SPRU
Science and Technology Policy Research

SPRU Electronic Working Paper Number 200

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

Martin Binder and Alex Coad

13 May 2012

SPRU – Science and Technology Policy Research

University of Sussex
Falmer, Brighton, BN1 9SL
http://www.sussex.ac.uk/spru

University of Sussex
SPRU – Science & Technology Policy Research

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

Martin Binder[*,a], Alex Coad[b,c,d]

[a] *Max Planck Institute of Economics, Evolutionary Economics Group, Kahlaische Str.10, 07745 Jena, Germany*

[b] *SPRU, University of Sussex, Falmer, Brighton, BN1 9QE, UK*

[c] *RATIO, P.O. Box 3203, SE-10364 Stockholm, Sweden*

[d] *Department of Business and Management, Aalborg University, Fibigerstrde 4, 9220 Aalborg , DK*

Abstract

Bad health can severely disrupt a person's life. We apply matching estimators to examine how changes in subjective health status as well as different (objective) conditions of bad health affect subjective well-being. The strongest effect is in the category alcohol and drug abuse, followed by anxiety, depression and other mental illnesses, stroke and cancer. Adaptation to health impairments depends strongly on the health impairment examined. There is also a puzzling asymmetry: strong adverse reactions to deteriorations in health are observed alongside weak increases in well-being after health improvements.

Key words: health, illness, happiness, subjective well-being, matching estimators, propensity score matching, BHPS
JEL-classification: I10, I31, C23

1. Introduction

How healthy we are determines many facets of our life. It has an impact on what employment opportunities we can pursue and what incomes we can earn (Arrow, 1996; Stewart, 2001); it also has a bearing on the social activities we can pursue (e.g. Umberson, 1987; Gardner and Oswald, 2004), and on many more things. But our health also impacts on our mood and our well-being more generally (Easterlin, 2003; Graham, 2008). Being in good health increases an individual's subjective well-being, just as illness or bad health conditions decrease it (Graham et al., 2011; Veenhoven, 2008).

☆The authors are grateful for having been granted access to the BHPS data set, which was made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-Social Change at the University of Essex (now incorporated within the Institute for Social and Economic Research). Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here. The authors wish to thank Paul Nightingale, Guido Buenstorf, Ivo Bischoff, Maria Savona, Nick von Tunzelman, Michael Hopkins, Juan Mateos Garcia and other participants at seminars at SPRU and the University of Kassel for helpful comments and suggestions. Errors are ours.

*Corresponding author
Email address: binder@econ.mpg.de (Martin Binder)

Subjective well-being research has analyzed the relationship between health and subjective well-being for quite some time, becoming increasingly aware of the complex mutual interdependencies involved. With the development of the field, simple cross-sectional analyses have been extended to panel contexts, allowing to better understand selection effects or to account for individual specific (fixed) effects that capture the more trait-like properties of subjective well-being (Diener and Lucas, 1999). Panel data techniques also allowed researchers to explore the dynamic properties of the happiness-health nexus, such as, for example, the pronounced differences in hedonic adaptation to pain or illnesses or disability (Frederick and Loewenstein, 1999; Oswald and Powdthavee, 2008). While regression techniques that account for fixed effects offer valuable insights into the variation within individuals over time and thus help to alleviate concerns about selection effects (Ferrer-i-Carbonell and Frijters, 2004), we seek to obtain improved estimates of the causal impact of different life events on subjective well-being by applying matching estimators.

The aim of our paper is thus threefold. First of all, we offer said econometric account of the causal impact of health on subjective well-being: to estimate the causal effect different health conditions have on subjective well-being, we apply matching estimators (Rubin, 1974; Imbens, 2004; Caliendo and Kopeinig, 2008). Matching is an econometric technique that one can best understand to be similar to an experimental setup in medical research, where two groups of participants are randomly selected, of which one is the control and the other the treatment group, which is subjected to a certain drug or medical treatment. Unlike in such a (natural) experiment, however, matching estimators can be applied to observational data. The health economist is thus not forced to select test persons who are subjected to some "illness conditions" in order to tease out the effects of these "treatments" on the participants' subjective well-being.

The matching estimators applied in this paper have an advantage over multivariate regressions techniques that are widely used in the related literature. While multivariate regressions can be a useful tool to analyze the happiness-health relationship, multivariate regression modelling 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 the same values for all covariates). Unless there is substantial overlap in the two sets of covariate distributions, multivariate regression estimates rely heavily on extrapolation, and can therefore be misleading (Imbens, 2004; Ichino et al., 2008, p. 312-13). Matching estimators are preferable because more care is taken to establish an appropriate control group. Another advantage of matching methods is that they require no assumptions on functional forms. While widely used in other subfields,[1] to our knowledge, matching estimators have only recently been introduced to the analysis of subjective well-being (Binder and Coad, 2012).

A second major contribution of our paper lies in analyzing said causal impact related to a set of different health conditions (impairments) on happiness. This extends analyses that focus on the relationship between a more general (self-assessed) subjective health status of individuals and happiness (see also Shields and Wheatley Price, 2005; Graham et al., 2011).

[1] In the health context, Böckerman and Ilmakunnas (2009) use matching estimators to analyze the causal impact of unemployment on self-assessed health for a Finnish panel data set.

Self-assessed health does predict more objective health functioning well in some cases (e.g., regarding morbidity), while it is a less suited measure in other cases (Johnston et al., 2009). Since self-assessed health is an attitude an individual states, it might be biased by intervening factors such as personality traits, for example when optimistic persons would overrate their subjective health, even when being (objectively) ill. Focussing thus on objective conditions of ill health offers new valuable knowledge on the impact this has on subjective well-being. Moreover, focussing on specific health conditions allows a more comprehensive picture of when 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 very sparse and relies mainly on cross-sectional data (Shields and Wheatley Price, 2005; Graham et al., 2011; Dolan, 2011). 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 a large number of 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.

In a similar vein, we extend the knowledge of the field as regards specific adaptation patterns for different health conditions as well as the effects of recovering from these health conditions. This third contribution of our paper lies in tracing the inter-temporal trajectory such health conditions have on subjective well-being, i.e. examining the extent of hedonic adaptation that follows in the years after the onset of the illness or bad health condition. By this we aim at extending our knowledge on the hypothesized domain specificity of hedonic adaption to different life events (Frederick and Loewenstein, 1999; Clark et al., 2008a). Exploiting the rich data set at hand, we are also the first to be able to analyze how recovery patterns differ over time for the bad health conditions analyzed.

The paper is structured as follows. In Section 2, we provide the theoretical background on the subjective well-being and health relationship. Section 3 offers a discussion of our matching methodology, before presenting our dataset, the British Household Panel Survey. In Section 4 we describe and discuss the findings of our analysis. Section 5 offers a conclusion.

2. Health and subjective well-being

An individual's subjective well-being (synonymously called "happiness" in this paper) depends on a complex interacting web of factors, comprising many economically relevant factors (such as income, status or employment), but also 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 an overview see, e.g., Frey and Stutzer, 2000; Easterlin, 2003; Dolan et al., 2008). As one can consider subjective well-being to be a broad aspect of an individual's mental health, it is no wonder that many of the determinants of subjective well-being also determine health more generally (see, e.g., Contoyannis and Jones, 2004; Gardner and Oswald, 2004; Fuchs, 2004).[2]

[2]We refrain from discussing the reliability and validity of subjective well-being constructs, as this has been established in psychological research (e.g., Diener et al., 1999; Helliwell, 2006), where it is shown that these measures capture indeed what they claim to do.

