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"I'm afraid I have bad news for you..." Estimating the impact of different health impairments on subjective well-being

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ABSTRACT

Bad health decreases individuals' happiness, but few studies measure the impact of specific illnesses. We apply matching estimators to examine how changes in different (objective) conditions of bad health affect subjective well-being for a sample of 100,265 observations from the British Household Panel Survey (BHPS) database (1996–2006). The strongest effect is for alcohol and drug abuse, followed by anxiety, depression and other mental illnesses, stroke and cancer. Adaptation to health impairments varies across health impairments. There is also a puzzling asymmetry: strong adverse reactions to deteriorations in health appear alongside weak increases in well-being after health improvements. In conclusion, our analysis offers a more detailed account of how bad health influences happiness than accounts focusing on how bad self-assessed health affects individual well-being.

Introduction

Our health determines many facets of our life. It affects our employment opportunities and our incomes (Arrow, 1996), influences social activities (Gardner & Oswald, 2004) and impacts our mood and well-being more generally (Easterlin, 2003; Graham, 2008). Being in good health increases subjective well-being, just as illness or bad health decreases it (Graham, Higuera, & Lora, 2011; Veenhoven, 2008).

An individual's subjective well-being (synonymously called "happiness" here) depends on a complex interacting web of factors, comprising economic (such as income, status or employment), situational (health, social relations), socio-demographic (gender, age, education), personal (personality and genes) and institutional factors (such as the extent of direct democratic participation), and the literature examining these relationships has vastly increased over the last few years (for overviews, see Dolan, Peasgood, & White, 2008; Easterlin, 2003; Frey & Stutzer, 2000). As one can consider subjective well-being to be a broad aspect of an individual's mental health, it is no wonder that many determinants of subjective well-being also determine health more generally (see, e.g., Contoyannis & Jones, 2004; Fuchs, 2004; Gardner & Oswald, 2004).

In subjective well-being research, the relationship between subjective well-being and (mostly: self-assessed) health is well-researched and "studies consistently reveal a strong relationship between health and happiness" (Graham, 2008, p. 73). This is less surprising, for instance, for broad "mental well-being" measures (such as the GHQ-12) that incorporate some (mental) health aspects (Dolan et al., 2008, p. 100). But the positive relationship also holds when using life satisfaction as the dependent variable in regressions (Dolan & Kahneman, 2008; Dolan et al., 2008; Easterlin, 2003). It seems that causality runs in both directions: a high level of well-being certainly seems relevant for subsequent good health, with significant positive effects of well-being on health being observed two or three years later (Binder & Coad, 2010; Lyubomirsky, King, & Diener, 2005).

The stronger relationship, however, seems to run from health to happiness. Numerous studies show that healthier individuals tend to be happier. Most studies here analyze the relationship between individuals' subjective health ratings and subjective well-being (Dolan et al., 2008; Easterlin, 2003) or the impact of disability on subjective well-being (Brickman, Coates, & Janoff-Bulman, 1978; Oswald & Powdthavee, 2008; Uppal, 2006), mostly for lack of more

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detailed data on objective health impairments. Very few studies also extend the analysis to more detailed health conditions (Dolan, 2011; Graham et al., 2011; Mukuria & Brazier, 2013; Shields & Wheatley Price, 2005). Even if large panel studies incorporate questions on individuals' health impairments, many of these illnesses are comparatively rare and typical multivariate regressions are ill-suited to deal with small numbers of observations in such cases (as well as lack of variation). In a cross-sectional analysis of Health Survey for England (HSE) data, Shields and Wheatley Price (2005) report significantly decreased psychological well-being for individuals with problems with muscular-arthritis-rheumatism, stomach problems and respiratory problems. For males, heart attack or stroke problems and migraine and epilepsy are associated with depressed psychological well-being, while hypertension and blood pressure problems seem associated with decreased psychological well-being in females (p. 529). Problems like cancer or diabetes are not related to psychological well-being in their sample. A similar cross-sectional study has been conducted by Graham et al. (2011) for a number of Latin American countries, where an EQ5D measure of health problems is related to health satisfaction and life satisfaction. Pain, anxiety and difficulties with usual activities are strongly negatively related to health satisfaction and, to a lesser degree, also to life satisfaction. Problems with mobility and self-care are not as clearly related to life satisfaction, which the authors interpret as evidence of a higher impact of acute and chronic mental illnesses over physical conditions (compare also Mukuria & Brazier, 2013). An explanation for this finding might include the uncertainty associated with some health problems, where the next anxiety or epilepsy attack cannot be anticipated (thus hindering adaptation). Similarly, Dolan (2011) finds that mental health has stronger effects on subjective well-being than physical health problems, while in preference elicitations, individuals value physical health more than mental health, probably due to focusing effects and faulty affective forecasting (Wilson & Gilbert, 2005).

In the cases discussed, the cross-sectional data structure hinders investigation of self-selection, duration of the health condition, and the role of personality traits mediating the happiness–health relationship; so these estimates should be taken with care. While panel data regression techniques might offer valuable insights into the variation within individuals over time and thus help alleviate concerns about selection effects, as well as account for individual-specific (fixed) effects that capture the trait-like properties of subjective well-being (Diener & Lucas, 1999; Ferrer-i-Carbonell & Frijters, 2004), these techniques are ill-suited to deal with dummy variables that exhibit little variation, as in the case of specific illnesses. We therefore seek to obtain improved estimates of the causal impact of such illnesses on subjective well-being by applying matching estimators (Caliendo & Kopeinig, 2008; Imbens, 2004; Rubin, 1974).

This allows us to address many of the above-mentioned shortcomings and estimate the impact of different health impairments on subjective well-being, at an improved level of detail. Similarly, we provide novel results concerning specific adaptation and recovery patterns for different health conditions. Indeed, the dynamics of illness conditions and their impact on subjective well-being need to be better understood, since it remains unclear to what extent subjective well-being can be permanently influenced by life events in general and health conditions in particular (Headey, 2010). This time dimension is also important in our context, as there is some evidence that individuals adapt differently to different health conditions. While some hedonic adaptation occurs, the level of adaptation seems far from complete: Oswald and Powdthavee (2008) find a rate of hedonic adaptation between 30% and 50% in their fixed-effects framework, depending on the degree of disability. As opposed to disability, patients who suffer from chronic diseases and chronic pain have difficulties adapting (Oswald & Powdthavee, 2008; Smith & Wallston, 1992). There are few studies in this field, and their results are complicated by the progressive nature of some of the diseases (Dolan & Kahneman, 2008, pp. 218–9). In sum, hedonic adaptation to adverse health conditions seems limited and domain-specific (Frederick and Loewenstein, 1999; Oswald & Powdthavee, 2008). The dynamic properties of subjective well-being and the extent of hedonic adaptation to adverse (but also to beneficial) life events motivates our later analysis of the causal effect of different health conditions on individuals' life satisfaction with different time lags.

The paper is structured as follows: we present the dataset in Section 2. Our analysis is detailed in Section 3, and we conclude with a discussion in Section 4.

Dataset

The British Household Panel Survey (BHPS), comprising about 10,000 individual interviews in 1991 and growing in subsequent years, is a well-known longitudinal survey of private households in Great Britain, containing rich information on diverse areas of respondents' lives. We use unbalanced panel data from 1996 to 2006 (waves f to n) – a total of 100,265 observations after cleaning the panel (ethical approval was not necessary for our secondary analysis of anonymized data). During the time period, two waves were deleted due to missing variables (one did not feature the life satisfaction variable, the other had different coding of subjectively-reported health status, finally the most recent waves do not provide net annualized household incomes), leaving us with 9 waves in total. Table 1 presents our variables.

From the 1996 wave onwards, the BHPS offers a life satisfaction question (our main dependent variable). It records an individual's answer to the question "How dissatisfied or satisfied are you with your life overall?" It measures an individual's life satisfaction ordinally on a seven-point Likert scale ranging from "not satisfied at all" (1) to "completely satisfied" (7). We cannot completely exclude measurement bias in this variable, e.g. resulting from demand effects when an interviewer is present (Conti & Pudney, 2011; Pudney, 2011), but measures of subjective well-being appear to be surprisingly valid and reliable despite their deceptive simplicity (Helliwell and Wang, 2012; Krueger & Schkade, 2008).

Our main explanatory variables are an individual's self-reported subjective health status as well as a number of objective health indicators and a list of health impairments. There is debate on whether objective health is sufficiently well-measured by a person's subjective health assessments (Johnston, Propper, & Shields, 2009). In the BHPS, an individual's subjective assessment of health (during the last 12 months) is ordinally scaled on a five-point Likert scale, reverse-coded to range from "excellent" (five) to "very poor" (one). In order to account for more objective aspects of individual health, we included the number of days spent in hospital (i.e., log(days + 1)), the number of visits to a general practitioner, and the number of serious accidents in the previous year (Table 1).

