity, in line with previous findings in the literature (WHO, 2018). Given that physical activity levels appear to be below current recommendations by health professionals (Boulton et al., 2018), policies and intervention programs should focus on providing more opportunities and appropriate infrastructure (e.g., walking parks) to help older adults become more physically active.

The approach to mediation employed here is the product-of-coefficients method. Although this approach is often used in social sciences, there are other longitudinal mediation analysis techniques, such as the inverse probability weighting methods, which also account for time-varying confounding factors. A comprehensive book-length overview of these topics can be found in Vanderweele (2015) and a recent study is VanderWeele and Tchetgen Tchetgen (2017).

Overall, this paper provides some of the first empirical evidence on the relationship between well-being, as measured by life satisfaction, and curative healthcare usage. The paper further contributes to the literature by exploring the underlying pathways. To the extent that participation in physical activity is responsive to the provision of incentives by policy makers, our findings could be useful in aiding the design of health policies.

Author statement

Dusanee Kesavayuth: Conceptualization, Methodology, Formal analysis, and Writing – review & editing; Prompong Shangkhum: Software, Data curation, and Formal analysis; Vasileios Zikos: Conceptualization, Methodology, Supervision, Writing – original draft, and Writing – review & editing.

Ethical approval

This paper is part of the project “Well-Being and Physical Health” (No. 226/63). It has been exempted from ethics review by The Research Ethics Review Committee for Research Involving Human Research Participants, Group I, Chulalongkorn University. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Appendix

Table A1
Descriptive statistics.

Variables	Description	Obs.	Mean	S.D.
Outpatient care	Number of doctor visits in the last 12 months	13,456	6.25	7.11
Inpatient care	Number of nights in hospital (at least one day) in the last 12 months	2,354	8.36	15.17
Life satisfaction baseline	0-10 scale; with 0 = totally dissatisfied with life, and 10 = totally satisfied with life (at baseline)	14,607	0	1
Physical health baseline (SF-36)	0-100 scale; with 0 = worst physical health, and 100 = best physical health (at baseline)	14,607	74.74	22.16
Lagged frequency of physical activity	0-5 scale; with 0 = not at all, and 5 = every day	14,607	0	1
Lagged frequency of social interaction	0-6 scale; with 0 = less often than once every 3 months, and 6 = every day	14,607	0	1
Lagged frequency of smoking	0-3 scale; with 0 = non-smoker, and 3 = smoke daily	14,607	0	1
Lagged frequency of drinking	0-6 scale; with 0 = non-drinker, and 6 = drink every day	14,607	0	1
Age	Age of the respondent	14,607	64.42	9.75
Male	1 if male, 0 if female	14,607	0.47	0.50
Household size	Number of persons living in the household	14,607	2.19	1.07
Real household income	Real household income in thousands of AUD (base year, 2012)	14,607	77.94	70.51
Married	1 if legally married, 0 otherwise	14,607	0.63	0.48
Higher education	1 if graduated at least from college, 0 otherwise	14,607	0.56	0.50
Employed	1 if employed, 0 otherwise	14,607	0.44	0.50
Unemployed	1 if unemployed, 0 otherwise	14,607	0.01	0.11
Not in the labor force	1 if not in the labor force, 0 otherwise	14,607	0.55	0.50

Table A2
Sobel-Goodman mediation tests between life satisfaction and outpatient care controlling for a dummy variable that takes the value one if the respondent leaves the survey in the following wave.

	Coefficient	Standard error
Panel A: The mediating effect of physical activity		
Indirect effect	−0.020**	(0.008)
Direct effect	−0.186**	(0.091)
Sobel-Goodman mediation test	−2.568**	

(*continued on next page*)

Table A2 (*continued*)

	Coefficient	Standard error
Panel B: The mediating effect of social interaction		
Indirect effect	−0.001	(0.010)
Direct effect	−0.208**	(0.091)
Sobel-Goodman mediation test	−0.051	
Panel C: The mediating effect of smoking		
Indirect effect	0.009	(0.008)
Direct effect	−0.226**	(0.092)
Sobel-Goodman mediation test	1.090	
Panel D: The mediating effect of drinking		
Indirect effect	0.003	(0.004)
Direct effect	−0.232**	(0.091)
Sobel-Goodman mediation test	0.656	

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

Table A3
Random effect regression models for outpatient care with XM interaction.

	Outpatient care			
	(1)	(2)	(3)	(4)
Life satisfaction baseline	−0.168*	−0.190**	−0.227**	−0.182**
	(0.0904)	(0.0907)	(0.0932)	(0.0864)
Physical health baseline	−0.0854***	−0.0923***	−0.0916***	−0.0880***
	(0.00592)	(0.00612)	(0.00629)	(0.00617)
Age	−0.338	−0.381	−0.399	−0.341
	(1.036)	(1.044)	(1.038)	(1.036)
Age squared	0.00758	0.00800	0.00800	0.00736
	(0.0156)	(0.0157)	(0.0156)	(0.0156)
Age cubed	−0.0000282	−0.0000283	−0.0000274	−0.0000251
	(0.0000775)	(0.0000778)	(0.0000775)	(0.0000774)
Male	−0.0523	−0.182	−0.130	0.126
	(0.192)	(0.196)	(0.196)	(0.200)
Household size	−0.301**	−0.291**	−0.277**	−0.286**
	(0.127)	(0.126)	(0.127)	(0.127)
Real household income	0.00248*	0.00244	0.00219	0.00219
	(0.00148)	(0.00150)	(0.00152)	(0.00151)
Married	0.324	0.315	0.330	0.328
	(0.449)	(0.459)	(0.462)	(0.464)
Higher education	−0.132	−0.190	−0.204	−0.112
	(0.153)	(0.155)	(0.154)	(0.155)
Unemployed	0.603	0.555	0.573	0.579
	(0.612)	(0.607)	(0.612)	(0.608)
Not in the labor force	0.679***	0.666***	0.629***	0.617***
	(0.226)	(0.229)	(0.231)	(0.231)
Mediator (t-1)	−0.402***	−0.00476	−0.244	−0.364*
	(0.129)	(0.109)	(0.204)	(0.197)
Life satisfaction baseline × Mediator (t-1)	0.0807	0.0956	0.0205	0.272***
	(0.0918)	(0.0691)	(0.0736)	(0.0783)
Inverse Mills ratio	3.849	3.611	2.731	2.802
	(2.679)	(2.834)	(2.940)	(2.940)
Observations	13,456	13,456	13,456	13,456

Note: See Table 2.

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