In subjective well-being research, the relationship between subjective well-being and health is probably the least contested 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 the regressions (Easterlin, 2003; Dolan and Kahneman, 2008; Dolan et al., 2008).[3] It seems that causality in this domain runs in both directions: a high level of well-being certainly seems relevant also for subsequent good health, with significant positive effects of well-being on health being observed two or three years later (Binder and Coad, 2010; Lyubomirsky et al., 2005).[4]

The much 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 (Easterlin, 2003; Dolan et al., 2008) or the impact of disability on subjective well-being (Brickman et al., 1978; Oswald and Powdthavee, 2008), mostly for lack of more detailed data on objective health impairments. Only very few studies also extend the analysis to more detailed health conditions (see Shields and Wheatley Price, 2005; Graham et al., 2011; Dolan, 2011). 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 (something we discuss more extensively in Section 4). In a cross-sectional analysis of British (non-BHPS) data, Shields and Wheatley Price (2005) report significantly decreased psychological well-being for individuals with problems with muscular-arthritis-rheumatism, stomach problems and respiratory system problems. For males, heart attack or stroke problems as well as 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 E5QD measure of health problems is related to health satisfaction and life satisfaction.[5] Pain, anxiety and difficulties with usual activities are strongly negatively related to health satisfaction and in a lesser degree also to life satisfaction. Problems with mobility and self-care are not as clearly related to lowered life satisfaction which the authors interpret as evidence in favor of a higher impact of acute and chronic mental illnesses over physical

[3] The importance of health for subjective well-being as compared to other influences becomes very clear when calculating income equivalents, "shadow prices", of changes in health conditions. Graham et al. (2011), p. 1143, report that individuals in their sample would require to be compensated with 13.5 times the average income for "extreme anxiety" conditions in order to hold life satisfaction at a level comparable to individuals without the anxiety condition.

[4] While there is the problem of happy individuals over-reporting subjective health assessments, the findings extend also to objective health measures (see especially Easterlin, 2003; Blanchflower and Oswald, 2008). A causal relationship from subjective well-being to health could play an important role for preventive healthcare (Veenhoven, 2008).

[5] Dolan (2011) also analyzes the association between subjective well-being and the E5QD measure, which does not consist of specific health conditions as in our case, but of five dimensions of individual health, namely mobility, self-care, usual activities, pain and mood (see EuroQol Group, 1990).

conditions. An explanation for this finding might lie in the uncertainty that is associated with some health problems, where the onset of the next anxiety or epilepsy attack cannot be anticipated and thus easily adapted to. Similarly, Dolan (2011) finds that mental health has a stronger impact on subjective well-being than physical health problems, while in preference elicitations, individuals value physical health more strongly than mental health, probably due to focussing effects and faulty affective forecasting (Wilson and Gilbert, 2005).

In the cases discussed, the cross-sectional nature of the data makes it difficult to address issues such as self-selection, time spent with the health condition, and the role of personality traits mediating the happiness-health relationship, and so these estimates are to be taken with care. Our study addresses these shortcomings and offers estimates of the impact of different health impairments on subjective well-being, at a level of detail that doesn't exist in the literature so far. In a similar vein, we extend the knowledge of the field as regards specific adaptation patterns for different health conditions as well as the effects of recovering from these health conditions. These examinations of the dynamics of illness conditions and their impact on subjective well-being need to be better understood since it is still debated 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 can adapt differently to different health conditions. While there is indeed reason to believe that some hedonic adaptation occurs, the level of adaptation seems far from complete: Oswald and Powdthavee (2008) find in a fixed effects framework a rate of hedonic adaptation between 30% and 50%, depending on the degree of disability.[6] As opposed to disability, patients who suffer from chronic diseases and chronic pain do not seem to adapt as easily to their conditions (Smith and Wallston, 1992; Oswald and Powdthavee, 2008). There are few studies in this field and their results are complicated by the progressive nature of some of the diseases (Dolan and Kahneman, 2008, pp. 218-9). In sum, hedonic adaptation to adverse health conditions seems limited and highly domain-specific (Frederick and Loewenstein, 1999; Oswald and Powdthavee, 2008). The dynamic properties of subjective well-being and the debate of 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.

Finally, personality traits might play a role in mediating the effects of different health conditions on subjective well-being (Diener and Lucas, 1999; Diener et al., 1999, p. 280), They have been recognised in the psychological literature on subjective well-being as equally important in determining SWB as socio-demographic variables (DeNeve and Cooper, 1998; Gutiérrez et al., 2005; Boyce et al., 2012), which is not surprising when one thinks about how these traits impact on individuals' lives and their experiences in important life domains. Here Neuroticism is of special interest for our study as it was found that the strong correlation between self-reported health and subjective well-being is decreased when controlling for Neuroticism (Okun and George, 1984).

[6] A discussion of the dynamics of self-rated health measures in the BHPS data set is provided by Contoyannis et al. (2004).

3. Empirical approach and data

3.1. Matching methodology

To investigate the causal effect of health on happiness, one must consider a counterfactual question of the following kind: "How happy would I be if I had not become ill?" The main problem for the econometrician is that if an individual becomes sick, then there is no data on exactly what would have happened had they not become sick. In the case of a randomized laboratory experiment, such as a clinical trial, an accurate counterfactual can be established by referring to a control group that was not exposed to the treatment of interest. The randomization process in clinical trials ensures that there are no systematic differences between the control group and the treatment group – that is why randomized experiments are considered to be positioned at the top of the hierarchy of empirical techniques (Imbens, 2010). Randomized trials can be expected to yield treatment and control groups that are comparable in terms of both observable and unobserved characteristics. However, establishing a counterfactual is much harder when the researcher is not dealing with randomized experimental data but instead observational data, because individuals can be expected to self-select into their desired treatment group on the basis of unobserved characteristics, leading to selection bias. Even assuming that it were possible to organise a randomized laboratory experiment in which half the participants are subjected to long-term ill-health, this would be morally unacceptable. As such, a randomized trial is not feasible here, and so the best we can do is aim to recreate the conditions of a randomized trial by applying matching methods. 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 identify the treatment effects of interest, we need to make two assumptions. The first assumption is called the "conditional independence assumption (CIA)", and is also known as "selection on observables." This assumption means that the potential outcome (subjective well-being and participation in the treatment (i.e. experience of the bad health condition) are independent for individuals with the same set of exogenous characteristics. Formally, this means that $Y(D=0), Y(D=1) \perp D|X$, where $Y(D)$ refers to the outcome and D is the treatment indicator, taking the value 1 if the individual experienced an adverse health condition and 0 otherwise. X is a matrix of individual characteristics. Under this CIA assumption, all individual characteristics (X) that influence both the treatment assignment (becoming sick) and potential outcomes simultaneously must be observed by the econometrician. Unobserved variables are not allowed to influence treatment assignment and potential outcome. CIA can be suspected to be a strong assumption, and moreover it cannot be verified directly.

The second assumption is known as "overlap", or the "common support condition", and can be expressed as $0 < P(D = 1|X) < 1$. This assumption ensures that those individuals with the same characteristics have a positive probability of being both "participants" (i.e. becoming sick) or nonparticipants (not becoming sick). If the overlap assumption does not hold, then the resulting estimates can be heavily biased (Heckman et al., 1996). Conventional regressions do not consider the possibility of limited overlap between treatment and control groups, and as a consequence, regression results may be based on off-support inference and linear extrapolation between fundamentally heterogeneous populations.

Our matching analysis involves two different matching procedures. Propensity score matching involves the estimation of a propensity score that is used as a univariate summary indicator for all the observable variables, which can then be used as the single matching criterion. Matching according to a propensity score implies that there is a (data-driven) tradeoff between the different dimensions — one observation might be matched to another observation that scores higher in one dimension but this is compensated for by a lower score in another dimension. These sorts of compensation lead to a supplementary corollary to Assumption 1 that is not required in multivariate nearest-neighbor matching (see below), which is $Y(0), Y(1) \perp D | P(X)$, where $P(X)$ is the propensity score given the observed covariates X.

We complement the propensity matching estimates with a nearest-neighbor matching estimator outlined in Abadie et al. (2004), which finds the nearest-neighbor from the control group for each of the dimensions of X.[7] Estimating effects via both matching techniques allows us to assess how robust our findings are with respect to the underlying technical assumptions of our matching estimators.