The BHPS includes several more specific health conditions (or impairments). These include so-called "health problems" grouped into categories. Individuals are asked: "Do you have any of the health problems or disabilities listed on this card?" The categories listed are "Problems or disability connected with: arms, legs, hands, feet, back, or neck (including arthritis and rheumatism)" (hereafter often referred to as "arms problems"), "Difficulty in seeing (other than needing glasses to read normal size print)", "Difficulty in hearing", "Skin conditions/allergies", "Chest/breathing problems, asthma, bronchitis", "Heart/blood pressure or blood circulation problems", "Stomach/liver/kidneys", "Diabetes", "Anxiety, depression or bad nerves, psychiatric problems", "Alcohol or drug related

Table 1
Summary statistics.

	(1) All mean	(2) Arms mean	(3) Sight mean	(4) Hearing mean	(5) Allergy mean	(6) Chest mean	(7) Heart mean	(8) Stomach mean	(9) Diabetes mean	(10) Anxiety mean	(11) Drugs mean	(12) Epilepsy mean	(13) Migraine mean	(14) Other mean	(15) Cancer mean	(16) Stroke mean
Life satisfaction	5.2262	5.0281	4.9714	5.1894	5.0214	4.9215	5.1561	4.7583	5.1062	4.0335	3.6811	4.6459	4.8157	4.8617	4.9887	4.6280
Health variables																
Subj. health	3.8031	3.2507	3.1803	3.4113	3.5915	3.1765	3.2276	2.9795	3.0714	2.8332	2.6735	3.1609	3.3600	3.0511	2.8375	2.7749
Doctor visits	2.4195	2.9707	3.0294	2.8580	2.7444	3.0891	3.2079	3.3012	3.3345	3.5055	3.3471	3.2593	2.9515	3.2131	3.3691	3.4137
Accidents	0.1197	0.1519	0.1490	0.1263	0.1365	0.1547	0.1109	0.1481	0.1185	0.1688	0.3096	0.2593	0.1609	0.1475	0.0824	0.1536
Log(hosp. days)	0.1827	0.3065	0.3914	0.3117	0.2187	0.3604	0.3737	0.4515	0.4040	0.3638	0.4861	0.4695	0.2367	0.4198	0.8605	0.7461
No. cigarettes	3.9447	4.1503	3.6068	3.4870	3.9693	4.9685	3.0214	4.7466	3.3653	7.0622	16.1069	6.1080	4.7415	3.8550	3.3815	3.9582
Disabled	0.0896	0.2374	0.3300	0.2357	0.1037	0.2144	0.2382	0.2244	0.3029	0.2490	0.2758	0.3866	0.1239	0.1907	0.3668	0.6496
Personality trait variables																
Extraversion	13.3742	13.1320	12.8153	12.6948	13.6287	13.4165	12.7579	13.2386	12.6088	12.7431	13.1667	12.9613	13.3605	13.3398	12.8857	12.2750
Agreeableness	16.3055	16.4313	16.4371	16.2384	16.2419	16.1869	16.4105	16.4853	16.3703	16.4264	15.6273	16.4143	16.5389	16.4645	16.2486	16.1265
Openness	13.3117	12.9495	12.7179	12.6524	13.7497	12.9776	12.4913	13.1403	12.3494	12.9989	13.2426	12.5089	13.4892	13.3378	12.7137	11.8794
Neuroticism	10.9366	11.2419	11.2679	10.5811	11.5899	11.4924	11.0251	11.9394	10.5473	14.4818	13.8270	12.5219	12.5191	11.8677	10.6119	11.0716
Conscientiousness	15.8604	15.7234	15.3164	15.4154	15.8515	15.4880	15.5076	15.7030	15.3425	15.2282	14.1617	14.2580	15.9608	15.7381	15.3465	14.7677
Demographic variables																
Log(income)	9.9552	9.8782	9.8356	9.8663	9.9844	9.8657	9.8741	9.8862	9.8704	9.7865	9.6267	9.8396	9.8978	9.9338	9.9355	9.8708
Gender	0.5327	0.5829	0.5937	0.4544	0.6288	0.5515	0.5562	0.5945	0.4612	0.6909	0.3546	0.5438	0.7536	0.6716	0.5316	0.4825
Age	45.8355	57.0551	60.9194	62.8138	43.2768	49.4102	62.9697	53.2943	61.1550	48.4892	40.2983	44.3758	43.3601	51.7197	64.4819	67.7763
No. children	0.5984	0.3713	0.2902	0.2572	0.6119	0.5122	0.2021	0.4378	0.2776	0.5888	0.4672	0.5894	0.7299	0.4759	0.1693	0.1159
Marital status dummies																
Never married	0.2795	0.1462	0.1723	0.1276	0.3204	0.2621	0.0939	0.1881	0.1338	0.2362	0.5347	0.3313	0.2717	0.1927	0.0937	0.0728
Married	0.5349	0.5627	0.4867	0.5736	0.5088	0.4907	0.5897	0.5434	0.5682	0.4525	0.1801	0.4910	0.5365	0.5685	0.6072	0.5202
Separated	0.0212	0.0193	0.0151	0.0103	0.0196	0.0231	0.0166	0.0239	0.0158	0.0476	0.0563	0.0312	0.0268	0.0210	0.0181	0.0323
Widowed	0.0814	0.1668	0.2357	0.2104	0.0682	0.1231	0.2069	0.1292	0.1852	0.1022	0.0432	0.0468	0.0608	0.1163	0.2088	0.2695
Divorced	0.0830	0.1049	0.0902	0.0780	0.0830	0.1010	0.0929	0.1155	0.0970	0.1615	0.1857	0.0996	0.1042	0.1014	0.0722	0.1051
Labor market status dummies																
Employed	0.5091	0.3221	0.2224	0.2533	0.5254	0.3715	0.2327	0.3511	0.2612	0.3164	0.2101	0.3301	0.5100	0.3801	0.1716	0.0943
Unemployed	0.0333	0.0238	0.0230	0.0201	0.0324	0.0385	0.0177	0.0340	0.0180	0.0542	0.2158	0.0564	0.0331	0.0185	0.0079	0.0148
Self-employed	0.0680	0.0508	0.0371	0.0465	0.0569	0.0482	0.0415	0.0470	0.0351	0.0395	0.0244	0.0336	0.0464	0.0499	0.0395	0.0081
Retired	0.2136	0.4102	0.5193	0.5549	0.1792	0.3079	0.5428	0.3362	0.4961	0.2239	0.0882	0.1849	0.1468	0.3011	0.5937	0.6563
Study, school	0.0522	0.0118	0.0247	0.0125	0.0577	0.0476	0.0060	0.0174	0.0109	0.0207	0.0281	0.0420	0.0425	0.0259	0.0023	0.0000
Maternity leave	0.0043	0.0015	0.0017	0.0013	0.0058	0.0032	0.0016	0.0026	0.0022	0.0019	0.0000	0.0000	0.0034	0.0024	0.0000	0.0027
Long-term sick	0.0440	0.1087	0.1109	0.0670	0.0520	0.1046	0.0953	0.1325	0.1185	0.2139	0.3771	0.2713	0.0949	0.1259	0.1208	0.1954
Family-care	0.0695	0.0665	0.0547	0.0415	0.0844	0.0723	0.0582	0.0740	0.0553	0.1204	0.0450	0.0720	0.1176	0.0878	0.0530	0.0256
Other	0.0061	0.0046	0.0062	0.0030	0.0062	0.0062	0.0041	0.0051	0.0027	0.0091	0.0113	0.0096	0.0053	0.0084	0.0113	0.0027
Education dummies																
None	0.2302	0.3693	0.4418	0.4093	0.1823	0.3319	0.4232	0.3376	0.4519	0.3444	0.3452	0.3133	0.2397	0.2915	0.4018	0.4973
Elementary	0.0367	0.0226	0.0166	0.0140	0.0326	0.0380	0.0129	0.0249	0.0158	0.0356	0.0600	0.0840	0.0398	0.0279	0.0056	0.0148
Basic vocational	0.0892	0.1111	0.1094	0.1304	0.0808	0.0935	0.1171	0.1030	0.1024	0.1007	0.0901	0.0948	0.0869	0.0878	0.1174	0.1402
Middle general	0.1599	0.1206	0.1066	0.0967	0.1625	0.1358	0.1004	0.1153	0.0981	0.1295	0.1651	0.1393	0.1638	0.1332	0.0847	0.0593
Middle vocational	0.0535	0.0494	0.0433	0.0409	0.0545	0.0435	0.0445	0.0551	0.0384	0.0555	0.0375	0.0480	0.0612	0.0521	0.0485	0.0391
High general	0.0714	0.0417	0.0444	0.0376	0.0823	0.0650	0.0354	0.0467	0.0343	0.0547	0.0507	0.0456	0.0689	0.0570	0.0451	0.0283
High vocational	0.0525	0.0374	0.0276	0.0288	0.0496	0.0433	0.0353	0.0358	0.0441	0.0404	0.0694	0.0600	0.0492	0.0456	0.0271	0.0350
Low tertiary	0.1822	0.1719	0.1439	0.1726	0.2045	0.1592	0.1654	0.1861	0.1566	0.1516	0.1295	0.1381	0.1896	0.1894	0.1659	0.1604
High tertiary	0.1245	0.0760	0.0663	0.0697	0.1508	0.0899	0.0659	0.0957	0.0583	0.0876	0.0525	0.0768	0.1009	0.1153	0.1038	0.0256
Health condition dummies																
Arms	0.2847															
Sight	0.0516															
Hearing	0.0868															
Allergy	0.1214															
Chest	0.1375															
Heart	0.1720															
Stomach	0.0806															

