Yes, health is important, but as much for its importance via social life: The direct and indirect effects of health on subjective well-being in chronically ill individuals

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Abstract

There is increasing evidence that health related quality of life, income and social relationships are important to our subjective well-being (SWB). Little is known, however, about the specific indirect pathways that link health to SWB via social relationships and income. Based on a unique data set of seven disease groups from six OECD-countries (N=6173), we investigate the direct and indirect effects of health on SWB by using structural equation modeling. Three alternative measures of health are used: For generic instruments (EQ-5D-5L; SF-6D), the total indirect effect was stronger (0.226; 0.249) than its direct effect (0.157; 0.205). For the visual analogue scale (VAS), the direct effect was stronger (0.322) than its total indirect effects (0.179). Most of the indirect effect of improved health on SWB transmitted through social relationships. The effect via income was small. Nevertheless, the presence of unmeasured confounders may bias the estimates. An important lesson for researchers is to include meaningful items on social relationships when measuring the benefits from improved health. An important lesson for policy makers is that social isolation appears to be more detrimental to overall well-being than ill health. Hence, the Health and Care Services should facilitate social arenas for people with chronic conditions.

Keywords: SWB, HRQoL, Social relationships, Income, Mediation analyses

1. **Introduction**

The health economics literature has in various ways distinguished between the *intrinsic* and the *instrumental* value of good health. In his seminal model on the demand for health, Michael Grossman (1972) made an important analytical distinction between the consumption value *vs* the investment value of improved health, the latter reflecting higher human capital, leading to increased income and consumption. Tony Culyer, influenced by Amartya Sen (1980), emphasized the importance of good health for the *capabilities to flourish* and function in other walks of life (Culyer, 1989; Culyer, 1990). In other words, the two important 'walks of life' appear to be work-life, which yield opportunities for higher consumption, and social life involving opportunities to connect with family and friends, as well as participate in the wider community.

In the widely used preference based generic descriptive systems for health attention is primarily drawn to its *intrinsic* value. To capture its additional *instrumental value* we need validated indicators of social relationships and subjective well-being, as well as precise measures of income and work-life participation. All these sets of variables are included in a comprehensive data set from six OECD-countries on people living with seven different chronic diseases. Based on this unique data, the current paper separates the *direct effect* of health on subjective well-being (SWB), i.e. the intrinsic value, from its *indirect effects* via income and social relationships, i.e. the instrumental value.

1.1. Existing literature

The association between health and income

While there is extensive evidence on a strong positive correlation between health and wealth (Deaton, 2013; Ettner, 1996; Jones and Wildman, 2008), the identification of causal effects has proven difficult (Fuchs, 2004). Richer individuals live and work in healthier environments, they can afford better medical care, and can acquire goods and services that contribute to better health (Meer et al., 2003). A reverse causal effect follows from the health production framework of Grossman (1972), in which good health is a prerequisite to work hard and accumulate wealth (Halla and Zweimüller, 2013). Finally, both variables may simply be correlated with a third factor, i.e. individuals with a low rate of time preference will invest more in human capital that enhance future earnings as well as engage in a healthier life-style that improve future health (Barsky et al., 1997).

The association between health and social relationships

Several studies have shown a significant positive effect of improved social relationships on individual health (Ahnquist et al., 2012; Cohen, 2004; Franks et al., 1992). A large social network and frequent contacts are associated with decreased mortality at all ages, even after controlling for socioeconomic status and health practices (Cohen and Syme, 1985). In addition to the positive effects of social relationships on health outcomes, there is strong evidence for a reverse causality as well (Sirven and Debrand, 2012; Yu et al., 2015; Li and Zhang, 2015).

The concept of subjective well-being (SWB) and its determinants

Subjective well-being (SWB) comprises a cognitive-judgmental dimension reflecting life satisfaction and an emotional evaluation characterized by positive and negative affect (Diener, 1984). The cognitive component refers to individuals' thoughts about the quality or goodness of their lives, or their overall *global life satisfaction* (Steptoe et al., 2015). It has been suggested that such life evaluation questions capture everything that matters to human well-being (Layard, 2011). In a review by Pavot and Diener (2009), the satisfaction with life scale

(SWLS), representing a widely used measure of SWB, has shown to have a negative correlation with depression, anxiety and general psychological disorders, and a positive correlation with marriage, health, self-esteem and optimism. Thus, SWB-measures provide valid and reliable information on how well people - and the wider societies - are doing, thereby assessing quality of life in addition to economic and social indicators (Diener and Suh, 1997).

The most appealing progress in the study of SWB is to identify and understand its determinants. Income correlates only modestly with SWB (Easterlin, 1973). Health enables social, economic and personal development fundamental to well-being (Breslow, 2006). Having good social relationships is one of the strongest predictors of SWB (Helliwell, 2006; Myers, 2003). Other important correlates of SWB include unemployment (Frey and Stutzer, 2010), education (Blanchflower and Oswald, 2008), genetic factors and personality (Nes et al., 2006; Schnittker, 2008), and other demographic factors (for a detailed review see Dolan et al. (2008)). Health, income and social relationships deserve special attention as they are fundamental to enhance capability and functioning. Yet, these determinants of well-being are also inter-correlated. In general, worsening health influences our SWB either directly by creating disability and distress, or indirectly through its influence on our social relationships and earnings.

Previous studies on direct vs indirect effects

An extensive empirical literature exist on the partial effect of health, income and social relationships on SWB. However, only to a limited extent have empirical studies distinguished between the direct effect of health on SWB and its indirect effects. As for the mechanisms behind the income-SWB relationship, there is compelling evidence for the mediating role of financial satisfaction: both a direct effect of income on SWB, and an indirect path through financial satisfaction (George, 1992). A study by Sengupta et al. (2012) tested a log-mediation model in which the relationship between income and multiple components of well-being were mediated by *the perceived ability to meet everyday life necessities*: more than half of the association of income with both happiness and quality of life was explained by this mediator.