3.2. Data set and indicator selection

The British Household Panel Survey (BHPS), comprising about 10,000 individual interviews at the start and growing over time, is a well-known longitudinal survey of private households in Great Britain that contains rich information on diverse areas of the respondents' lives.[8] We are using unbalanced panel data from 1996 to 2006 (waves f to n) and have a total of $100,278$ observations after cleaning the panel: during the time period, two waves had to be deleted since not all of our variables have been asked in them (one did not feature the life satisfaction variable, the other used a different coding of subjective reported health status, finally the most recent waves do not provide net annualized household incomes), leaving us with a total of 9 waves. Our variables are presented in Table 1.

From the 1996 wave onwards, the BHPS offers a life satisfaction question which is 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 and ranges from "not satisfied at all" (1) to "completely satisfied" (7). Our main explanatory variables of interest 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 et al., 2009). In the BHPS, an individual's subjective assessment of health (during the last 12 months) is ordinally scaled on a five point

[7]The drawback of this procedure is that with many matching covariates X, it may become prohibitively difficult to find good matches for individuals in all dimensions simultaneously: too few variables included might increase bias while too many might increase the variance of the estimates (Heckman et al., 1997; Dehejia and Wahba, 1999). Caliendo and Kopeinig (2008, p. 39) write that "there are both reasons for and against including all of the reasonable covariates available", and suggest that the choice of matching covariates be undertaken with reference to theory and previous empirical findings. Propensity score matching does not suffer from dimensionality problems when a large number of matching covariates are considered.

[8]The survey is undertaken by the ESRC UK Longitudinal Studies Centre with the Institute for Social and Economic Research at the University of Essex, UK (BHPS, 2010). Its aim is to track social and economic change in a representative sample of the British population (see Taylor, 2010). Starting in 1991, up to now, there have been 18 waves of data collected with the aim of tracking the individuals of the first wave over time (in general, attrition is quite low, see Taylor, 2010).

Likert scale, ranging from "excellent" (five) to "very poor" (one).[9] In order to account for more objective aspects of individual health, we also included the (log) number of days spent in hospital, the number of visits to a general practitioner as well as the number of serious accidents in the previous year (see the descriptive statistics in Table 1).[10] The large effect of health on life satisfaction can be seen in Figure A.1 in the Appendix, where mean life satisfaction is plotted according to the five different health categories (from "very poor" (1) to "excellent" (5)).

The BHPS offers several more specific health conditions (or impairments) which individuals can report. These include so called "health problems" grouped according to different 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 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) between one year and 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.

As discussed in Section 2, personality has long been hypothesized to play a major role in influencing individuals' well-being through various life channels. In the BHPS wave 2005, a short inventory for the Big Five personality traits has been included. The five traits were elicited via fifteen short descriptions with which respondents can agree to varying degrees.[11] Typical inventories in psychological questionnaires use much larger personality inventories with 44 or more questions (e.g. the "Big Five Inventory", BFI, John et al., 1991), but shorter inventories were analyzed in several studies and have proven to be reliable (Gosling et al., 2003; Gerlitz and Schupp, 2005; Donnellan and Lucas, 2008).

[9] We have reversed the numerical order of the Likert scale to consistently use higher values for better health.

[10] Hospital days are given as (log) days (to be precise, we computed the log(days+1) to cope with the fact the the logarithm of zero days would not be defined). Visits to the general practitioner are coded on a 5 point ordinal scale (from "none" to "more than ten") and number of serious accidents is quasi-cardinal with values from 0 to 4 giving the number of serious accidents, but the number of four also being used for coding cases with more than four serious accidents in this year. In all cases, higher values denote worse health situation of the individual.

[11] Sample descriptions include "I see myself as someone who is sometimes rude to others" (referring to Agreeableness), "I see myself as someone who is outgoing, sociable" (Extraversion) or "I see myself as someone who worries a lot" (Neuroticism). Three questions capture each of the five traits (each is answered on a 7-point Likert scale from "Does not apply" to "Applies perfectly"). A full list is provided, e.g., by Clark and Georgellis (2010).