(*continued on next page*)

Table 1 (*continued*)

	(1) All mean	(2) Arms mean	(3) Sight mean	(4) Hearing mean	(5) Allergy mean	(6) Chest mean	(7) Heart mean	(8) Stomach mean	(9) Diabetes mean	(10) Anxiety mean	(11) Drugs mean	(12) Epilepsy mean	(13) Migraine mean	(14) Other mean	(15) Cancer mean	(16) Stroke mean
Diabetes	0.0366															
Anxiety	0.0823															
Drugs	0.0053															
Epilepsy	0.0083															
Migraine	0.0827															
Other	0.0490															
Cancer	0.0145															
Stroke	0.0121															
Observations	100,265	28,543	5176	8706	12,169	13,789	17,248	8081	3671	8250	533	833	8289	4909	886	742

Notes: observations pooled over years.

problems", "Epilepsy", "Migraine or frequent headaches", "Cancer", "Stroke", and "Other health problems". Individuals can solely answer "yes" or "no", but not the degree or other specifics of the condition. In the panel context, we can nevertheless use this information to see whether an individual became ill (according to one of these categories) from one year to the next. We also use a dummy variable for disability, to account for the fact that many of these conditions do not necessarily lead to disability. It can be conjectured that measurement bias resulting from answering simple yes/no health questions is smaller than ranking oneself according to five categories of subjective health status, so that our objective health conditions offer a valuable complement to individuals' subjectively assessed health ratings.

Since the subjective well-being and health variables were asked in different survey sections, we would expect no systematic bias between them. However, subjective well-being questions were elicited via self-completion, while health condition answers by an interviewer. Bias could result if individuals systematically answer health questions differently in the interviewer's presence (Conti & Pudney, 2011). Health problems like alcohol/drug abuse or mental health issues might also be underreported to an interviewer, and this would likely bias our results downwards for these categories, since well-being in the control group would decrease through unhappy and sick individuals who "neglect" to mention these types of illnesses. The large-scale anonymous questionnaire design might alleviate this form of bias.

In the BHPS wave 2005, a short inventory for the Big Five personality traits has been included – we also use these personality traits as matching covariates (these variables were coded by adding up the ordinal responses to the three questions relating to each personality trait). It is not implausible to assume that personality evolves over time, especially during young ages, or over long time horizons (see Boyce, Wood, & Powdthavee, 2013; Donnellan & Lucas, 2008; Srivastava, John, Gosling, & Potter, 2003). But much evidence has also accumulated that the Big Five character traits prove to be quite stable from age thirty onwards (Costa & McCrae, 1994) and if they change, they do so only quite slowly over the course of a human life (Hampson & Goldberg, 2006). Since the Big Five were only asked once in the BHPS in our sample horizon, we are forced by data limitations to consider personality traits to be fixed for individuals over the course of our sample horizon (for a more extensive exposition of the Big Five in the BHPS and justification of their use as fixed variables see also Binder & Freytag, 2013).

Lastly, we include a number of ordinary control variables. We use net equivalised annual household income (in British Pound Sterling), before housing costs and deflated to 2008 price levels, as provided and detailed by Levy and Jenkins (2008). As equivalence scales, we have opted for applying the widely-accepted McClements scale (McClements, 1977). We use the logarithm of the income measure as a regressor in our analysis (Easterlin, 2001, p. 468; Stevenson & Wolfers, 2008), assuming that a given change in the proportion of income leads to the same proportional change in well-being (Layard, Mayraz, & Nickell, 2008).

Other control variables (see Table 1) comprise gender, age, and age^2 (we use the squared difference between age and mean-age instead of age^2 to avoid problems of multicollinearity) as well as employment dummies (being unemployed, self-employed, retired, long-term sick, on maternity leave, studying or being in school, caring for family members as well as other conditions not captured). The reference group here is being in employment. We have also marital status dummies (never married, separated, divorced or widowed). We control for regions (Metropolitan counties and Inner and Outer London areas, results not reported). Of our sample, 53.27% were female (the gender variable is one if female, zero if male). The mean age is 45.84 years. Also included is the number of children and an educational control variable (an individual's highest education level, measured by the CASMIN scale). This is measured ordinally from one ("none") to nine ("higher tertiary"). Also relevant in the health context is an individual's smoking habits – hence we include the number of cigarettes smoked per day as a further control variable. Table 2 reports pairwise correlations between the variables of interest – most of our indicators are significantly correlated, although we find no problems of multicollinearity.

Results

Fixed-effects regressions

Table 3 presents a baseline model of the life satisfaction health relationship using standard fixed-effects (FE) regressions. Accounting for fixed-effects in subjective well-being regressions is the standard model choice (Ferrer-i-Carbonell & Frijters, 2004), since happiness is partly determined by genes and stable personality traits (Diener, Suh, Lucas, & Smith, 1999; Lykken & Tellegen, 1996).

Regarding our health variables, the FE models exhibit strong positive effects of good subjective health status on life satisfaction and strong negative effects from disability, long-term sickness, as well as health conditions such as anxiety. Ceteris paribus effect sizes (the coefficient magnitudes) are small for most objective health impairments, and insignificant for many of these problems. With reference to our subsequent matching analysis, it can be conjectured that this is not due to absence of effects, but rather an artifact resulting from small numbers of observations for these conditions, as well as their slow-changing nature (circumstances under which FE models underperform).

The two health conditions referring to having a stroke or cancer are not shown in Table 3, as they have been only elicited halfway into our sample horizon. When we included both conditions, our sample size fell from 100,265 observations to 61,143. In this model, neither health problem was significantly related to life satisfaction (stroke: $b = -0.0891$, t-stat -1.27; cancer: $b = 0.0342$, t-stat 0.59) and due to the nearly halved sample size, some other (health) coefficients were also insignificant.

We find typical results in our model regarding other variables. Income has a significant effect on life satisfaction, which seems to be driven by males. Being unemployed has a strong negative impact on life satisfaction, irrespective of gender. We find no relationship between self-employment and life satisfaction in the unmatched sample, as do most studies (Dolan et al., 2008, but see Binder & Coad, in press). We also find a significant negative relationship for separation and widowhood, while being divorced has no significant impact (as expected, if divorce finalizes a long decline in quality of marriage). In the gender disaggregation, education is unrelated to life satisfaction for males, but it influences female life satisfaction more strongly. However, the relationship between education and subjective well-being appears rather unstable in the literature (Binder & Coad, 2011; Dolan et al., 2008). We also find evidence of gender differences in subjective well-being, which can be conjectured to interact with other variables of interest, such as job status (in our case) or age (Plagnol & Easterlin, 2008).[1]

[1] We also calculated a version of this model without the subjective-health measure. The idea behind this lies in dissipating econometric reservations one could have in using objective and subjective health measures in a regression simultaneously. While this does not cause multicollinearity problems, nevertheless the subjective health assessment might pick up variance associated with the objective health conditions on which we focus. Indeed we find that coefficients of negative health conditions increase in size as opposed to the model where subjective health ratings are included. Results are provided upon request.

Table 2
Contemporaneous correlations.

	Life satisfaction	Subj. health	Log(income)	Disabled	Unemployed	Employed	Education	Age	Gender
Life satisfaction	1.0000								
Subj. health	0.3304*** (0.0000)	1.0000							
Log(income)	0.0743*** (0.0000)	0.1387*** (0.0000)	1.0000						
Disabled	−0.1472*** (0.0000)	−0.3679*** (0.0000)	−0.0764*** (0.0000)	1.0000					
Unemployed	−0.0880*** (0.0000)	−0.0255*** (0.0000)	−0.1156*** (0.0000)	−0.0237*** (0.0000)	1.0000				
Employed	0.0067* (0.0334)	0.2263*** (0.0000)	0.3016*** (0.0000)	−0.2525*** (0.0000)	−0.1889*** (0.0000)	1.0000			
Education	−0.0063* (0.0456)	0.2027*** (0.0000)	0.3099*** (0.0000)	−0.1702*** (0.0000)	−0.0542*** (0.0000)	0.2763*** (0.0000)	1.0000		
Age	0.0881*** (0.0000)	−0.1910*** (0.0000)	−0.0414*** (0.0000)	0.2513*** (0.0000)	−0.1102*** (0.0000)	−0.3839*** (0.0000)	−0.2718*** (0.0000)	1.0000	
Gender	−0.0038 (0.2240)	−0.0658*** (0.0000)	−0.0646*** (0.0000)	0.0041 (0.1960)	−0.0488*** (0.0000)	−0.0740*** (0.0000)	−0.0606*** (0.0000)	0.0316*** (0.0000)	1.0000
Observations	100,265								

Notes: Observations pooled over years. p-Values in parentheses.
Key to significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3
Baseline regression analysis: Fixed-Effect (FE) regressions for the full sample as well as for subsamples by gender.