A study of the link between social relationships and health in older adults suggests that leisure activities mediate this link in these age groups (Chang et al., 2014). Another study revealed the mediating effects of social relationships on the association between socio-economic status (education, income and occupational status) and subjective health (Vonneilich et al., 2012). A most recent study shows the positive effect of gratitude on self-reported physical health symptoms to be mediated by lower level of loneliness (O'Connell et al., 2016)

1.2 Aims and contributions

Several studies have investigated the partial links between health and income; income and SWB; health and social relationships, and; social relationships and SWB. However, to our knowledge no previous research exists on whether income and social relationships simultaneously mediate the link between health and SWB. In the current paper, we adopt structural equation model (SEM) to examine whether both income and social relationships mediate the association between HRQoL and SWB in patients with chronic illness, i.e. we seek to test the simple conceptual model depicted in Figure 1.

As for causality, by choosing a sample of individuals with chronic conditions, it is more plausible to assume that their health affects their income, as well as their capabilities to maintain good social relationships, than that the reverse scenario would dominate. There is much evidence that individuals with chronic conditions experience restrictions in social relationships and role fulfilment (Verbrugge and Jette, 1994). As for the effects of ‘health shocks’ on income, there is overwhelming evidence of a causal link (see e.g. García Gómez and López Nicolás (2006)).

In this conceptual model, although HRQoL independently predicts SWB, we hypothesize that both household income and social relationships mediate this link. We posited that better HRQoL would be associated with enhanced SWB and that income and social relationships would explain part of that association. Hence, the primary objective is to identify the *instrumental* value of health on SWB, i.e. its indirect effect via income and social relations, as distinct from the *intrinsic* value of health, which bears direct effect on SWB.

2. Method

2.1. Data

Data was obtained from a large international study designed to compare various instruments for measuring health and subjective well-being (Richardson et al., 2012). This Multi Instrument Comparison (MIC) study includes seven major ‘disease groups’ (arthritis, asthma, cancer, depression, diabetes, hearing loss, heart diseases) in six OECD-countries (Australia, Canada, Germany, Norway, UK, US) (N=6173). Responses were subject to several stringent edit procedures based upon a comparison of duplicated or similar questions as well as a minimum completion time. The detailed edit procedures has been reported elsewhere (Richardson et al., 2012).

Table I. Respondents by country and disease group

	Country						
	Australia	Canada	Germany	Norway	UK	USA	Total
Arthritis	163	139	159	130	159	179	929
Asthma	141	138	147	130	150	150	856
Cancer	154	138	115	80	137	148	772
Depression	146	145	160	140	158	168	917
Diabetes	168	144	140	143	161	168	924
Hearing problems	155	144	136	115	126	156	832
Heart diseases	149	154	152	151	167	170	943
Total	1076	1002	1009	889	1058	1139	6173

2.2. Variable Measures

Subjective well-being (SWB)

SWB is assessed by the satisfaction with life scale (SWLS) (Diener et al., 1985), which has been widely used in previous studies with favorable psychometric properties (Steinfield et al., 2008). We use the first three of the five SWLS-items: *In most ways my life is close to my ideal; The condition of my life is excellent*, and; *I am satisfied with my life*. The response options ranged from 1 (strongly disagree) to 7 (strongly agree). Cronbach's alpha for the scale was 0.935, indicating a good internal consistency. The omitted two items are sensitive to age as they implicate experience of life satisfaction in the past (Hultell and Gustavsson, 2008; Zou et al., 2013), and they have poorer psychometric properties than the first three items of the scale (Oishi, 2006). Here SWB is a latent construct estimated from the first three items of the observed SWLS indicators using confirmatory factor analysis (CFA), which is a measurement model that estimates continuous latent variables based on observed indicator variables.

Health related quality of life (HRQoL)

HRQoL is measured by the two most widely applied preference-based generic descriptive systems; the EQ-5D and the SF-6D, as well as a visual analogue scale (VAS). The EQ-5D defines health along five-dimensions (mobility, self-care, usual activities, pain/discomfort, anxiety/depression). In the new 5L version used here, each dimension has five response categories ranging from no problems to unable to/extreme problems (Herdman et al., 2011). The SF-6D includes six dimensions (physical functioning, social functioning, role limitations, pain, mental health, vitality), each with four to six levels (Brazier et al., 2002). In the context of the current paper, we chose to apply non-preference based values using the simple summary scores (ignoring the scaling of health state utility that uses preferences from the general population). Thus, both EQ-5D and SF-6D summary scores are normalized to a [0 – 1] scale, with 1 indicating 'no problems' on every dimension and 0 representing the 'pits' (the worst health state). Separate analyses (not reported here) using preference based values gave similar results. In other words, whether HRQoL was measured by simple summary scores or the preference weighted tariffs did not matter much (Lamu et al., 2016). The direct assessment of health (VAS) is based on answers to the question*: "Think about a scale of 0 to 100, with zero being the least desirable state of health that you could imagine and 100 being perfect health (physical, mental and social). What rating from 0 to 100 would you give to the state of your health?"* These values are then normalized to a [0 – 1] scale.

Household income

Since household income is measured as categorical variable with different income brackets in each country, we chose the mid-point of these income brackets, and treated it as a continuous variable. For an open-ended top category, we imputed the median using a more rigorous approach in line with Parker and Fenwick (1983). Thus, each respondent has been assigned with the mid-point income value of the corresponding income range. Then, income measure for each country has been converted to a common currency expressed in US dollars[1]. Eventually, income measures have been transformed into natural logarithm to allow for a non-linear relationship between income and SWB.