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	5.0233	4.9511	5.1806	5.0274	4.9234	5.1512	4.7615	5.0997	4.0505	3.6972	4.6550	4.8128	4.8731	4.9890	4.6262
subj. health	3.8031	3.2490	3.1926	3.4141	3.5897	3.1867	3.2483	2.9943	3.1015	2.8413	2.7046	3.2025	3.3628	3.0797	2.8722	2.7748
Gender	0.5327	0.5854	0.5951	0.4591	0.6310	0.5590	0.5554	0.5987	0.4603	0.6949	0.3501	0.5455	0.7567	0.6720	0.5386	0.4845
Age	45.8371	57.3095	60.4686	62.9447	43.6579	49.6334	63.1084	53.5110	61.4731	48.5135	40.5273	44.5833	43.4569	51.7271	64.8099	68.1058
Log(income)	9.9181	9.8412	9.7995	9.8289	9.9475	9.8290	9.8376	9.8492	9.8336	9.7500	9.5897	9.8037	9.8601	9.8973	9.8970	9.8335
Marital status dummies																
married	0.5349	0.5644	0.4889	0.5751	0.5104	0.4918	0.5946	0.5442	0.5738	0.4499	0.1861	0.4845	0.5343	0.5656	0.6309	0.5039
separated	0.0212	0.0189	0.0149	0.0099	0.0189	0.0231	0.0162	0.0236	0.0157	0.0451	0.0517	0.0310	0.0260	0.0218	0.0189	0.0282
widowed	0.0814	0.1628	0.2259	0.2070	0.0682	0.1206	0.2008	0.1248	0.1835	0.0988	0.0355	0.0484	0.0584	0.1141	0.1830	0.2670
divorced	0.0830	0.1080	0.0934	0.0811	0.0833	0.1001	0.0949	0.1195	0.0993	0.1610	0.1861	0.1017	0.1058	0.1026	0.0789	0.1175
Labour market status dummies																
employed	0.5091	0.3210	0.2343	0.2562	0.5235	0.3743	0.2384	0.3540	0.2646	0.3153	0.1935	0.3333	0.5138	0.3839	0.1680	0.0913
unemployed	0.0333	0.0230	0.0222	0.0192	0.0308	0.0371	0.0163	0.0325	0.0181	0.0532	0.2245	0.0543	0.0335	0.0182	0.0063	0.0126
selfemployed	0.0680	0.0509	0.0361	0.0478	0.0564	0.0468	0.0421	0.0449	0.0358	0.0384	0.0281	0.0310	0.0449	0.0490	0.0339	0.0078
retired	0.2136	0.4133	0.5046	0.5542	0.1832	0.3086	0.5416	0.3382	0.5000	0.2246	0.0857	0.1870	0.1472	0.3019	0.5994	0.6650
studyschool	0.0521	0.0116	0.0265	0.0132	0.0575	0.0483	0.0060	0.0177	0.0110	0.0226	0.0251	0.0446	0.0427	0.0279	0.0016	0.0000
maternityleave	0.0043	0.0016	0.0020	0.0014	0.0065	0.0035	0.0018	0.0023	0.0022	0.0021	0.0000	0.0000	0.0038	0.0027	0.0000	0.0019
longtermsick	0.0440	0.1088	0.1130	0.0650	0.0545	0.1036	0.0933	0.1324	0.1137	0.2163	0.3826	0.2665	0.0948	0.1245	0.1238	0.1951
familycare	0.0695	0.0648	0.0547	0.0399	0.0805	0.0714	0.0561	0.0725	0.0519	0.1183	0.0487	0.0727	0.1134	0.0832	0.0576	0.0243
other	0.0061	0.0049	0.0066	0.0031	0.0072	0.0064	0.0044	0.0056	0.0026	0.0091	0.0118	0.0107	0.0059	0.0086	0.0095	0.0019
disabled	0.0896	0.2479	0.3304	0.2454	0.1113	0.2209	0.2441	0.2335	0.3102	0.2600	0.2777	0.3895	0.1293	0.2020	0.3557	0.6427
Education dummies																
elementary	0.0367	0.0236	0.0178	0.0146	0.0319	0.0374	0.0135	0.0258	0.0171	0.0371	0.0694	0.0833	0.0387	0.0291	0.0047	0.0136
basic voc.	0.0892	0.1117	0.1114	0.1286	0.0812	0.0937	0.1175	0.1028	0.1054	0.0971	0.0931	0.0940	0.0855	0.0876	0.1199	0.1456
middle gen.	0.1599	0.1218	0.1127	0.0982	0.1624	0.1387	0.1036	0.1181	0.1041	0.1390	0.1462	0.1415	0.1670	0.1316	0.0915	0.0612
middle voc.	0.0535	0.0494	0.0446	0.0415	0.0527	0.0433	0.0451	0.0548	0.0384	0.0541	0.0384	0.0465	0.0575	0.0522	0.0481	0.0350
gen: hi gen.	0.0713	0.0433	0.0492	0.0393	0.0857	0.0667	0.0361	0.0480	0.0348	0.0571	0.0591	0.0494	0.0730	0.0608	0.0379	0.0282
voc: hi voc.	0.0525	0.0387	0.0305	0.0318	0.0505	0.0440	0.0366	0.0381	0.0448	0.0422	0.0694	0.0591	0.0507	0.0477	0.0315	0.0408
low tert.	0.1822	0.1721	0.1423	0.1710	0.2014	0.1565	0.1689	0.1836	0.1554	0.1499	0.1211	0.1357	0.1910	0.1942	0.1774	0.1660
high tert.	0.1245	0.0789	0.0676	0.0741	0.1531	0.0919	0.0674	0.1002	0.0633	0.0871	0.0473	0.0785	0.1042	0.1173	0.0962	0.0243
No. children	0.5984	0.3638	0.2893	0.2526	0.6013	0.5023	0.1991	0.4228	0.2651	0.5781	0.4815	0.5804	0.7159	0.4725	0.1593	0.1049
Extraversion	13.3738	13.1398	12.8366	12.7297	13.6229	13.4005	12.7854	13.2458	12.6768	12.7746	13.0915	12.9302	13.3987	13.3337	12.9256	12.3675
Agreeableness	16.3056	16.4415	16.4650	16.2758	16.2775	16.2113	16.4245	16.4907	16.3631	16.4378	15.5364	16.4357	16.5463	16.4925	16.2571	16.1058
Openness	13.3113	12.9458	12.7504	12.6714	13.7297	12.9515	12.5254	13.1342	12.3827	12.9912	13.0203	12.5236	13.5149	13.3900	12.7929	12.0527
Neuroticism	10.9365	11.2509	11.2453	10.6110	11.6181	11.4991	11.0254	11.9645	10.6039	14.4561	13.7093	12.4523	12.5445	11.8455	10.6590	11.0697
Conscientiousness	15.8605	15.7414	15.3632	15.4192	15.8545	15.4942	15.5510	15.7185	15.3972	15.2702	14.0122	14.3358	15.9514	15.7551	15.4802	14.7845
Doc visits	2.4195	2.9708	3.0102	2.8597	2.7483	3.0854	3.1797	3.2967	3.2996	3.4949	3.3235	3.2180	2.9560	3.1935	3.3502	3.3650
Accidents	0.1197	0.1501	0.1499	0.1225	0.1348	0.1529	0.1125	0.1465	0.1180	0.1693	0.2910	0.2384	0.1555	0.1458	0.0883	0.1660
Log(hosp. days)	0.1827	0.3065	0.3915	0.3117	0.2188	0.3604	0.3737	0.4515	0.4040	0.3638	0.4861	0.4695	0.2367	0.4197	0.8605	0.7461
No. cigarettes	3.9444	4.0324	3.6143	3.3233	3.8671	4.8133	2.9308	4.6041	3.2795	6.8550	16.3530	6.1202	4.6156	3.6875	3.3099	3.9184
Health condition dummies																
arms	0.2846															
sight	0.0516															
hearing	0.0868															
allergy	0.1213															
chest	0.1375															
heart	0.1720															
stomach	0.0806															
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	100278	35630	6564	10993	15313	17292	22159	10182	4916	10484	677	1032	10226	6247	1268	1030

Notes: observations pooled over years.

Therefore we have chosen to also use these personality traits as matching covariates.[12] 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 in the individuals over the course of our sample horizon.[13]

Lastly, we have included a number of ordinary control variables. We use net equivalised annual household income (in British Pound Sterling), before housing costs and deflated to price level of 2008, 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 (Stevenson and Wolfers, 2008; Easterlin, 2001, p. 468), assuming that a given change in the proportion of income leads to the same proportional change in well-being (Layard et al., 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 (e.g., being never married, being separated, divorced or widowed). We control for regions (Metropolitan counties and Inner and Outer London areas, which we do not report, however). 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 a variable for the number of children and an educational control variable, viz. an individual's highest level of education, as measured by the CASMIN scale. This is measured ordinally, ranging from one ("none") to nine ("higher tertiary"). Also relevant in the health context might be an individual's smoking habits, which prompted us to include the number of cigarettes smoked per day as a further control variable (Table A.1 in the Appendix reports pairwise correlations between the variables of interest. The correlations of most of our indicators are highly statistically significant and we find no problems of multicollinearity.)

4. Results

Our results are grouped in two parts. A preliminary baseline regression exercise is depicted in Table 2. These regressions are repeated for high trait characteristics in Table A.2 in the Appendix, and then we give the estimates of our main analysis of the causal impact of

[12] These variables were coded by adding up the ordinal responses to the three questions relating to each personality trait (some of them were reverse-coded). It is still an open question whether one would best add up these components are use averages (Heineck, 2011). As the personality distributions are quite skewed in some cases (especially for Agreeableness and Conscientiousness), we decided to interpret the highest quartile as an expression of a high personality trait and the lowest quartile as an expression of a low personality trait, leading to somewhat more even groups for the analysis. Since we are interested in comparing the extreme ends of the personality trait distributions, we think this choice is appropriate.

[13] Personality can evolve over time especially when young or over long time horizons (for evidence from the BHPS, see Donnellan and Lucas, 2008). But there is evidence that the traits mentioned prove to be quite stable from the age of thirty onwards (Costa and McCrae, 1994) or only change quite slowly over the course of a human life: test-retest reliability in childhood ranges between 0.22-0.53 and increases to 0.70-0.79 for adults (Hampson and Goldberg, 2006).

different health impairments (as well as recovery from such health conditions) in Tables 3 and 4.