	(1) Life satisfaction (FE)	(2) Life satisfaction (male)	(3) Life satisfaction (female)
Subj. health	0.1840*** (28.64)	0.1690*** (18.64)	0.1957*** (21.72)
Doctor visits	−0.0080 (−1.79)	−0.0190** (−2.91)	−0.0001 (−0.02)
Accidents	−0.0203* (−2.08)	−0.0257* (−2.07)	−0.0138 (−0.90)
Log(hosp. days)	−0.0123 (−1.62)	−0.0274* (−2.26)	−0.0016 (−0.16)
Disabled	−0.1520*** (−6.79)	−0.1438*** (−4.69)	−0.1565*** (−4.89)
No. cigarettes	−0.0025* (−2.13)	−0.0027 (−1.80)	−0.0023 (−1.21)
Health condition dummies			
Arms	−0.0307** (−2.69)	−0.0129 (−0.82)	−0.0477** (−2.91)
Sight	−0.0489* (−2.25)	−0.0355 (−1.09)	−0.0596* (−2.05)
Hearing	−0.0533** (−2.59)	−0.0491 (−1.83)	−0.0587 (−1.84)
Allergy	−0.0277 (−1.82)	−0.0236 (−1.02)	−0.0301 (−1.49)
Chest	0.0033 (0.18)	0.0065 (0.26)	0.0004 (0.02)
Heart	−0.0014 (−0.09)	−0.0054 (−0.25)	0.0042 (0.19)
Stomach	−0.0123 (−0.70)	−0.0133 (−0.51)	−0.0108 (−0.46)
Diabetes	0.0276 (0.64)	0.0224 (0.40)	0.0340 (0.53)
Anxiety	−0.3890*** (−17.93)	−0.4695*** (−12.43)	−0.3515*** (−13.28)
Drugs	−0.1261 (−1.48)	−0.1648 (−1.57)	−0.0347 (−0.24)
Epilepsy	−0.0741 (−0.86)	−0.1706 (−1.21)	0.0130 (0.13)
Migraine	−0.0611** (−3.13)	−0.0392 (−1.13)	−0.0688** (−2.92)
Other	−0.0496* (−2.48)	−0.0537 (−1.60)	−0.0483 (−1.95)
Log(income)	0.0301*** (3.46)	0.0335** (2.89)	0.0282* (2.20)
Age	−0.0137 (−1.01)	0.0089 (0.48)	−0.0310 (−1.70)
(Age-mean age)^2	−0.0001 (−1.33)	0.0001 (1.60)	−0.0002** (−3.07)
No. children	−0.0023 (−0.27)	0.0097 (0.83)	−0.0150 (−1.18)
Education dummies			
Elementary	0.0378 (0.28)	0.0317 (0.18)	0.0880 (0.44)
Basic vocational	−0.0607 (−0.63)	−0.2339 (−1.88)	0.1036 (0.75)
Middle general	0.1985* (2.07)	0.0667 (0.56)	0.3477* (2.29)
Middle vocational	0.3079* (2.17)	0.3549 (1.64)	0.3648 (1.88)
High general	0.2475* (2.56)	0.1178 (0.97)	0.3976** (2.60)
High vocational	0.1326 (1.27)	0.0302 (0.24)	0.2764 (1.62)
Low tertiary	0.2483* (2.42)	0.1022 (0.84)	0.4170* (2.50)
High tertiary	0.1788 (1.74)	0.0458 (0.35)	0.3249* (2.02)
Marital status dummies			
Never married	−0.0307 (−1.23)	−0.0695 (−1.92)	0.0051 (0.15)
Separated	−0.1451*** (−3.56)	−0.1863** (−3.20)	−0.1120* (−2.00)
Divorced	−0.0081 (−0.23)	−0.0017 (−0.03)	−0.0134 (−0.28)
Widowed	−0.2344*** (−4.19)	−0.1830* (−2.05)	−0.2568*** (−3.59)
Labor market status dummies			
Unemployed	−0.3111*** (−10.99)	−0.3428*** (−8.74)	−0.2829*** (−6.93)
Self-employed	−0.0049 (−0.22)	0.0124 (0.46)	−0.0387 (−0.96)
Retired	0.0616* (2.50)	0.0744* (2.03)	0.0549 (1.66)
Study, school	0.0472 (1.62)	0.0357 (0.82)	0.0574 (1.46)
Maternity leave	0.2865*** (6.61)	0.3459 (1.43)	0.2734*** (6.11)
Long-term sick	−0.2869*** (−7.52)	−0.3319*** (−5.67)	−0.2434*** (−4.85)
Family-care	−0.0523* (−2.20)	−0.2179* (−2.25)	−0.0406 (−1.58)
Other	−0.0162 (−0.30)	−0.1271 (−1.58)	0.0707 (0.98)
Observations	100,265	46,850	53,415
R^2	0.047	0.050	0.047

t statistics in parentheses. Key to significance levels: *$p < 0.05$, **$p<0.01$, ***$p<0.001$.

Matching estimates

While FE models are preferable to simple pooled models for panel data, we may be "overcontrolling" – removing some slow-changing variables of interest. Moreover, fixed-effect regression suffers from other drawbacks of regression models (in particular, potential lack of a common support for treatment and control groups). Both points are germane to our context. Consider the dummies for different illness conditions. These would exhibit little variation if individuals mostly transition into a health problem and stay there, due to chronic illness. For those categories that refer mostly to conditions with chronic or progressive disease characteristics, our dummies will not capture much variation, making FE estimates unreliable. Moreover, the above FE regressions with the *prima facie* high number of observations obscures a crucial fact regarding illness conditions, namely the comparatively few cases available in the sample. By disaggregating descriptive statistics into different illness conditions (Table 1), one can clearly see that a sickness condition can include as few as 533 observations (in the case of drugs), which in consequence leads to non-significant results in the FE regressions. Despite an overall high number of observations, coefficients in such cases are derived from smaller numbers of observations. Matching estimates do not obscure this fact, as the smaller numbers of observations in Tables 4 and 5 reveal.

In order to obtain improved estimates of the causal impact of different health conditions on life satisfaction, we turn to our matching estimates (Caliendo & Kopeinig, 2008; Imbens, 2004; Rubin, 1974). Matching is an econometric technique that bears similarities to an experimental setup in medical research, with two groups of randomly-selected participants, whereby one is the control and the other the treatment group, which is subjected to medical treatment. Unlike clinical trials, however, matching estimators can be applied to observational data, to ensure that "treatment" and "control" groups are closely comparable in terms

Table 4
Matching estimates: propensity score matching (PSM), nearest-neighbor matching (NN), and transitions into the sickness condition. Lower part of the table refers to changes in subjective health status.