Social relationships

Social relationship is measured by a composite score based on four questions from the Assessment of Quality of Life instrument (Richardson et al., 2014). Two questions consider the extent of enjoyment and satisfaction with ones close relationships [*How much do you enjoy your close relationships (family and friends)?*; *Your close relationships (family and friends) are*: …], and two questions evaluate ones feelings with respect to isolation and exclusion (*How often do you feel socially isolated?*; *How often do you feel socially excluded or left out?*). A *social relationship* index is constructed by calculating the total score of the five/six-point scale response levels to these four questions (reverse-coded, 1 = immensely/very satisfied/never to 5/6 = I hate it/Very unpleasant/always). The reliability coefficient (as measured by Cronbach's alpha) is 0.843, showing good internal consistency. The total score is linearly transformed to a [0–1] scale.

Control variables

Socio-demographic factors, such as age, gender, education, marital status, and employment status were included as control variables. Age is a categorical variable with five groups: 18 – 34, 35 – 44, 45 – 54, 55 – 64, and 65 and above. Education is accounted for by dummy variables (high school, diploma/certificate, and university). Marital status (living with

[1] Purchasing power parity (PPP) for actual individual consumption conversion factor in the year 2012 from OECD database was used. (http://stats.oecd.org/Index.aspx?datasetcode=SNA_TABLE4#).

spouse/partner or not), and employment status (*unemployed* vs. *all others*) were both dichotomized. In addition, we controlled for chronic diseases and country dummies to capture disease and country specific heterogeneity, respectively. Controlling for such variables minimize any possible differential effects due to differences in the characteristics of these variables Table II provides the description of variables used.

Table II. Mean values (and SD) of all variables used (N=6,173)

Variable	Mean	SD
SWLS	0.548	0.264
EQ-5D-5L	0.815	0.166
SF-6D	0.596	0.222
VAS	0.631	0.218
HHI	3.501	0.844
Social relationships	0.724	0.201
Age (ref. 18-34 years)		
35-44 years	0.132	-
45-54 years	0.208	-
55-64 years	0.273	-
65+ years	0.241	-
Gender		
Female	0.522	-
Living with partner/spouse		
Yes	0.643	-
Education (ref. High school)		
Diploma	0.409	-
University	0.285	-
Employment status		
Unemployed	0.081	-

Note: For categorical variables (Age, Gender, Marital status, Education, Employment status), mean values represent the percentage share of the indicated group in the sample; see Table I for summary information of country and disease group dummies. HHI, household income (in natural logarithm with 691 missing information); SD, standard deviation; SWLS, satisfaction with life scale measured by its first three items.

Missing information

Nearly all missing information was on the income variable, 11% of respondents (N=691). The second highest missing information was observed for the SWB variable, however, only 14 subjects missing. Hence, we will investigate missingness only in income.

If data is *missing completely at random* (MCAR), and missingness is independent of the outcome variable given the covariates under *missing at random* (MAR) assumption, the complete case analysis has negligible bias (White and Carlin, 2010). The most commonly invoked missingness is MAR, where missingness is related to other measured variables in the analysis model, but not to the underlying values of the incomplete variable (Rubin and Little, 2002). Providing conclusive evidence that the data are MAR is hardly possible because it requires information on missing data. However, the examination of whether income is predicted by other measured variables in the data or not would make the assumption of MAR more plausible. Thus, to understand the mechanism of missingness in income, we created a binary indicator of missingness and fit a logistic regression model to investigate which variables are predictive of missingness in income. Chi-square test for MCAR assumption proposed by Little was also conducted (Little, 1988).

The results of logistic regression with gender, age, and health (EQ-5D) as covariates demonstrate a strong evidence against the household income variable being MCAR ($p < 0.05$) (results not reported here). Little's chi-squared test provides similar result ($p < 0.01$). Thus, our (exploratory) analyses indicate that missingness in income variable is significantly correlated with measured variables in the model, implying data are not MCAR but rather consistent with imputation of MAR data. Multiple imputation (MI) and full information maximum likelihood (FIML) are widely used modern techniques for handling missing information. Both depend on the MAR assumption. With large samples, FIML is more efficient, and hence better than MI. For instance, with a relatively small number of imputations (say, 10), MI is just slightly less efficient at producing the parameter estimates (Rubin, 1987), but much less efficient at estimating standard errors and confidence intervals

(Graham et al., 2007). More recently, von Hippel (2016)) and Yuan et al. (2012) showed that FIML estimates have less bias and smaller sampling variance than MI estimates even in small samples. Therefore, we apply the FIML approach in this study.

2.3. Model specification and estimation

The model illustrated in Figure 1 is most common in the literature and assumes no causal association between the mediators, i.e. no mediator casually influences another (Hayes, 2013). Furthermore, the model requires four other key assumptions for identification and estimation of the direct and indirect effects (MacKinnon, 2008; VanderWeele and Vansteelandt, 2014): i) no exposure-outcome confounder conditional on a set of measured covariates; ii) no mediator-outcome confounder conditional on both exposure and control variables; iii) no exposure-mediator confounder conditional on measured covariates, and; iv) no mediator-outcome confounder that is itself affected by the exposure. Under these assumptions, the hypothesized conceptual model can easily be identified and estimated. If the two mediators were causally related after accounting for the exposure, the problem of intermediate confounding arises which requires complex estimation procedures for the decomposition of direct and indirect effects (Daniel et al., 2015; De Stavola et al., 2015). Nevertheless, preliminary analysis of a model with intermediate confounding in which income is allowed to influence social relationships and SWB revealed negligible difference from the model with no causal association between the mediators. Thus, the hypothesized model that assumes no causal association between mediators has been chosen based on the principle of parsimony.