4.1. Fixed-Effects Regressions

Table 2: 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	0.1839***	(28.61)	0.1690***	(18.62)	0.1956***	(21.69)
doc visits	-0.0080	(-1.81)	-0.0190**	(-2.91)	-0.0003	(-0.05)
accidents	-0.0202*	(-2.08)	-0.0257*	(-2.07)	-0.0136	(-0.89)
log(hosp. days)	-0.0123	(-1.63)	-0.0274*	(-2.26)	-0.0017	(-0.17)
Disabled	-0.1519***	(-6.79)	-0.1436***	(-4.68)	-0.1565***	(-4.89)
no. cigarettes	-0.0026*	(-2.16)	-0.0027	(-1.83)	-0.0023	(-1.23)
Health condition dummies						
arms	-0.0308**	(-2.70)	-0.0132	(-0.84)	-0.0476**	(-2.90)
sight	-0.0488*	(-2.25)	-0.0351	(-1.07)	-0.0598*	(-2.06)
hearing	-0.0535**	(-2.59)	-0.0499	(-1.86)	-0.0582	(-1.82)
allergy	-0.0272	(-1.78)	-0.0229	(-0.99)	-0.0297	(-1.47)
chest	0.0033	(0.18)	0.0064	(0.26)	0.0004	(0.01)
heart	-0.0016	(-0.10)	-0.0057	(-0.26)	0.0041	(0.18)
stomach	-0.0122	(-0.69)	-0.0135	(-0.52)	-0.0105	(-0.44)
diabetes	0.0277	(0.65)	0.0224	(0.40)	0.0341	(0.53)
anxiety	-0.3887***	(-17.92)	-0.4695***	(-12.43)	-0.3510***	(-13.27)
drugs	-0.1262	(-1.48)	-0.1648	(-1.57)	-0.0349	(-0.25)
epilepsy	-0.0739	(-0.86)	-0.1704	(-1.21)	0.0129	(0.13)
migraine	-0.0610**	(-3.12)	-0.0391	(-1.13)	-0.0686**	(-2.91)
other	-0.0496*	(-2.48)	-0.0539	(-1.61)	-0.0482	(-1.94)
log(income)	0.0295***	(3.36)	0.0328**	(2.74)	0.0278*	(2.16)
age	-0.0141	(-1.05)	0.0087	(0.48)	-0.0318	(-1.75)
(age-mean age)^2	-0.0001	(-1.35)	0.0001	(1.60)	-0.0002**	(-3.11)
no. children	-0.0027	(-0.31)	0.0093	(0.79)	-0.0153	(-1.21)
Labour market status dummies						
Unemployed	-0.3120***	(-11.04)	-0.3429***	(-8.74)	-0.2849***	(-7.00)
Self-employed	-0.0049	(-0.22)	0.0124	(0.46)	-0.0390	(-0.97)
Retired	0.0612*	(2.48)	0.0737*	(2.01)	0.0548	(1.65)
Schooling	0.0479	(1.65)	0.0376	(0.86)	0.0574	(1.46)
Maternity leave	0.2867***	(6.61)	0.3456	(1.43)	0.2736***	(6.11)
Long-term sick	-0.2872***	(-7.53)	-0.3322***	(-5.68)	-0.2439***	(-4.86)
Family care	-0.0524*	(-2.21)	-0.2180*	(-2.25)	-0.0408	(-1.59)
Other	-0.0162	(-0.30)	-0.1271	(-1.58)	0.0705	(0.98)
Marital status dummies						
Never married	-0.0305	(-1.22)	-0.0698	(-1.93)	0.0056	(0.16)
Separated	-0.1446***	(-3.55)	-0.1868**	(-3.21)	-0.1108*	(-1.98)
Divorced	-0.0073	(-0.21)	-0.0019	(-0.04)	-0.0119	(-0.25)
Widowed	-0.2341***	(-4.18)	-0.1829*	(-2.05)	-0.2562***	(-3.58)
Education dummies						
elementary	0.0376	(0.28)	0.0307	(0.18)	0.0884	(0.45)
basic voc.	-0.0621	(-0.65)	-0.2373	(-1.91)	0.1035	(0.75)
middle gen.	0.1987*	(2.07)	0.0669	(0.56)	0.3476*	(2.29)
middle voc.	0.3090*	(2.18)	0.3566	(1.65)	0.3650	(1.88)
gen: hi gen.	0.2488*	(2.57)	0.1209	(1.00)	0.3972**	(2.60)
voc: hi voc.	0.1332	(1.28)	0.0313	(0.25)	0.2760	(1.62)
low tert.	0.2491*	(2.43)	0.1038	(0.86)	0.4169*	(2.50)
high tert.	0.1800	(1.75)	0.0492	(0.38)	0.3242*	(2.02)
Region dummies	yes		yes		yes	
Year dummies	yes		yes		yes	
Observations	100278		46856		53422	
R^2 (overall)	0.0318		0.1286		0.0051	

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

Table 2 presents a baseline model of the life satisfaction health relationship using a standard fixed-effects (FE) regression framework, taking into account individual-specific time-invariant components (with standard errors clustered on the individual). Accounting for fixed effects in subjective well-being regressions does substantively alter regression results (Ferrer-i-Carbonell and Frijters, 2004) and is, due to the fact that happiness is partly determined by genes and stable personality traits (Lykken and Tellegen, 1996; Diener et al., 1999), the preferable model choice. Note that we implicitly interpret our well-being measure as cardinal in our regressions. Such an interpretation is common in the psychological literature on subjective well-being, and it has been shown that there are no substantial differences between cardinal and ordinal estimation approaches (such as ordered probit models) in terms of the results they generate (Ferrer-i-Carbonell and Frijters, 2004).[14]

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. There are also less strong negative effects on life satisfaction with respect to the number of accidents one had in a given year as well as problems with arms, sight, hearing, migraine and other health problems. Ceteris paribus effect sizes (the coefficient magnitudes) are rather small for most objective health impairments and are insignificant for many of these problems. With reference to the latter 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, with which FE models do not perform well.[15]

We find typical results in our model regarding the other variables. There is a significant effect of income on life satisfaction, which in the gender disaggregation seems to be driven by the male subsample. 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 (see Dolan et al., 2008). We find highly significant positive coefficients for maternity leave, where this effect seems solely restricted to females — no big surprise considering the negligible number of males being on paternity leave in this sample (6 obs.). A slightly negative effect of having to go into family care is found in the overall sample, the effect of which is driven by males (strong negative effect, highly significant, as opposed to no effect in the female subsample; while the number of males doing family care (229 obs.) is much smaller than that of females (6739 obs.), their well-being loss is much higher than that of females). It can be conjectured that for males, who more strongly define themselves through their employment experience, caregiving for the family is much more strongly experienced as negative than females. An explanation why family care is negatively related to life satisfaction (as opposed to e.g. voluntary caring activities

[14]Individuals seem to convert ordinal response labels into similar numerical values such that these cardinal values equally divide up the response space (van Praag, 1991; Clark et al., 2008b).

[15]The two health conditions referring to having a stroke or having cancer are not shown in Table 2, as they have been only elicited halfway into our sample horizon. We have computed a model where we included both conditions, which reduced our sample size from 100,278 observations to 61,135. In this model, neither health problem was significantly related to life satisfaction (stroke: b=−0.0891, n.s., t-stat −1.27, cancer: b=0.0341, n.s., t-stat 0.59) and due to the nearly halved sample size, some other (health) coefficients were insignificant as well, as compared to the model reported here.

in the community) is because it is non-voluntary and strongly decreases an individual's self-determination (see, e.g., Hirst, 2005).

We also find a significant negative relationship for separation and widowhood, while being divorced has no significant impact. Given that divorce finalizes an (often) long decline in quality of marriage and the associated subjective well-being loss, it is not very surprising that no negative effect should be found if a separation dummy is also included in the regressions. At the time of divorce, the negative effect of separation is already taken into account. Moreover, hedonic adaptation might have occurred and individuals might experience divorce actually as the positive starting point for a new chapter of life that ends the less happy years of marriage preceding it.