Condition	$t+1$				$t+2$				Transitions			
	PSM: ATT NN: SATE	SE SE	*t*-stat *z*-stat	Obs Obs	PSM: ATT NN: SATE	SE SE	*t*-stat *z*-stat	Obs Obs	Sick $t+1$	Healthy $t+1$	Sick $t+2$	Healthy $t+2$
Arms	−0.4067***	0.0288	−14.1176	15,491	−0.5331***	0.0504	−10.5675	9379	5357	20,782	1970	13,746
	−0.3012***	0.0267	−11.2854	15,529	−0.3894***	0.0480	−8.1170	9617				
Sight	−0.6319***	0.0619	−10.2099	13,025	−0.6988***	0.1066	−6.5543	6920	1906	20,782	491	13,746
	−0.4372***	0.0570	−7.6741	13,398	−0.4100***	0.1196	−3.4271	8725				
Hearing	−0.5309***	0.0574	−9.2487	13,126	−0.4053***	0.0761	−5.3258	7679	1831	20,782	707	13,746
	−0.3743***	0.0565	−6.6269	13,440	−0.1833*	0.0881	−2.0806	8877				
Allergy	−0.4736***	0.0406	−11.6533	13,898	−0.3769***	0.0622	−6.0573	8916	2921	20,782	948	13,746
	−0.3330***	0.0362	−9.2038	14,050	−0.1740**	0.0582	−2.9896	9004				
Chest	−0.5915**	0.0528	−11.2005	13,544	−0.4700***	0.0904	−5.1988	8629	2373	20,782	799	13,746
	−0.4872***	0.0456	−10.6913	13,682	−0.4173***	0.0753	−5.5443	8905				
Heart	−0.5852***	0.0465	−12.5942	14,089	−0.5493***	0.0648	−8.4821	9150	3147	20,782	1449	13,746
	−0.4501***	0.0412	−10.9140	14,201	−0.4621***	0.0605	−7.6404	9316				
Stomach	−0.6113***	0.0572	−10.6946	13,647	−0.6598***	0.0824	−8.0031	8767	2531	20,782	761	13,746
	−0.5280***	0.0435	−12.1323	13,837	−0.5468***	0.0779	−7.0231	8895				
Diabetes	−0.5858***	0.1048	−5.5886	11,883	−0.6941***	0.1366	−5.0800	7100	431	20,782	275	13,746
	−0.7552***	0.1399	−5.3969	12,594	−0.7855***	0.1800	−4.3625	8582				
Anxiety	−1.1024***	0.0526	−20.9616	13,444	−1.2213***	0.0932	−13.1027	8453	2385	20,782	712	13,746
	−1.0980***	0.0500	−21.9534	13,707	−1.0426***	0.0898	−11.6128	8862				
Drugs	−1.3839***	0.1692	−8.1802	8006	−1.0139***	0.2745	−3.6933	958	171	20,782	33	13,746
	−1.3846***	0.2220	−6.2354	12,424	−1.0824*	0.4385	−2.4684	8428				
Epilepsy	−0.3906	0.2110	−1.8512	6360	−1.1355**	0.4382	−2.5913	702	85	20,782	34	13,746
	−0.2013	0.3250	−0.6194	12,371	−0.5242	0.4468	−1.1733	8426				
Migraine	−0.5820***	0.0475	−12.2527	13,299	−0.7317***	0.0859	−8.5217	8446	2034	20,782	584	13,746
	−0.4683***	0.0441	−10.6136	13,465	−0.5920***	0.0812	−7.2934	8750				
Other	−0.5678***	0.0487	−11.6662	13,603	−0.5615***	0.0978	−5.7399	8217	2237	20,782	445	13,746
	−0.4338***	0.0438	−9.9033	13,694	−0.4354***	0.1014	−4.2953	8690				
Cancer	−0.7364***	0.1176	−6.2605	8687	−0.5552**	0.1703	−3.2604	5737	364	20,782	152	13,746
	−0.6012***	0.1404	−4.2827	12.574	0.0200	0.2058	0.0970	8520				
Stroke	−0.6851***	0.1539	−4.4524	6084	−0.9297***	0.2689	−3.4578	4372	284	20,782	105	13,746
	−0.1259	0.2354	−0.5348	12.514	−0.1206	0.3774	−0.3196	8477				
Δhealth >+1	−0.0970*	0.0415	−2.3357	24,226	−0.0443	0.0634	−0.6988	19,644	21,015	46,142	593	31,077
	0.0020	0.0467	0.0434	24,532	0.0386	0.0749	0.5156	19,825				
Δhealth +1	−0.0440**	0.0165	−2.6678	30,896	0.0067	0.0237	0.2819	22,516	12,694	46,142	4950	31,077
	0.0270	0.0160	1.6831	30,900	0.0611*	0.0244	2.5061	22,530				
Δhealth −1	−0.2116***	0.0172	−12.3089	30,880	−0.1433***	0.0262	−5.4591	22,067	12,637	46,142	4250	31,077
	−0.1486***	0.0165	−9.0065	30,887	−0.0507	0.0269	−1.8866	22,102				
Δhealth >−1	−0.4890***	0.0433	−11.2935	24,550	−0.5948***	0.1084	−5.4868	18,622	2188	46,142	330	31,077
	−0.3556***	0.0454	−7.8339	24,710	−0.5362***	0.1275	−4.2072	19,648				

Notes: Sample Average Treatment Effects (SATEs) and Average Treatment effects for the Treated (ATTs), with *z*-statistics in parentheses. Key to significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

of observed characteristics. This means no actual trial is conducted, where randomly-chosen individuals are subjected to some "illness conditions" to identify the effects of these "treatments" on the participants' subjective well-being. Matching techniques applied to observational data can recreate a control group that is comparable to the treatment group in terms of observed variables, although we cannot entirely rule out differences between the control and treatment groups in terms of unobserved variables. To deal with this latter point, a conditional independence assumption (CIA) is invoked, which holds that the potential outcome (subjective well-being) and "treatment" participation (experience of the bad health condition) are independent for individuals with the same exogenous characteristics. CIA may be a strong assumption, and moreover it cannot be verified directly; only with reference to theoretical considerations of what drives treatment and outcome (in order to assure that CIA holds, we have selected our matching variables with respect to findings from the subjective well-being literature first, see Dolan et al., 2008, Graham et al., 2011, Helliwell and Wang, 2012, Veenhoven, 2008. Secondly our variables conform to different criterion schemes presented by the UN on factors driving bad health, see Lechner and Vazquez-Alvarez, 2011, pp. 395–396). The CIA is more reasonable for some conditions (e.g. "arms") than for others, where decreases in well-being may for instance be endogenous to decisions to turn to alcohol or drugs (Veenhoven, 2008, p. 461).

The second matching assumption is known as "overlap", or the "common support condition." This assumption ensures that individuals with the same characteristics have a positive probability of being either "participants" (i.e. becoming sick) or "non-participants" (not becoming sick). In further analysis we find considerable support for the common support condition (the methodological background of matching is further discussed in Binder & Coad, in press; Caliendo & Kopeinig, 2008; Oakes & Kaufman, 2006).

We match our treatment group (those experiencing a change in health; more specifically, entry into a certain health impairment category) with a control group with unchanged health, at time *t*. We then track these individuals over time and observe differences between the treatment and control groups. Our analysis applies two different types of matching – propensity-score matching as well as multidimensional nearest-neighbor matching. Nearest-neighbor matching finds a match in many dimensions simultaneously, while propensity score matching collapses all covariates into one composite variable (the so-called "propensity score"). Our numbers of observations and variables allow us to use the same covariates for both matching estimators. Our covariates are:

Table 5
Matching estimates: recovery. Propensity score matching (PSM), nearest-neighbor matching (NN), and transitions into the sickness condition.

Condition	$t+1$				$t+2$				Transitions			
	PSM: ATT NN: SATE	SE SE	*t*-stat *z*-stat	Obs Obs	PSM: ATT NN: SATE	SE SE	*t*-stat *z*-stat	Obs Obs	Sick $t+1$	Healthy $t+1$	Sick $t+2$	Healthy $t+2$
Arms	0.1568***	0.0303	5.1792	11,538	0.2145***	0.0401	5.3499	7882	4854	19,964	2357	17,424
	0.2626***	0.0314	8.3647	11,605	0.3242***	0.0445	7.2880	8756				
Sight	0.1120	0.0726	1.5429	1984	0.1992*	0.0966	2.0624	1222	1781	2749	1042	2109
	0.0969	0.0684	1.4167	2005	0.1669	0.0868	1.9230	1323				
Hearing	−0.1002	0.0549	−1.8242	3420	−0.0586	0.0736	−0.7963	2288	1559	6040	723	5269
	−0.0227	0.0572	−0.3970	3445	0.0317	0.0789	0.4017	2563				
Allergy	0.0241	0.0383	0.6292	4871	−0.0400	0.0517	−0.7744	3035	2958	7695	1599	6147
	0.0590	0.0386	1.5274	4895	0.0234	0.0533	0.4393	3415				
Chest	−0.0256	0.0465	−0.5518	5168	−0.0268	0.0626	−0.4274	3651	2256	9724	1154	8572
	0.0070	0.0484	0.1451	5195	0.0871	0.0650	1.3403	4041				
Heart	−0.0090	0.0429	−0.2111	7391	−0.0308	0.0630	−0.4891	5321	2538	12,583	1112	11,227
	0.0341	0.0447	0.7635	7421	−0.0039	0.0688	−0.0567	5823				
Stomach	0.1541**	0.0528	2.9205	3215	0.2181**	0.0680	3.2078	1981	2363	4684	1360	3598
	0.2384***	0.0517	4.6101	3243	0.2737***	0.0672	4.0752	2158				
Diabetes	−0.0177	0.1594	−0.1111	1620	−0.0473	0.2280	−0.2073	1136	179	3091	71	2980
	0.1682	0.1792	0.9387	1706	−0.0206	0.3154	−0.0654	1515				
Anxiety	0.5621***	0.0589	9.5412	3196	0.7146***	0.0825	8.6575	2021	2228	4938	1231	3909
	0.7326***	0.0572	12.8009	3212	0.8526***	0.0738	11.5499	2229				
Drugs	0.0069	0.3445	0.0199	165	−0.0182	0.4436	−0.0410	63	155	323	90	250
	0.5941*	0.2461	2.4142	202	0.5966*	0.2847	2.0952	145				
Epilepsy	0.1489	0.3769	0.3949	199	−0.1982	0.6252	−0.3171	37	81	638	40	595
	−0.0029	0.3536	−0.0083	341	0.2995	0.3837	0.7804	288				
Migraine	0.0908	0.0516	1.7596	3174	0.1300	0.0682	1.9061	1915	2181	4972	1160	3956
	0.1538**	0.0497	3.0975	3179	0.2622***	0.0670	3.9164	2212				
Other	0.0067	0.0700	0.0954	1974	−0.2100*	0.0976	−2.1502	1235	2018	2138	1344	1419
	−0.0338	0.0654	−0.5173	1996	−0.0484	0.0803	−0.6027	1358				
Cancer	0.2127	0.1350	1.5758	490	0.2927	0.1893	1.5461	324	274	27,039	190	26,920
	0.1949	0.1680	1.1603	4947	0.1691	0.1911	0.8845	4738				
Stroke	0.3600*	0.1814	1.9845	361	0.3733	0.2628	1.4205	230	223	26,946	119	26,851
	−0.2189	0.2286	−0.9574	4835	0.2054	0.3025	0.6793	4652				