The hypothesized conceptual model with two mediators, as illustrated in Figure 1, is tested using structural equation modeling (SEM). It uses a conceptual model, path diagram and system of linked regression-style equations to capture complex and dynamic relationships within a web of observed and unobserved variables (Gunzler et al., 2013). Although similar in appearance, SEM is fundamentally different from standard regression. In a standard regression model, there exists a clear distinction between dependent and independent variables, whilst in SEM such concepts only apply in relative terms since a dependent variable in one model equation can become an independent variable in other components of the SEM system (Bollen, 1989). Thus, with SEM, the set of equations are solved at the same time to test model fit and estimate parameters. SEM simplifies testing of mediation hypotheses because it is designed, in part, to test these more complicated mediation models in a single analysis (MacKinnon, 2008), and it is even more important when extending to multiple mediators. Another advantage is that SEM provides model fit information about the consistency of the hypothesized conceptual model to the data (Imai et al., 2010).

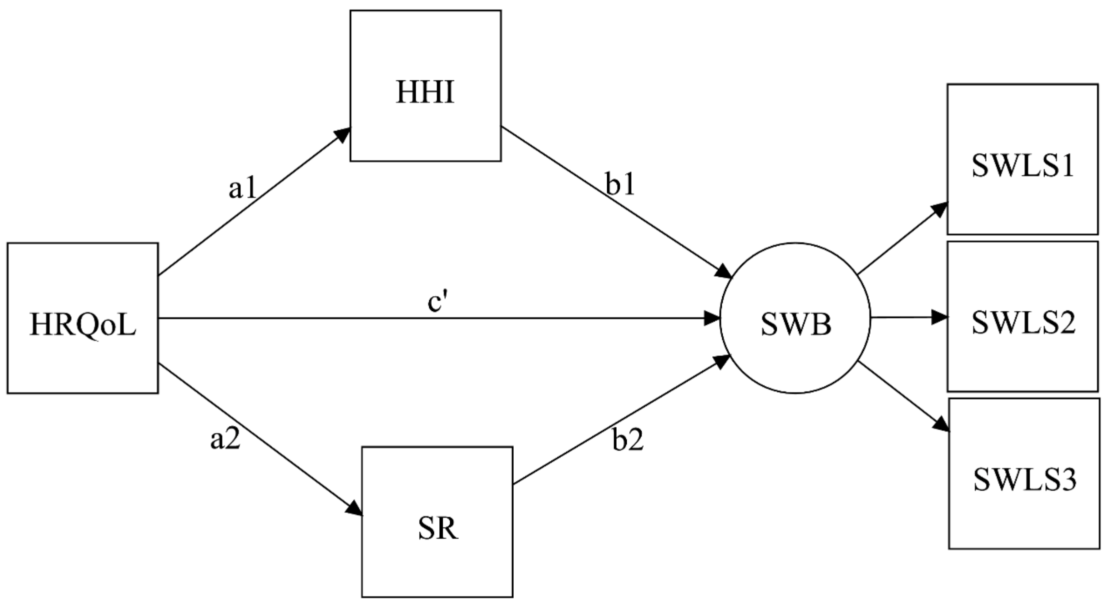

Figure 1. The conceptual model

Structural equations model (SEM) for the associations among health related quality of life (HRQoL), social relationships (SR), household income (HHI, in natural logarithm) and subjective well-being (SWB). A circle represents a latent variable and rectangles depict observed variables. The paths from the latent construct (SWB) to the observed variables (the first three items of satisfaction with life scale; SWLS1, SWLS2, SWLS3) represent the loading of each variable onto its construct. SEM coefficients are represented by a_1, a_2, b_1, b_2, and c’.

In addition to the paths depicted in the figure, the model specifies covariance between each pair of the exogenous and control variables as well as among control variables (not shown in the conceptual model to maintain a better overview). Three distinct models were estimated that differ only in terms of how health is being measured: Model-1 applies the EQ-5D descriptive system; Model-2 applies the SF-6D, and; Model-3 applies the VAS.

Three regression equations are constructed from this conceptual model: 1) the household income (the mediator) was regressed on HRQoL (path a_1); 2) the social relationship (the mediator) was regressed on HRQoL (path a_2), and; 3) the outcome equation was constructed by fitting SWB on HRQoL (path c'), household income (path b_1) and social relationships (path b_2). The equations are expressed as follows:

$$HHI_i = k_1 + a_1 HRQoL_i + \gamma_1 C + \varepsilon_{1i} \tag{1}$$

$$SR_i = k_2 + a_2 HRQoL_i + \gamma_2 C + \varepsilon_{2i} \tag{2}$$

$$SWB_i = k_3 + b_1 HHI_i + b_2 SR_i + c' HRQoL_i + \gamma_3 C + \varepsilon_{3i} \tag{3}$$

where k, a, b, γ and c' are the parameters to be estimated; HHI is household income (in natural logarithm); SR is social relationships; HRQoL is health related quality of life (as measured by EQ-5D, SF-6D or VAS), C is a vector of control variables, and; ε_i are error terms. Note that the three structural equations are linked together, and inference about them is simultaneous, unlike three independent standard regression equations. All three equations were adjusted for control variables, such as gender, age, marital status, education, unemployment, disease groups and country dummies.

Assuming that data was MAR, full information maximum likelihood (FIML) method was applied, which handles the missing data problem by using all information contained in the complete dataset (Enders and Bandalos, 2001). The indirect effects were estimated following the product-of-coefficient approach (MacKinnon et al., 2002). That is, indirect effect of HRQoL through household income alone is a_1*b_1, whilst the indirect effect that passes through social relationships alone is a_2*b_2. The total indirect effect of HRQoL on SWB is the sum of the two indirect effects ($a_1*b_1 + a_2*b_2$). Thus, the total effect is the sum of the direct and indirect effects [$c' + (a_1b_1+a_2b_2)$]. The proportion of mediated effects was estimated as the ratio of the indirect effect to the total effect. Finally, for correct specification of standard errors and tests of significance, all parameters were estimated using 5000 bootstrapped resamples which avoids dependence on the assumption of normality (Preacher and Hayes, 2008).