We find a significant positive influence of education on life satisfaction for middle (secondary) education levels (control group here is an incomplete educational attainment), but not for very low or very high education levels. In the gender disaggregation, education is not related to life satisfaction for males, but it is influencing female life satisfaction much more strongly than in the full sample. Education can be conjectured to influence well-being in many ways, most of which, however, seem rather indirect (e.g., education influences life satisfaction through more healthy behaviors). Therefore, the relationship between education and subjective well-being has been shown to be rather unstable in the literature (Dolan et al., 2008; Binder and Coad, 2011). Overall and despite the fact that FE regressions do not allow to directly estimate the effect gender has on life satisfaction, we find some gender differences in our data disaggregation. While some studies find that women tend to be happier than men (e.g., Di Tella et al., 2003), not all studies consistently find such an effect (Dolan et al., 2008, p. 99). Our study here also reinforces the point that there seem to be 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 and Easterlin, 2008).[16]

We have also run regressions for subgroups grouped according to personality characteristics (results are given in Table A.2 in the Appendix). We find some interesting differences on the opposite ends of the trait distributions. For sake of space, we only highlight a few of these differences. Similar to conscientious and open individuals, extroverts suffer more from anxiety disorders than less extrovert, conscientious or open individuals, while the relationship is reversed for agreeable and neurotic individuals. It is also interesting to note that extroverts suffer much less from unemployment than their introvert peers (the large coefficient size is halved, a finding also established by Clark and Georgellis, 2010). While their outgoing nature seems to shield them somewhat from the drop in well-being of losing their job, they also seem to profit less from positive life events such as becoming parents. This might be a case of diminishing returns to subjective well-being as extroverts are already happier than introverts (e.g., DeNeve and Cooper, 1998). Neurotic individuals on the other

[16]We have also calculated a version of this model, where we excluded the subjective health measure. The idea behind this lies in dissipating some econometric reservations one could have in using objective and subjective health measures in such a regression simultaneously. While this does not cause problems of multicollinearity, nevertheless the subjective health assessment might pick up variance associated with the objective health conditions that are the focus of our paper. 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 on request.

hand suffer more strongly from unemployment, disability or being long-term sick than their less neurotic peers, but then they also profit more from positive life events such as maternity leave. It seems that neurotic individuals experience stronger influences on life satisfaction no matter the direction of influence (i.e. coefficients are larger independent of direction). The influence of subjective health on subjective well-being is nearly twice as large for highly neurotic individuals than for less neurotic ones (compare Okun and George, 1984, who show that controlling for Neuroticism decreases the predictive power of self-rated health for subjective well-being). Conscientious individuals suffer less from long-term sickness and, in general, their subjective health has a smaller impact on subjective well-being. They share the former relationship with agreeable individuals.[17]

4.2. Matching estimates

While FE models are certainly preferable to simple pooled models for panel data, we may be "over-controlling" and removing some slow-changing variables of interest. Moreover, fixed-effect regression suffers from other drawbacks of regression models discussed above (in particular, potential lack of a common support for treatment and control groups). Both points are very relevant in our case. Consider the dummies for different illness conditions. These would exhibit very 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 and estimates in a FE framework will not be very reliable. 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 listing descriptive statistics broken down to different illness conditions (see Table 1), one can clearly see that the observations where a sickness condition exists can be as low as 677 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, the coefficients in such cases are derived from much smaller numbers of observations. Matching estimates do not obscure this fact as one can see from the smaller numbers of observations used in the following estimates (Tables 3 and 4).

In order to come to more reliable estimates of the causal impact of different health conditions on life satisfaction, we turn now to our matching estimates. We focus our attention on individuals that are similar, along a number of dimensions, at time t. We then track these individuals over time and observe differences between the treatment group (those experiencing a *change* in health; more specifically, entry into a certain health impairment category) and the control group (their matched counterparts with unchanged health). We are carrying out our analysis for two different types of matching, viz. 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"). With the number of observations and variables used, we have no pressing concerns of dimensionality with nearest-neighbor

[17]These relationships are by and large replicated also if looking only at the subsample of individuals aged 30 to 60. As argued above, in this age range, personality traits are arguably much less malleable than in young or extremely older age.

matching and can use the same covariates for both matching estimators. The covariates we are use are: previous change in life satisfaction, log(income), gender, age, a quadratic age term, number of children, education, personality trait scores, dummies for being disabled, being never married, being separated, divorced or widowed, as well as for being unemployed, being retired, still studying or in school, being on maternity leave or on family care or being self-employed, ethnicity dummies, and finally year dummies, as well as regional dummies for the different former Metropolitan counties and Inner and Outer London.

Table 3: 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.

	t+1				t+2				transitions			
									sick	healthy	sick	healthy
Condition	PSM: ATT	SE	t-stat	obs	PSM: ATT	SE	t-stat	obs	t+1	t+1	t+2	t+2
	NN: SATE	SE	z-stat	obs	NN: SATE	SE	z-stat	obs				
arms	-0.4072***	0.0288	-14.1286	15491	-0.5342***	0.0506	-10.5589	9380	5360	20774	1971	13743
	-0.3018***	0.0267	-11.3214	15528	-0.3901***	0.0480	-8.1339	9617				
sight	-0.6318***	0.0619	-10.2088	13027	-0.6975***	0.1066	-6.5418	6960	1906	20774	491	13743
	-0.4371***	0.0570	-7.6678	13396	-0.4094**	0.1196	-3.4230	8725				
hearing	-0.5300***	0.0574	-9.2324	13124	-0.4035***	0.0762	-5.2983	7682	1831	20774	707	13743
	-0.3760 ***	0.0565	-6.6604	13438	-0.1852*	0.0880	-2.1042	8877				
allergy	-0.4736***	0.0407	-11.6490	13894	-0.3768***	0.0622	-6.0552	8916	2921	20774	947	13743
	-0.3326***	0.0362	-9.1887	14047	-0.1743**	0.0582	-2.9960	9004				
chest	-0.5913***	0.0528	-11.1992	13542	-0.4699***	0.0904	-5.1978	8629	2373	20774	799	13743
	-0.4870***	0.0456	-10.6878	13680	-0.4170***	0.0753	-5.5411	8905				
heart	-0.5847***	0.0465	-12.5853	14087	-0.5483***	0.0648	-8.4662	9149	3148	20774	1449	13743
	-0.4497***	0.0412	-10.9151	14199	-0.4628***	0.0605	-7.6526	9316				
stomach	-0.6106***	0.0571	-10.6844	13648	-0.6568***	0.0824	-7.9697	8768	2531	20774	761	13743
	-0.5298***	0.0435	-12.1816	13835	-0.5496***	0.0777	-7.0703	8895				
diabetes	-0.5856***	0.1048	-5.5868	11874	-0.6939***	0.1366	-5.0780	7103	431	20774	275	13743
	-0.7554***	0.1399	-5.4000	12592	-0.7839***	0.1799	-4.3567	8582				
anxiety	-1.1005***	0.0526	-20.9333	13445	-1.2180***	0.0931	-13.0793	8460	2386	20774	712	13743
	-1.1002***	0.0500	-22.0055	13706	-1.0314***	0.0900	-11.4660	8862				
drugs	-1.3751***	0.1692	-8.1276	7995	-0.9938***	0.2752	-3.6115	946	171	20774	33	13743
	-1.3883***	0.2221	-6.2517	12422	-1.0966*	0.4348	-2.5218	8428				
epilepsy	-0.3911	0.2110	-1.8537	6391	-1.1347**	0.4382	-2.5896	703	85	20774	34	13743
	-0.2011	0.3250	-0.6187	12369	-0.5224	0.4470	-1.1688	8426				
migraine	-0.5816***	0.0475	-12.2435	13287	-0.7317***	0.0859	-8.5202	8449	2034	20774	584	13743
	-0.4686***	0.0441	-10.6266	13463	-0.5927***	0.0812	-7.3029	8750				
cancer	-0.7367***	0.1175	-6.2715	8686	-0.5564**	0.1701	-3.2707	5732	364	20774	152	13743
	-0.6010***	0.1405	-4.2787	12572	0.0197	0.2055	0.0958	8520				
stroke	-0.6851***	0.1539	-4.4522	6086	-0.9299***	0.2688	-3.4591	4372	284	20774	105	13743
	-0.1263	0.2353	-0.5367	12512	-0.1209	0.3773	-0.3203	8477				
other	-0.5686***	0.0486	-11.6894	13605	-0.5613***	0.0978	-5.7374	8216	2238	20774	445	13743
	-0.4348***	0.0438	-9.9312	13693	-0.4351***	0.1013	-4.2941	8690				
Δ health $> +1$	-0.0967*	0.0416	-2.3259	24231	-0.0442	0.0634	-0.6982	19643	21013	46149	593	31083
	0.0023	0.0467	0.0482	24537	0.0380	0.0749	0.5079	19827				
Δ health $+1$	-0.0439**	0.0165	-2.6604	30901	0.0063	0.0237	0.2670	22517	12696	46149	4950	31083
	0.0268	0.0160	1.6751	30905	0.0603*	0.0244	2.4728	22532				
Δ health -1	-0.2114***	0.0172	-12.2945	30885	-0.1434***	0.0262	-5.4626	22069	12637	46149	4251	31083
	-0.1490***	0.0165	-9.0251	30892	-0.0507	0.0268	-1.8902	22104				
Δ health > -1	-0.4889***	0.0433	-11.2912	24554	-0.5947***	0.1084	-5.4858	18624	2188	46149	330	31083
	-0.3530***	0.0454	-7.7739	24716	-0.5361***	0.1275	-4.2055	19650				