Notes: Sample Average Treatment Effects (SATEs) and Average Treatment effects for the Treated (ATTs), with *z*-statistics in parentheses. Key to significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

previous change in life satisfaction, log(income), gender, age, a quadratic age term, number of children, education, personality trait scores, dummies for being disabled, never married, separated, divorced or widowed, as well as being unemployed, retired, still studying or in school, on maternity leave or on family care, or self-employed; ethnicity dummies, year dummies, and regional dummies for former Metropolitan counties and Inner/Outer London.

Table 4 shows the estimates. While the two matching algorithms produce similar results, we focus our interpretation mostly on propensity-score estimates.[2] First, note the decreased number of observations. These are partly because matching estimators are clearer about which observations are used for the estimates (only the few occurrences of a sickness condition are presented here, as opposed to being obfuscated in a FE regression with many observations). Second, we only consider cases where individuals report sickness conditions for at least two periods, so that transitions from healthy to sick can be observed (for the second lag specification, this is extended to individuals reporting health conditions for three consecutive periods). Third, the matching algorithm allows us to discard observations where off-support inference would take place (individuals that are very different in terms of matching covariates are not compared with each other, in order to avoid "comparing apples with oranges"). These properties render matching estimates more informative than standard FE regressions. Note finally that it would be inappropriate to directly compare coefficient sizes between matching estimators and FE regressions (not because of the different sample sizes but) because matching estimates refer to total effects on life satisfaction while regression coefficients are ceteris paribus effect sizes, holding other variables of interest constant (Oakes & Kaufman, 2006, p. 382). By making treatment and control groups more comparable (finding the "perfect twin", Almus & Czarnitzki, 2003, p. 231), we achieve significant results for most sickness conditions with the same dataset used for FE regressions. Carefully establishing a well-suited control group by discarding the "evil twins" thus increases precision and significance of our estimates.

The lower part of Table 4 shows that the causal impact of a two-category (or more) decrease in subjective health assessment is highly significant (−0.49) and even increases after two years (−0.59). A smaller decrease in health (by one category) still affects subjective well-being quite strongly (−0.21 in $t+1$, −0.14 in $t+2$). With the above-mentioned caveat in mind, it is instructive to compare these effect sizes to those of the few other studies *using matching estimators*: the impact of self-employment on subjective well-being has been found to be around 0.11 (Binder & Coad, in press), the effect of sustained volunteering at 0.11 (Binder & Freytag, 2013), and getting unemployed decreases well-being by −0.72 (unpublished results by the authors). This shows that the effects we report here are large. Surprisingly, we cannot find a reciprocal effect of increased subjective health rating — the effect is

[2] We also carried out sensitivity checks, summarily reported here. These tests include visual inspection of covariate histograms and kernel density plots of transitions into a sickness condition versus staying healthy, and more formal calculations regarding bias-reduction achieved through matching (Caliendo & Kopeinig, 2008). Both aim at verifying whether covariate overlap after matching treatment and control groups is obtained. We achieved substantial bias reductions that usually go below the 10%-threshold demanded in the literature (D'Agostino, 1998) for most covariates and health conditions. One notable exception to this is age, where matching was difficult (it was difficult to find good twins for age from both treatment and control group). This suggests many health conditions are age-dependent. These matching diagnostics are available upon request.

negative in the first lag and sometimes insignificant. Further research could explore why hedonic adaptation to increases in health should be so strong. For our specific health impairments, a number of conditions display significant negative effects on subjective well-being. The strongest treatment effect concerns alcohol and drug abuse (−1.38), followed by anxiety, depression and other mental illnesses (−1.10), cancer (−0.74) and stroke (−0.69). Sight (−0.63), stomach (−0.61), chest (−0.59), heart (−0.59), migraines (−0.58), diabetes (−0.59) and the catch-all “other” condition (−0.57) also depress subjective well-being. Smaller causal effects appear for “arms” (that is, arms, legs, hands, feet, back, or neck problems; the estimate is −0.41) and for hearing (−0.53) and allergy problems (−0.47). Comparatively severe health impairments such as epilepsy (in the first lag) yield no significant results, however, but a strong negative impact in the second lag, despite a minuscule sample size of only 34 individuals who transitioned into the condition and remained there for two years (see the last columns of Table 4).

Our results can be related to the few studies’ results that also addressed the impact of objective health conditions on subjective well-being. Shields and Wheatley Price (2005) found a strong negative (cross-sectional) association between mental well-being and migraines, heart-conditions-and-stroke, and epilepsy. Graham et al. (2011) found strong negative impacts of anxiety and strong pain for Latin American countries (also cross-sectional). Opposed to severe adverse physical conditions, extreme pain and anxiety in their study remained significantly associated with unhappiness even after including an optimism personality variable (in an attempt to control for individual fixed-effects). These independent findings support the conclusion that adaptation is easier for physical conditions than chronic pain, or psychological conditions such as anxieties (Dolan, 2011). Even if personality traits mediate problems of bad health and their impact on individual life satisfaction, this is less true for the above-mentioned health conditions. Our study goes beyond both studies in establishing that, in many objective health conditions, there is a strong significantly negative effect on life satisfaction (even after matching individuals by personality traits). We can corroborate the one consistent finding from the aforementioned studies, that mental health matters greatly for subjective well-being, and adaptation to it is not easy (the effect increases in the second lag, see below). However, our findings extend beyond the few studies tackling objective health conditions in that we can establish clear negative impacts of other physical ailments that (substantially) decrease subjective well-being even when taking personality into account. The high negative impact of drug abuse on subjective well-being is a case in point, providing further evidence against theories of rational addiction. But also cancer and stroke are physical conditions that severely impact individuals’ subjective well-being (in the case of stroke, even increasing over time). In this respect, our findings show the limits of the current interpretation in the literature that physical impairments are less relevant to subjective well-being. What seems more plausible is that “concrete” ailments play an important role, and physical conditions relating to arm problems or allergies might indeed have less hedonic impact than mental problems, but that severe physical impairments (e.g. stroke, cancer) approach the impact that anxieties or migraines can have on the individual. Clearly, further research should delve deeper into these differences in health conditions.

It also should be noted that our estimates are conservative in the sense that they might underestimate the impact of these health conditions on life satisfaction because of attrition – if an illness is so severe that it hinders the individual from responding, the existing sample might represent the comparatively less severe cases of bad health conditions. We cannot completely rule out this source of downward bias, but in general, a decreasing health condition has been shown not to affect response rates in the BHPS (Uhrig, 2008, p. 28). We investigated attrition bias in several ways (available on request): we re-estimated Table 4 focusing on transitions into a sickness condition for these individuals who get sick in $t + 1$, yet recover in $t + 2$. These individuals represent the (arguably) less severe or short-term cases in the respective sickness categories. For cancer, anxiety, diabetes and sight problems, the lighter cases lead to noticeable reductions in coefficient size; for the other cases, the reduction is modest (−0.10 or less).