As chi-squared is usually significant with large samples (Kenny and Milan, 2012), several alternative fit indices were examined to assess model fit. These fit indices included the comparative fit index (CFI), the Tucker–Lewis index (TLI) , the root mean square error of approximation (RMSEA) and the standardized root mean squared residual (SRMR). CFI and TLI values equal to or greater than 0.95, and SRMR equal to or less than 0.05 are considered excellent model fits (Hu and Bentler, 1999). TLI and CFI values greater than 0.90 are considered acceptable (Kline, 2011). RMSEA values smaller than 0.05 and 0.08 are considered close fit and reasonable fit respectively (McDonald and Ho, 2002). All statistical analyses were conducted using Stata® ver. 14 (StataCorp LP, College Station, Texas, USA) and Mplus version 7.4.

3. Results

3.1. The descriptive

Table III summarizes Pearson and Spearman correlation coefficients for main variables. The pairwise correlation coefficients are all significant (p<0.01). All explanatory variables are strongly correlated with SWB except income, which is weakly correlated, but still significant. SWB has the highest correlation coefficient (0.62) with social relationships followed by health (0.44 with EQ-5D; 0.52 with SF-6D, and; 0.55 with VAS).

Table III. Correlation coefficients[a] of main variables (N=6,173)

Variables	SWLS	EQ-5D	SF-6D	VAS	HHI	SR
SWLS	**1.000**	0.448*	0.511*	0.550*	0.312*	0.605*
EQ-5D	0.444*	**1.000**	0.823*	0.582*	0.272*	0.485*
SF-6D	0.521*	0.817*	**1.000**	0.610*	0.294*	0.583*
VAS	0.551*	0.601*	0.625*	**1.000**	0.231*	0.457*
HHI	0.313*	0.256*	0.290*	0.228*	**1.000**	0.245*
SR	0.616*	0.487*	0.594*	0.470*	0.257*	**1.000**

[a] Lower- and upper-diagonal values represent Pearson and Spearman correlation coefficients, respectively. HHI; household income (in natural logarithm with 691 missing information); SWLS, satisfaction with life scale (measured by the first three items); SR, social relationship.
* p < 0.01; † p < 0.05.

3.2. Tests of model fit

The fit indices suggest that all models fitted the data very well. The chi square values 500.85 (Model 1); 485.98 (Model 2), and; 521.28 (Model 3) were all significant (p < 0.001), which is usually the case with large sample size. The CFI=0.98 was the same in all models; the TLI was also excellent (0.96 in Model 1 and Models 2; and 0.95 in Model 3). An RMSEA value of 0.04 (90% CI: [0.036-0.045]), and an SRMR=0.007 in all models indicate close fit and excellent fit, respectively.

The standardized loadings from the latent construct (SWB) to its observed variables were very large (0.90 and above) and statistically significant ($p < 0.001$), indicating strong evidence of convergent validity. Preacher and Hayes (2008) propose that investigating multiple mediation should involve at least two conditions: the set of mediators (total indirect effect) should transmit the effect of the independent variable to the outcome variable, and; the specific indirect effect associated with each mediator should be significant. Furthermore, they held that a significant total indirect effect is not a prerequisite for investigating specific indirect effects. All these conditions were met.

3.3. Structural equation model results

The results of the structural equation modeling (with standardized coefficients) are presented in Figure 2 and Table IV, after adjusting for age, gender, marital status, education, unemployment, disease groups and country dummies. Unstandardized results are reported in Appendix Table A1.

The results reported in Table IV suggest that each of the separate indirect effects, as well as the direct effects, are significant ($p < 0.001$). As for the indirect effect of health via income, the path model indicated the significant effect of HRQoL (e.g. EQ-5D) on logarithmic income ($\beta = 0.169$, $p < 0.01$). The logarithm of income has, in turn, a positive association with SWB ($\beta = 0.102$, $p < 0.01$). Thus, HRQoL has a significant partial indirect effect on SWB via household income ($\beta = 0.017$, $p < 0.01$). Similarly, health has a positive significant effect on SWB (the standardized coefficient varies between 0.157 for EQ-5D to 0.322 for VAS). This implies that HRQoL retained a stronger direct effect on SWB after accounting for all covariates including household income. The effect through income, though significant, is weak. It explains only 4.5% of the total effect of health (EQ-5D) on SWB.

Table IV. The direct and indirect effects of HRQoL on SWB: Standardized model results (N=6,173)

	Model-1		Model-2		Model-3	
Variables	β	S.E.	β	S.E.	β	S.E.
Direct effects						
HRQoL → HHI	0.169*	0.012	0.193*	0.012	0.135*	0.012
HRQoL → SR	0.434*	0.011	0.526*	0.010	0.408*	0.012
HRQoL → SWB	0.157*	0.013	0.205*	0. 013	0.322*	0.012
HHI → SWB	0.102*	0.013	0.094*	0. 013	0.092*	0.012
SR → SWB	0.480*	0.013	0.439*	0. 013	0.409*	0.013
Indirect effects						
HRQoL via HHI	0.017*	0.003	0.018*	0.003	0.012*	0.002
HRQoL via SR	0.208*	0.008	0.231*	0.008	0.167*	0.007
Total indirect effects	0.226*	0.008	0.249*	0.008	0.179*	0.007
Total effect‡	0.383*		0.454*		0.501	

Note: HRQoL, health related quality of life (EQ-5D in Model-1; SF-6D in Model-2; VAS in Model-3); β, standardized coefficient; S.E., standard error; HHI, household income (in natural logarithm); SR, social relationships; SWB, subjective well-being (measured by the first three items of the satisfaction with life scale). All models are controlled for age, gender, marital status, education, unemployment, country, and disease dummies.
‡ Total effect of health on SWB (the sum of direct effect of HRQoL and its total indirect effect).
*Denotes statistical significance at less than 1%, based on bootstrapping approach with 5000 repetitions.