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

Table 3 shows the estimates obtained. While the two matching algorithms produce rather similar results, in our interpretation we focus mostly on the propensity score estimates.[18] First of all, note the decreased number of observations that are used in the estimations. These are on the one hand due to the fact that matching estimators are much more transparent about what observations are used for the estimates (i.e. only the few cases where a sickness condition is observed are presented transparently here, as opposed to being hidden in a high observation number of FE regression estimates). Second, we are looking only at cases where individuals report sickness conditions in at least two time points so that transitions from healthy to sick can be observed (for the second lag specification, this is even extended to individuals reporting their health conditions three times in a row). Third, the matching algorithm allows us to discard these observations where off-support inference would take place, i.e. 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 transparent and useful than standard FE regressions in our case. Apart from this, note finally that it would be inappropriate to directly compare coefficient sizes between matching estimators and the FE regressions (not so much based on the different sample sizes but) because of the fact that matching estimates refer to total effects on life satisfaction while regression coefficients are *ceteris paribus* effect sizes, holding all other variables of interest constant (Oakes and Kaufman, 2006, p. 382). Due to the creation of better comparable treatment and control group (finding the "perfect twin", Almus and Czarnitzki, 2003), we achieve significant results for nearly all sickness conditions with the same data set as used in the FE regressions. Taking care in establishing a well-suited control group, by discarding the 'evil twins', thus significantly increases the explanatory power of the estimates. However, we remind the reader that the reliability of our matching estimates hinges on the CIA assumption (Section 3.1), which assumes that all relevant variables are observed and included as matching covariates.

Let us look into the results in more detail: In the lower part of Table 3, we can see that the causal impact of a two category (or more) decrease in subjective health assessment is highly significant ($-.49$) and even a bit stronger after two years ($-.59$). A slighter decrease in health (by one category) still affects subjective well-being quite strongly ($-.21$ in $t+1$ and $-.14$ in $t+2$). Surprisingly, we cannot find a reciprocal effect of increased subjective health rating — the effect is negative in the first lag and in some cases not significant. It is subject to further research whether hedonic adaptation to increases in health should wear off this quickly. For our specific health impairments, we can see significant negative effects on subjective well-being for a number of conditions. The strongest treatment effect is in the category alcohol and drug abuse (-1.38), followed by anxiety, depression and other mental illnesses (-1.10),

[18] We have also carried out several sensitivity checks which we only report summarily here. These tests range from visual inspection of the kernel density plots of going into a sickness condition versus staying healthy to more formal calculations regarding the reduction of bias achieved through matching (Caliendo and Kopeinig, 2008). Both tests aim at verifying whether covariate overlap after matching treatment and control group is obtained. In sum, we have achieved substantial bias reductions that usually go below the maximum bias of 10%-threshold demanded in the literature (see D'Agostino, 1998) for most covariates and most health conditions. The one notable exception to this is the age variable, where matching was difficult, i.e. it was difficult to find good twins in terms of age from both treatment and control group. This suggests that many of the health conditions are age-dependent. The authors will provide these matching diagnostics on request.

cancer ($-.74$) and stroke ($-.69$). Sight ($-.63$), stomach ($-.61$), chest ($-.59$), heart ($-.58$), migraines ($-.58$), diabetes ($-.59$) and the heterogeneous catch-all "other" condition ($-.57$) also depress subjective well-being. Smaller causal effects can be found for "arms" (that is, arms, legs, hands, feet, back, or neck problems; the effect size is $-.41$) and for hearing and allergy problems ($-.53$ and $-.47$, respectively). A comparatively severe health impairment such as epilepsy (in the first lag) yields no significant results, however, but then yields a highly significant 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 the results table).

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 for a different British (cross-sectional) sample a strong negative association between mental well-being and migraines, heart conditions-and-stroke as well as epilepsy. Graham et al. (2011) found strong negative impacts of anxiety and strong pain for a sample of 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 (so as to try and control for individual fixed effects). These independent findings support the conclusion that physical conditions are more easily adaptable to than chronic pain, or psychological conditions such as anxieties (see also Dolan, 2011). Even if personality traits mediate problems of bad health and their impact on individual life satisfaction, this is much less true for the above-mentioned health conditions. Our study can go beyond both cited studies in establishing that in many objective health conditions, there is a significant and strong negative effect on life satisfaction (after matching individuals also according to personality traits, thus taking into account the effects of different personality traits). We can corroborate the one consistent finding from the studies mentioned, that mental health plays an eminently important role 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 and also provides further evidence against theories of rational addiction. But also cancer and stroke are physical conditions that severely impact on 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 to be more plausible is that the concrete ailments play an important role so that physical conditions relating to arm problems or allergies might indeed have less hedonic impact than mental problems but that severe physical impairments such as stroke or cancer come close to the impact that anxieties or migraines can have on the individual. Clearly, further research needs to delve into these differences in health conditions in more detail.

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. The reason for this lies in attrition: if an illness is so severe that it hinders the individual in answering the survey, the existing sample might represent the comparatively less severe cases of bad health conditions. If individuals get sick and die quickly, such cases would not figure in our estimates, thus leading to an underestimation of the true impact of the illness on life satisfaction. 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). While attrition due to sickness might increase non-contact due to death or hospitalization, the aforementioned study (quite surprisingly) found that refusal rates decreased for sick individuals. Other studies have shown that while health-related attrition exists in the BHPS, especially for individuals starting out poor or very poor self-assessed health, this does not seem to bias estimates (regarding socio-economic status covariates) very much (Contoyannis et al., 2004; Jones et al., 2006). We have analyzed the susceptibility of our results to bias from attrition in two ways. First, we computed simple descriptive statistics of how transitioning into a sickness condition is correlated with subsequent non-response in the next wave of the BHPS. Attrition for healthy individuals is 5.2%. Attrition rates for problems with arms, sight allergies, chest, diabetes, hearing, stomach and anxieties are nearly the same as for the healthy population (slightly higher up to 6.4%), while attrition rates in the cases of problems with epilepsy (8.2%) and stroke (8.5%) are much higher. Cancer (12.1%) and drug problems (12.9%) show the highest attrition rates and thus might be most heavily biased due to attrition. Migraines (4.8%) and the category for other problems (4.9%) actually exhibit lower attrition rates than the healthy population. This pattern is also prevalent when narrowing down the non-response categories to death, infirm condition or age-related refusal.[19] Finally, in line with findings of Uhrig (2008), in our sample, sickness conditions lead to higher attrition rates in terms of death or non-contact, but actually lead to lower attrition rates due to refusal: if anything, bad health conditions seem to make individuals more eager to reply to these health questions compared to healthy individuals. A second sensitivity analysis consists in looking at the estimates for health conditions of two subsamples: as opposed to the results reported in Table 3 above, we have also estimated the causal impact of transitioning into a sickness condition for these individuals who get sick in $t + 1$ and recover from the condition in $t + 2$. These individuals represent the (arguably) less severe or short-term cases in the respective sickness categories. We find that this model quite consistently shows the lighter cases. With the one exception of chest problems (small positive difference), the difference in coefficients is negative between the full model and the lighter case model. For cancer, anxiety, diabetes and sight problems, the lighter cases lead to somewhat larger reductions in coefficient size; for the other cases, the reduction is moderate ($-.10$ or less). The largest difference is cancer, which is not particularly surprising given the huge variety of cancer types, some of which can be successfully treated if discovered early, while others have much lower chances of treatment, especially if discovered late. While this difference accounts for a roughly one-third reduction in coefficient size for cancer, the diagnosis of cancer nevertheless leads to a significant decrease in subjective well-being, even in those (arguably) light cases. Allergies, stomach problems, and migraines (and the "other" category) show no difference in their effect on subjective well-being for lighter cases. Getting these health problems makes the individual experience the full negative impact on their well-