As we are interested in the dynamic aspects of well-being, we also investigate lagged effects of these health conditions. A robust finding in happiness research is that individuals often adapt to changes in life circumstances. Hedonic adaptation, the hedonic dulling of repeated or constant affective stimuli (Frederick and Loewenstein, 1999) is highly domain-specific, varying with the concrete stimulus (e.g. hedonic adaptation to marriage is faster and more complete than hedonic adaptation to repeated unemployment, see Clark, Diener, Georgellis, & Lucas, 2008; Dolan & Kahneman, 2008). These relationships are complicated by different effects taking place, in the case of unemployment, for example, a “saddening effect” of unemployment can be mitigated by a “time composition effect” when the unemployed can pursue more leisure activities (Knabe, Rätzel, Schöb, & Weimann, 2010, p. 868). Our panel dataset allows us to include a second year to check for hedonic adaptation. In three cases, the effect remains comparable (sight, stomach, and the “other” category). For other conditions, we find a few cases with significant changes in life satisfaction two years after the individual became ill. In many cases, the impact of the health problem becomes smaller (cancer, hearing, allergy, chest, heart and drug abuse). In other cases, however, the point estimates increase at the second lag (arms, diabetes, anxiety, epilepsy, migraine, and stroke), which means that the health impairment’s negative effect increases with time. We attribute this increasing impact to a gradual worsening of the health conditions (e.g. progressive diseases/health impairments) in some cases. The strong deterioration in well-being caused by epilepsy is particularly striking in the second year. These findings underline how specific the phenomenon of hedonic adaptation is in the health domain (Dolan & Kahneman, 2008, pp. 218–9). Note that dynamic effects vary only in a small number of health conditions when considering the nearest-neighbor-matching estimates, suggesting our estimates are robust.

Finally, we examine to what extent individuals recover their lost life satisfaction after recovering from health impairments (Table 5). In line with the asymmetric finding regarding positive (subjectively-assessed) health changes, it is striking to observe that transitioning out of different health conditions does not usually lead to significantly higher life satisfaction in subsequent years (with the exception of conditions such as anxiety, stomach, arm problems but also migraines and strokes). Overall it seems that “objective” physical conditions (problems with arms, sight etc.) have smaller negative impacts, and that subsequent recovery brings less noticeable improvements in life satisfaction. Mental conditions, on the other hand, apparently lead to much stronger decreases in life satisfaction and exhibit more pronounced recovery patterns. Graham et al. (2011) conjecture that it might be easier to adapt to such “objective” physical conditions than to mental problems such as anxiety, which would explain our findings. Due to our dataset’s lag structure, however, we cannot say whether the positive effect on life satisfaction after recovery never occurs, or whether it occurs within a year and the individual has adapted after just one year. It could also occur after two years, when recovery takes longer to fully set in; this alternative explanation seems unlikely, however – it is not clear why there should be a delay of more than two years between absence of the sickness condition and any resulting increase in subjective well-being.

Pain or negative health impairments do have — by their biological origin and purpose — a higher behavioral relevance and it seems that nature has endowed individuals with the corresponding mechanism that we might call a "psychological immune system" (Dolan & Kahneman, 2008, p. 222): going into states of ill-health decreases well-being much more strongly than subsequent recovery, presumably to motivate the individual to modify behavior accordingly.

Discussion

We offered an econometric account of the causal impact of health on subjective well-being. We found that the effect is considerable for general decreases in health (−0.49 if subjective health decreases by more than one category) and extends over a longer time period. More puzzling, we could not find a positive impact of positive health changes on subjective well-being — it seems that adaptation to positive shocks is stronger and quicker than adaptation to negative shocks.

Moreover, we analyzed the causal impact related to different health conditions (impairments, mostly) on happiness. Causal effects of these conditions on subjective well-being varied substantially (from −0.41 for "arms" to −1.38 for drug abuse). We also see that hedonic adaptation is highly domain-specific and that the impact of bad health conditions can increase with time (most likely due to the progressive nature of certain illnesses).

Our paper's contribution was threefold. First, we estimated the causal effect different health conditions have on subjective well-being by applying matching estimators, which have a strong advantage over standard multivariate regression techniques. While regressions can be useful tools to analyze the happiness–health relationship, multivariate regression modeling gives no consideration to the distribution of covariates in the treatment versus control groups (although presumably the researcher is interested in comparing individuals that have similar values for covariates). Unless there is substantial overlap in the two sets of covariate distributions, multivariate regression estimates rely heavily on extrapolation, and can be misleading (Ichino, Mealli, & Nannicini, 2008, pp. 312–313; Imbens, 2004). Matching estimators are preferable because an appropriate control group is established. Another advantage of matching methods is that they avoid assumptions on functional forms. While widely used elsewhere, to our knowledge, matching estimators have only recently been introduced to subjective well-being research (Binder & Coad, in press; Lechner, 2009).

Our second major contribution involves analyzing said causal impact related to a set of different health conditions on happiness. This extends analyses focusing on the relationship between a more general (self-assessed) subjective health status of individuals and happiness (Graham et al., 2011; Shields & Wheatley Price, 2005). Self-assessed health predicts more objective health functioning well in some cases (e.g., morbidity), while it is less suited to other cases (Johnston et al., 2009). Since self-assessed health reflects an individual's attitude, intervening factors such as personality traits may lead to bias, for example when optimistic persons overrate their subjective health, even when (objectively) ill. Focusing thus on objective conditions of ill health offers new valuable knowledge on the impact this has on subjective well-being. Moreover, focusing on specific health conditions improves our understanding of when

Table 6
Matching estimates, mental well-being: propensity score matching (PSM), nearest-neighbor matching (NN), and transitions into the sickness condition.

Condition	$t+1$				$t+2$				Transitions			
	PSM: ATT NN: SATE	SE SE	*t*-stat z-stat	Obs Obs	PSM: ATT NN: SATE	SE SE	*t*-stat z-stat	Obs Obs	Sick $t+1$	Healthy $t+1$	Sick $t+2$	Healthy $t+2$
Arms	−1.9332***	0.1260	−15.3453	14,996	−2.3730***	0.2206	−10.7576	9072	5357	20,782	1970	13,746
	−1.6934***	0.1206	−14.0446	15,028	−2.0163***	0.2257	−8.9316	9297				
Sight	−2.6645***	0.2641	−10.0906	12,687	−2.8510***	0.4251	−6.7060	6826	1906	20,782	491	13,746
	−1.9775***	0.2526	−7.8281	12,954	−2.1799***	0.5341	−4.0816	8444				
Hearing	−2.4632***	0.2511	−9.8110	12,753	−2.3215***	0.3436	−6.7573	7274	1831	20,782	707	13,746
	−1.9161***	0.2592	−7.3911	12,998	−2.0502***	0.4013	−5.1090	8599				
Allergy	−2.1126***	0.1819	−11.6121	13,444	−2.0463***	0.2758	−7.4185	8636	2921	20,782	948	13,746
	−1.4618***	0.1666	−8.7750	13,612	−1.5206***	0.2675	−5.6855	8723				
Chest	−2.6244***	0.2342	−11.2038	13,099	−3.2742***	0.3940	−8.3097	8377	2373	20,782	799	13,746
	−2.2656***	0.2203	−10.2864	13,230	−2.6321***	0.3762	−6.9962	8615				
Heart	−2.4680***	0.2007	−12.2940	13,612	−2.7043***	0.2841	−9.5179	8851	3147	20,782	1449	13,746
	−2.1450***	0.1860	−11.5293	13,716	−2.4928***	0.2759	−9.0344	9014				
Stomach	−3.0779***	0.2451	−12.5599	13,081	−3.0913***	0.3696	−8.3632	8465	2531	20,782	761	13,746
	−2.6014***	0.2028	−12.8294	13,362	−2.4591***	0.3505	−7.0161	8607				
Diabetes	−2.8231***	0.4623	−6.1061	11,425	−2.6355***	0.6241	−4.2230	6535	431	20,782	275	13,746
	−2.8965***	0.6417	−4.5136	12,189	−3.3747***	0.9489	−3.5566	8307				
Anxiety	−6.5646***	0.2474	−26.5379	12,995	−6.9317***	0.4473	−15.4957	8211	2385	20,782	712	13,746
	−7.4255***	0.2550	−29.1190	13,255	−6.1796***	0.4739	−13.0403	8584				
Drugs	−5.9775***	0.9791	−6.1050	7046	−4.2533*	1.8660	−2.2794	737	171	20,782	33	13,746
	−6.8054***	1.4219	−4.7860	12,026	−7.3787***	2.2198	−3.3241	8165				
Epilepsy	−2.7131**	1.0470	−2.5912	6226	−5.3699**	2.0637	−2.6021	594	85	20,782	34	13,746
	−2.4674**	1.3614	−1.8124	11,979	−2.6755**	1.8565	−1.4411	8163				
Migraine	−2.9836***	0.2217	−13.4610	12,894	−4.0725***	0.3985	−10.2208	8189	2034	20,782	584	13,746
	−2.4561***	0.2041	−12.0326	13,037	−3.3192***	0.3938	−8.4286	8477				
Other	−2.8578***	0.2224	−12.8480	13,174	−2.5826***	0.4498	−5.7419	7995	2237	20,782	445	13,746
	−2.4078***	0.2077	−11.5913	13,253	−2.1177***	0.5076	−4.1717	8420				
Cancer	−3.9857***	0.5033	−7.9186	7983	−3.2264***	0.7525	−4.2878	4919	364	20,782	152	13,746
	−4.4171***	0.6715	−6.5778	12,175	−2.2527***	1.3411	−1.6797	8253				
Stroke	−3.4807***	0.6600	−5.2741	6186	−4.1711***	1.0620	−3.9275	3946	284	20,782	105	13,746
	−1.3634***	1.2948	−1.0530	12,107	−1.9194***	1.3523	−1.4194	8206				

Notes: Dependent variable "mental well-being" GHQ-12 measure from the "General Health Questionnaire" of the BHPS, which consists of the answers to twelve different questions relating to happiness, anguish, mental distress and so on; We have added up answers to subquestions to form a 36 point mental well-being scale. Sample Average Treatment Effects (SATEs) and Average Treatment effects for the Treated (ATTs), with z-statistics in parentheses. Key to significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 7
Results of matching estimates, mental well-being: PSM matching, NN matching; recovery from sickness condition.