The effect of HRQoL through social relationships is substantial. Social relationship is strongly associated with both HRQoL and SWB, and as such explains a larger proportion of the link between HRQoL and SWB. For instance, when EQ-5D is used as a measure of HRQoL, it has a significant indirect effect on SWB via social relationships (β=0.208, $p < 0.001$). Again, social relationships partially mediated this effect as HRQoL retained a direct effect on SWB after accounting for all covariates including social relationships ($\beta = 0.157$, $p < 0.01$). In general, these results suggest a strong mediated effect of HRQoL on SWB via social relationship, with a smaller direct effect capturing all other pathways. It appears that more than 54% of the total effect of health (EQ-5D) is transmitted via social relationship. When SF-6D is used as a measure of HRQoL (Model 2), this percentage mediated through SR remains just above 50%. When VAS is used, this mediation link is 33% of the total effect.

To reiterate, the total indirect effect of EQ-5D on SWB is 0.226 ($p < 0.001$), which is by far greater than its direct effect (β=0.157). A similar result is obtained when SF-6D is applied. However, when self-reported health (VAS) is used, the direct effect (β=0.322) of health on SWB is stronger as compared to its indirect effect (β=0.179). From these results, it is possible to estimate the extent to which both household income and social relationships mediate the association between HRQoL and SWB. For instance, the proportion of total effect that is mediated via both income and social relationships is around 59%, 55%, and 35% when HRQoL is measured by EQ-5D, SF-6D, and VAS respectively.

A preliminary examination of a model with intermediate confounding, where income is permitted to influence social relationships and SWB, revealed negligible improvement in the model result. For instance, a parametric G-computation procedure via Monte Carlo simulation approach, which is a more general and flexible approach that enables us to estimate the model in the presence of intermediate confounding (De Stavola et al., 2015), yield similar result as a model with no intermediate confounding. Over 54% of the total effect of health (EQ-5D) is transmitted via social relationship under both cases. Thus, results for a simpler model with no intermediate confounding were reported.

Figure 2 extracts the key results in Table IV: The direct effect of health on SWB is stronger when a self-reported health score (VAS) is applied, as compared to the generic descriptive instruments (EQ-5D and SF-6D). Overall, HRQoL have large positive direct effects on social relationships, which in turn have a large direct effect on SWB, i.e. health is important, but as much for its importance via social life.

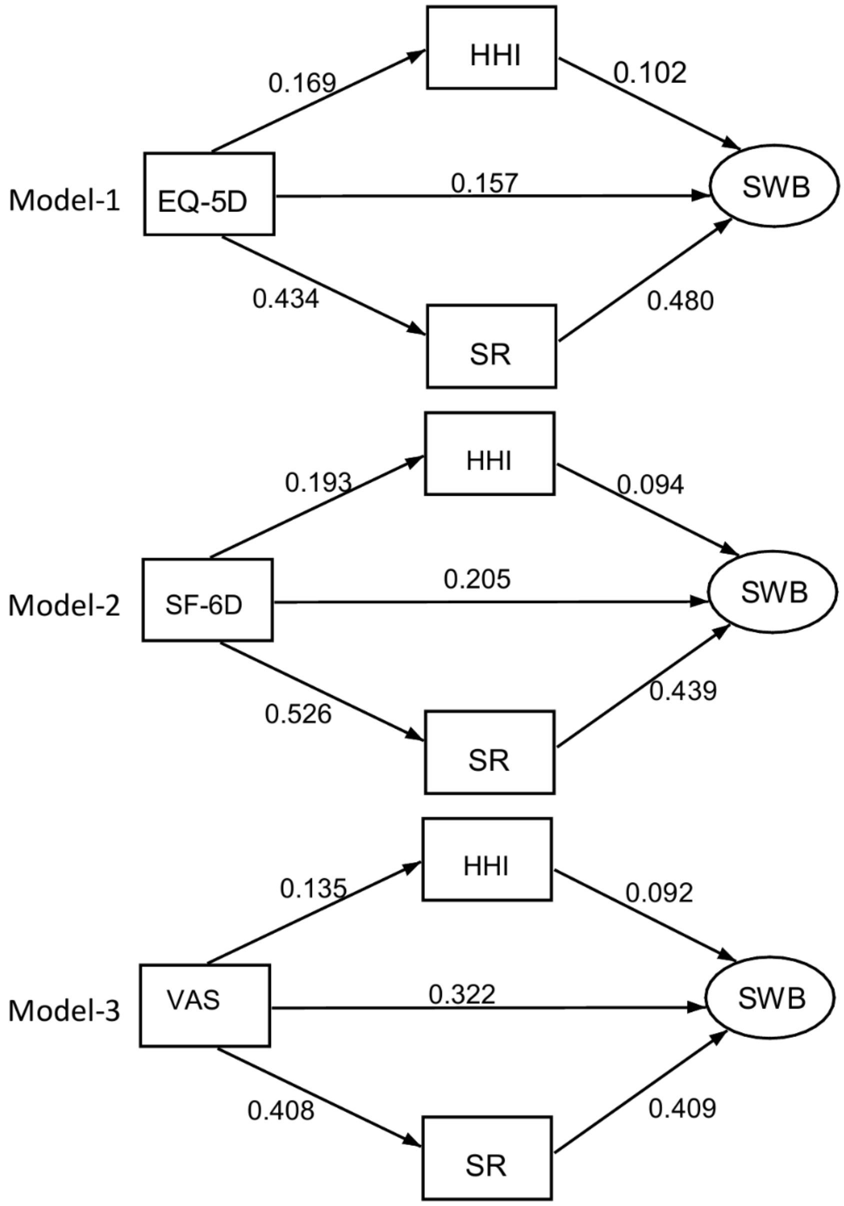

Figure 2. Structural equations model results

The associations among health related quality of life (EQ-5D in Model-1; SF-6D in Model-2; VAS in Model-3), social relationships (SR), household income (HHI) and subjective well-being (SWB). The circle represents a latent construct estimated from the first three items of satisfaction with life scale (measurement part not included here). All coefficients are significant at less than 1% level.

Discussion

This paper has examined the indirect effects of health (HRQoL) on subjective well-being (SWB), via income and social relationships, among adults with various chronic conditions. Two important findings emerged through structural equation modeling: HRQoL is significantly associated with both household income and social relationships, and; HRQoL has significant indirect effects (via income and social relationships) and direct effects on SWB. However, although we have controlled for potentially relevant confounders, any other important omitted variables, including unobservable individual characteristics, could bias the reported results.

Consistent with previous studies, SWB was found to be strongly associated with social relationships and with health, but weakly associated with income (Binder and Coad, 2011; Lamu and Olsen, 2016). However, the novel aspect of this study is the evaluation of how HRQoL trigger social relationships (and productivity), and thereby overall well-being of individuals with chronic conditions. Whilst the indirect effect of health through income is very small, its indirect effect through social relationships is substantial.

Our results confirm the wide array of research that indicate only a weak effect of absolute income on SWB (Easterlin, 1973; Rojas, 2011). One possible explanation is the relative income hypothesis, which states that people become happier when their income compared to others increase (Diener et al., 1999). The theory of hedonic adaptation suggests that the change in the level of income raises new expectations, thereby creating a gap between the targeted and the achieved level of income, which also reduces the perceived happiness arising from past endeavors (Clark et al., 2008; Easterlin, 2001). Becchetti et al. (2008) further argued that income is among those goods and activities characterized by extrinsic attributes with evidence of strong adaptation. That is, the level of material possessions that makes people happy changes at the same rate as changes in income, implying little improvement in SWB with rising income. Another possible explanation for the trivial indirect effect of HRQoL via income is related to the nature of our sample: Individuals with chronic conditions might have relatively more attention to their illness as compared to material well-being.

In contrast, both the effect of health on social relationships and that of social relationships on SWB are very strong, thereby producing a strong indirect effect of health on well-being through social relationships. This study clearly demonstrates that HRQoL is crucial for both good social relationships and improved SWB.

Most previous studies have considered social relationships as a predictor of health and hence SWB. However, the findings of a longitudinal study by Sirven and Debrand (2012) indicated that the average causal effect of health on social participation is always significantly greater than the reverse effect from social participation to health, something which is consistent with the current study. The rationale is that deterioration in health conditions may compel individuals to withdraw slowly from their social network. Studies have shown that physical and cognitive limitations can deter a person from social participation and interacting with friends (Cornwell, 2009). Health problems also make people feel guilty for not adequately fulfilling their responsibility in their social contacts, eventually leading to loose social relationships (Aartsen et al., 2004). Therefore, in addition to its direct effect, health problems causes changes in the existing social environment leading to poor SWB. Berkman (1983) argued that as chronic illness endures social relationships are weakened, leaving individuals with chronic illness at greater risk for social isolation. This may produce discomfort and feelings of alienation from family members and friends, and hence worsen their overall well-being. Since social relationships with family, friends, and the wider communities hold the keys to our wellbeing, an important policy implication is to facilitate the conditions for healthy social connections.

Further explanation for the strong effect of health on SWB via social relationship hinges on the intrinsic nature of social relationships. Unlike income that has an extrinsic value, social relationships are characterized by intrinsic attributes. Studies reveal evidence of little or no adaptation for goods and activities characterized by intrinsic attributes, and of strong adaptation for those with extrinsic attributes (Becchetti et al., 2008). Thus, social relationship has intrinsic attributes that give rise to long-term positive experiences with lower adaptation. That is, adaptation is partial with regard to social relationships, and hence its effect remains permanent in the long-run.

The size of the indirect effect of health on SWB (via social relationships) was weaker when measured by the self-reported VAS than with the generic descriptive instruments (EQ-5D; SF-6D). A plausible explanation lies in the wording of the VAS question, which explicitly *includes* a social dimension (i.e. ‘the physical, mental, and social’). Consequently, the HRQoL-measure of VAS provides a stronger *direct* effect on SWB, while weakening its *indirect* effect via the indicator used to measure social relationships.

The present study has a number of strengths. First, the data set is large and unique, including seven disease-groups in six-countries. Second, most past studies on the health-SWB relationship have used a simple single item measure of self-rated health. Here, the use of two multi-item measures of HRQoL, such as EQ-5D and SF-6D, in addition to VAS, have proven consistent direct and indirect effects of health on SWB. Third, the use of a multi-item satisfaction with life scale has better psychometric properties than a single-item global life satisfaction as a measure of SWB. Fourth, social relationship is measured by four items that captures both one's ties with family and friends, and connectedness with the wider community, something of particular relevance to individuals with chronic conditions. Finally, we used multiple mediators in our model, which possibly reduce the likelihood of parameter bias due to omitted variables (Preacher and Hayes, 2008).