Condition	$t+1$				$t+2$				Transitions			
	PSM: ATT NN: SATE	SE SE	*t*-stat z-stat	Obs Obs	PSM: ATT NN: SATE	SE SE	*t*-stat z-stat	Obs Obs	Sick $t+1$	Healthy $t+1$	Sick $t+2$	Healthy $t+2$
Arms	0.5598***	0.1325	4.2259	11,063	0.8898***	0.1783	4.9905	7537	4854	19,964	2357	17,424
	1.1114***	0.1341	8.2876	11,125	1.5832***	0.1922	8.2381	8402				
Sight	0.6647*	0.3076	2.1612	1888	1.1380**	0.4331	2.6273	1177	1781	2749	1042	2109
	0.7741**	0.2843	2.7224	1911	0.9415**	0.3601	2.6146	1270				
Hearing	−0.2062	0.2251	−0.9161	3255	−0.1383	0.3272	−0.4227	2187	1559	6040	723	5269
	0.1681	0.2286	0.7351	3290	0.2484	0.3278	0.7576	2446				
Allergy	−0.2514	0.1837	−1.3688	4714	−0.1374	0.2464	−0.5575	2939	2958	7695	1599	6147
	0.0053	0.1843	0.0286	4744	0.0486	0.2589	0.1876	3305				
Chest	0.0891	0.2064	0.4314	4987	0.0777	0.2771	0.2805	3502	2256	9724	1154	8572
	0.2312	0.2154	1.0735	5009	0.3580	0.2888	1.2395	3884				
Heart	−0.0800	0.1850	−0.4324	7036	−0.2874	0.2679	−1.0729	5079	2538	12,583	1112	11,227
	0.1416	0.1872	0.7565	7071	−0.2229	0.2832	−0.7872	5566				
Stomach	0.5426*	0.2386	2.2744	3062	1.0775***	0.3112	3.4626	1886	2363	4684	1360	3598
	0.9051***	0.2369	3.8214	3094	1.2385***	0.3072	4.0310	2059				
Diabetes	−0.7300	0.7518	−0.9711	1533	−1.3803	0.9802	−1.4082	1086	179	3091	71	2980
	−0.3118	0.8136	−0.3833	1614	−0.1514	1.2544	−0.1207	1451				
Anxiety	3.4875***	0.2755	12.6587	3068	4.0929***	0.3946	10.3723	1940	2228	4938	1231	3909
	4.2118***	0.2747	15.3344	3088	4.5819***	0.3570	12.8337	2130				
Drugs	2.4132	1.8338	1.3159	167	−2.1703	2.4826	−0.8742	60	155	323	90	250
	3.1159**	1.1654	2.6737	192	1.6287	1.5569	1.0461	136				
Epilepsy	0.8229	1.4608	0.5634	200	−2.3138	2.8554	−0.8103	23	81	638	40	595
	0.3363	1.3993	0.2403	336	1.6973	1.5699	1.0812	280				
Migraine	0.6591**	0.2421	2.7221	3097	0.8755**	0.3346	2.6162	1845	2181	4972	1160	3956
	0.7624**	0.2398	3.1798	3101	1.2883***	0.3255	3.9582	2139				
Other	−0.1079	0.3151	−0.3423	1899	−0.1400	0.4329	−0.3234	1189	2018	2138	1344	1419
	−0.0387	0.2999	−0.1291	1917	0.0984	0.3643	0.2702	1308				
Cancer	−0.0922	0.5840	−0.1579	467	0.7803	0.8078	0.9660	313	274	27,039	190	26,920
	0.0705	0.7327	0.0962	4812	−0.1418	0.9621	−0.1474	4642				
Stroke	0.3295	0.7369	0.4472	335	0.9138	1.1677	0.7825	208	223	26,946	119	26,851
	−1.1080	1.1969	−0.9257	4690	0.8506	1.3829	0.6151	4548				

Notes: Dependent variable "mental well-being" GHQ-12 measure from the "General Health Questionnaire" of the BHPS, which consists of the answers to twelve different questions relating to happiness, anguish, mental distress and so on; We have added up answers to subquestions to form a 36 point mental well-being scale. Sample Average Treatment Effects (SATEs) and Average Treatment effects for the Treated (ATTs), with *z*-statistics in parentheses. Key to significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

and how ill health decreases well-being and to what extent. So far, the literature dealing with specific health impairments and their effect on subjective well-being is sparse and relies mainly on cross-sectional data (Dolan, 2011; Graham et al., 2011; Shields & Wheatley Price, 2005). This makes it difficult to address issues of self-selection or the role of personality traits mediating the happiness–health relationship. Our study addresses these shortcomings and offers causal estimates for many different health impairments and their respective effects on subjective well-being in a level of detail that, to our knowledge, doesn't exist in the literature so far.

Relatedly, we extend the knowledge of the field as regards specific adaptation patterns for different health conditions as well as the effects of recovery. This third contribution of ours lies in tracing the very domain-specific inter-temporal trajectory health conditions have on subjective well-being, examining the extent of hedonic adaptation in the years following the onset of the illness or bad health condition (Clark et al., 2008; Frederick and Loewenstein, 1999). Exploiting our rich dataset, we are also the first to analyze how recovery patterns differ over time for the health conditions analyzed.

Our findings have a high political relevance when it comes to prioritizing health care policies to different health conditions. With limited budgets for health care, tradeoffs have to be made between what conditions to prioritize. Our findings that show how differently individuals adapt to different health conditions might help decision-makers in allocating scarce resources. If hedonic adaptation is nearly absent (or even worse: if one experiences anti-adaptation), such a condition might be considered normatively more urgent than conditions where adaptation is quick and strong (Dolan & Kahneman, 2008). Of course, this is not to marginalize the negative impact of health conditions that are subject to adaptation and should in no way trivialize these. Even in conditions where hedonic adaptation occurs, it is unclear whether this happens quickly and completely, and so mitigation of this negative impact can also be the target of public policies (Graham, 2008, p. 77).

Moreover, findings such as ours help better assess the impact of different health conditions on individuals' well-being. Other methods that directly elicit individuals' evaluations may suffer from many focusing effects and biases that can be avoided via the indirect measurement through happiness regressions in large datasets (Dolan, 2011, pp. 7–8).

Our analysis is not without limitations, one of which is that we measure well-being in terms of life satisfaction. Krueger and Schkade (2008) show that alternative indicators of well-being are far from perfectly correlated and have different reliability. We did, however, obtain similar, and perhaps more consistent, results for getting sick and recovering after repeating the analysis with a broader concept of "mental well-being" (i.e., the so-called GHQ-12 measure from the "General Health Questionnaire" of the BHPS, which consists of the answers to twelve different questions relating to happiness, anguish, mental distress etc. (Gardner & Oswald, 2007), see Tables 6 and 7). Future work might replicate our analysis with other well-being indicators.

Mental and drug abuse problems might raise issues of endogeneity, i.e. unhappy individuals self-select into these categories through unhealthy life-styles resulting from frustration. We cannot completely exclude this explanation. In the literature, the related evidence is scarce (Veenhoven, 2008, pp. 460–461) while evidence exists that these unhealthy behaviors cause unhappiness. Also, concerning mental problems, there are valid substantive explanations why the effect found should be so strong, *inter alia* the associated uncertainty with many mental illnesses (individuals cope badly with uncertainty) as well as individuals' expectations regarding different illnesses (individuals wrongly attribute more harm to physical ailments, and this moderates the effect on subjective well-being (Graham et al., 2011)).

Further work might also disentangle the constituent elements of changes in well-being following health impairments that include: psychological adaption to constant conditions; deteriorating health conditions; positive effects of healthcare and medical assistance; and lifestyle changes (such as a patient who pursues a less stressful lifestyle after a heart attack). In our analysis, we focused on changes in well-being following the onset of health problems (as implied in our title).

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