With regard to the limitation of the study, some degree of self-reported bias may have occurred, as individuals have volunteered to participate in the online survey. The violation of one or more confounding assumptions required in mediation analysis might bias the casual inferences. Unmeasured common causes such as genetic factors, personality, and any other confounders of mediators and outcome or exposure and outcome not explicitly controlled may bias the reported results. In the presence of such unmeasured common causes, conditioning on a common effect (a *collider*) that could be an intermediate variable between the exposure and the outcome can lead to bias, which is commonly referred to as collider/selection bias (Cole et al., 2010). Furthermore, the application of cross-sectional data made it less probable to establish causality. However, we controlled for a number of confounding variables that could produce spurious correlations between predictors and outcome variables. Still, more research is needed to establish the causal pathways between HRQoL, social relationships and SWB using longitudinal studies.

4. Conclusions

We acknowledge that the general problems of omitted variables and unobserved individual heterogeneity represent challenges to drawing causal inferences, particularly in cross-sectional studies. However, since we have controlled for many potential confounders, the results of this paper are consistent. The novel finding of this analysis is to show the importance of health through social relationships. An important lesson for researchers in the field of measuring the wider benefits of health outcomes is to include meaningful items on social relationships. An important lesson for policy makers is to be aware of the fact that people living with a chronic condition, not only suffer a disease burden, but a social burden: Social isolation appears to be more detrimental to their overall well-being than is their ill health. Hence, public health interventions should be even more oriented towards facilitating social arenas for people with chronic conditions.

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Table Appendix I. The direct and indirect effects of HRQoL on SWB: Unstandardized model results (N=6,173)

	HHI			SR			SWB		
Variables	Model-1	Model-2	Model-3	Model-1	Model-2	Model-3	Model-1	Model-2	Model-3
Direct effect									
HRQoL	0.860*	0.732*	0.519*	0.526*	0.476*	0.376*	1.434*	1.403*	2.232*
HHI	-	-	-	-	-	-	0.183*	0.168*	0.166*
SR	-	-	-	-	-	-	3.620*	3.315*	3.087*
Gender (Ref. Male)									
Female	-0.153*	-0.141*	-0.168*	0.015*	0.023*	0.005	0.141*	0.168*	0.100*
Age (Ref. 18-34 years)									
35 - 44 years	0.183*	0.174*	0.168*	0.003	-0.003	-0.004	-0.161*	-0.176*	-0.130†
45 - 54 years	0.202*	0.178*	0.173*	0.026*	**0.012**	0.011	-0.197*	-0.231*	-0.173*
55 - 64 years	0.145*	0.115*	0.114*	0.056*	0.037*	0.039*	-0.083	-0.122†	-0.071
65+ years	0.007	-0.030	-0.022	0.084*	0.061*	0.065*	0.170*	0.126†	0.138*
Marital (Ref. No partner)									
Partner/Spouse	0.528*	0.521*	0.524*	0.051*	0.046*	0.047*	0.244*	0.254*	0.216*
Employement status (Ref. all others)									
Unemployed	-0.434*	-0.426*	-0.438*	-0.042*	-0.035*	-0.041*	-0.474*	-0.475*	-0.469*
Education (Ref. High school)									
Diploma	0.171*	0.170*	0.174*	0.003	0.002	0.004	0.072†	0.073†	**0.061**
University	0.506*	0.500*	0.514*	-0.001	-0.006	0.001	0.181*	0.174*	0.141*
Disease groups (Ref. Depression)									
Arthritis	0.111*	**0.067**	0.093†	0.150*	0.121*	0.134*	0.263*	0.226*	0.209*
Asthma	0.058	0.027	0.086†	0.123*	0.099*	0.134*	0.233*	0.208*	0.217*
Cancer	0.080†	0.054	0.116*	0.126*	0.106*	0.146*	0.000	-0.014	0.097
Diabetes	-0.001	-0.032	0.030	0.122*	0.100*	0.137*	0.093	0.068	0.143†
Hearing problem	0.089†	0.048	0.121*	0.096*	0.065*	0.106*	0.329*	0.276*	0.251*
Heart problem	0.034	0.002	0.070	0.134*	0.111*	0.153*	0.129†	**0.106**	0.212*

Table Appendix I. The direct and indirect effects of HRQoL on SWB (***Continued*** …)

	HHI			SR			SWB		
Variables	Model-1	Model-2	Model-3	Model-1	Model-2	Model-3	Model-1	Model-2	Model-3
Country (Ref. High school)									
Australia	-0.141*	-0.134*	-0.128*	-0.011	-0.008	-0.004	0.140*	0.150*	0.127†
Canada	0.297*	0.293*	0.291*	-0.003	-0.006	-0.008	0.228*	0.227*	0.156*
Germany	-0.008	-0.006	0.002	-0.001	0.000	0.005	0.242*	0.246*	0.243*
Norway	0.481*	0.490*	0.514*	0.036*	0.040*	0.054*	0.075	0.111†	0.106†
USA	0.231*	0.232*	0.214*	0.001	0.003	-0.011	0.049	0.059	-0.048
Indirect effect									
HRQoL via HHI	-	-	-	-	-	-	0.157*	0.081*	0.086*
HRQoL via SR	-	-	-	-	-	-	1.905*	1.040*	1.119*
Total indirect	-	-	-	-	-	-	2.062*	1.121*	1.243*
R-square	*0.325*	*0.331*	*0.316*	*0.371*	*0.442*	*0.354*	*0.487*	*0.497*	*0.545*

Note: HRQoL; health related quality of life (measured by EQ-5D in Model-1, SF-6D in Model-2, VAS in Model-3); SR, social relationships; SWB, subjective well-being (measured by the first three items of satisfaction with life scale); S.E., standard error.
* $p < 0.01$; † $p < 0.05$.