[19]These are descriptive statistics not controlling for other influences. We provide these calculations on request. Note, however, that these are highly imprecise and incomplete (Contoyannis et al., 2004, p. 474, fn. 2): while reasons for non-response are elicited in the BHPS, they cannot be reliably established for a large number of missing values.

being, even if recovery sets in after a short time. It is beyond the scope of the present paper to analyze the reasons for these dynamics in more detail. But it is worth stressing the importance of establishing the very different patterns of how different health conditions impact on subjective well-being, something only ill-captured through the subjective-health-subjective-well-being analyses usually found in the literature.[20] In sum, attrition is likely to bias our estimates for some conditions and the estimates provided here offer a first benchmark of this bias (the detailed results from the sensitivity models are available on request). Further research could fruitfully explore this potential source of bias for the different health conditions in more detail.

As we are interested in the dynamic aspects of well-being, we have also examined whether there are lagged effects of these health conditions. A robust finding in happiness research is that individuals often adapt to changes in their life circumstances. Hedonic adaptation, the hedonic dulling of repeated or constant affective stimuli (Frederick and Loewenstein, 1999) is highly domain-specific and varies with the concrete stimulus (for example, hedonic adaptation to marriage is faster and more complete than hedonic adaptation to repeated unemployment, see, e.g., Clark et al., 2008a; Dolan and Kahneman, 2008). The panel structure of our data-set allows us to include a second year to check for hedonic adaptation. In three cases, the effect seems to remain at a comparable level (sight, stomach and the 'other' category). For the other conditions, we find quite 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 negative effect of the health impairment 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 and Kahneman, 2008, pp. 218-9). Note that the dynamic effects vary only in a small number of health conditions when considering the nearest-neighbor-matching estimates pointing to the robustness of the estimates.

Finally, we have examined to what extent individuals recover their lost life satisfaction after recovering from their health impairments (see Table 4). In line with the asymmetric finding regarding positive (subjectively assessed) health changes, it is striking to observe

[20] We also computed the causal impact of sickness conditions in $t+1$ restricted to these individuals who remain in the sample and are sick in $t+2$ as well. As opposed the the main results, we here restrict the effects estimates for $t+1$ to the group of sick individuals of whom we know they will not attrite in $t+2$, again offering a measure to gauge the effect for cases that do not lead to immediate attrition. On the one hand, this excludes the most severe attriting cases, but this also excludes the cases who recover quickly. This makes it difficult to discern a general pattern in this case: there are some conditions, where the chronic model generates largely comparable coefficients than the full model (stroke, other, allergies, hearing). For migraines, drugs and chest problems, the chronic model shows smaller coefficients, with the largest difference in coefficients for drugs (-1.25 here vs. -1.38 in the full model propensity estimates). In these cases, attrition seems to lead to inflation of the full model coefficients. In all other cases, estimates in the chronic model show larger negative coefficients, the largest differences relating to anxiety (chronic: -1.23 vs. full: -1.10) and diabetes (chronic: -0.72 vs full: -0.59). Overall, the differences seem small.

Table 4: Matching estimates: recovery. Propensity score matching (PSM), nearest-neighbor matching (NN), and transitions into the sickness condition.

	t+1				t+2				transitions			
									sick	healthy	sick	healthy
Condition	PSM: ATT	SE	t-stat	obs	PSM: ATT	SE	t-stat	obs	t+1	t+1	t+2	t+2
	NN: SATE	SE	z-stat	obs	NN: SATE	SE	z-stat	obs				
arms	0.1547***	0.0302	5.1170	11539	0.2142***	0.0399	5.3627	7861	4879	19939	2392	17345
	0.2596***	0.0314	8.2779	11608	0.3225***	0.0441	7.3064	8730				
sight	0.1303	0.0729	1.7869	1982	0.2090*	0.0971	2.1530	1224	1789	2740	1059	2093
	0.1183	0.0683	1.7311	2004	0.1684	0.0871	1.9341	1326				
hearing	-0.1017	0.0548	-1.8570	3425	-0.0539	0.0728	-0.7405	2284	1572	6027	740	5240
	-0.0274	0.0570	-0.4810	3445	0.0229	0.0781	0.2932	2554				
allergy	0.0272	0.0382	0.7128	4871	-0.0274	0.0519	-0.5274	3031	2977	7673	1617	6106
	0.0628	0.0385	1.6314	4893	0.0249	0.0533	0.4666	3395				
chest	-0.0242	0.0463	-0.5227	5170	-0.0269	0.0625	-0.4305	3629	2275	9704	1169	8519
	0.0090	0.0482	0.1877	5194	0.0845	0.0647	1.3045	4014				
heart	-0.0009	0.0427	-0.0210	7395	-0.0177	0.0626	-0.2828	5299	2560	12562	1128	11170
	0.0374	0.0446	0.8403	7425	0.0024	0.0684	0.0346	5802				
stomach	0.1535**	0.0528	2.9087	3214	0.2112**	0.0679	3.1085	1985	2370	4677	1380	3575
	0.2423***	0.0516	4.6929	3242	0.2723***	0.0670	4.0644	2160				
diabetes	-0.0060	0.1553	-0.0386	1630	-0.0473	0.2280	-0.2072	1132	183	3087	72	2966
	0.1747	0.1736	1.0061	1706	-0.0228	0.3148	-0.0723	1505				
anxiety	0.5660***	0.0589	9.6136	3200	0.7374***	0.0821	8.9799	2010	2236	4929	1243	3880
	0.7323***	0.0572	12.8070	3213	0.8772***	0.0734	11.9504	2217				
drugs	0.1212	0.3368	0.3597	164	-0.1883	0.4762	-0.3953	62	158	320	92	243
	0.6015*	0.2434	2.4710	202	0.5863*	0.2863	2.0480	142				
epilepsy	0.1526	0.3773	0.4044	198	-0.5666	0.5366	-1.0558	26	81	638	40	593
	-0.0044	0.3533	-0.0124	341	0.3094	0.3858	0.8020	286				
migraine	0.0913	0.0515	1.7706	3175	0.1258	0.0683	1.8426	1900	2187	4966	1173	3930
	0.1491**	0.0498	2.9909	3180	0.2617***	0.0669	3.9105	2198				
cancer	0.2001	0.1343	1.4894	492	0.2426	0.1926	1.2599	325	276	27052	191	26932
	0.1943	0.1672	1.1625	4953	0.1603	0.1913	0.8379	4747				
stroke	0.3590*	0.1814	1.9786	361	0.3153	0.2591	1.2171	224	224	26960	120	26863
	-0.2156	0.2292	-0.9407	4841	0.2213	0.2992	0.7396	4659				
other	0.0028	0.0700	0.0407	1978	-0.1888	0.0975	-1.9354	1239	2028	2129	1357	1404
	-0.0252	0.0656	-0.3834	1997	-0.0323	0.0811	-0.3988	1361				

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

that transitioning out of the different health conditions in most cases does not lead to significantly higher life satisfaction in the following years (with the exception of some 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 the subsequent recovery brings less noticeable improvements in life satisfaction. Mental conditions on the other hand seem to lead to much stronger decreases in life satisfaction and exhibit also 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 the lag structure of the data set, however, we cannot say whether the positive effect of life satisfaction after recovery does not occur at all, or whether it occurs within a year and the individual has already adapted to it after one year. 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 and Kahneman, 2008, p. 222): going into states of ill-health decreases well-being much more strongly than the subsequent recovery, probably in order to motivate the individual to modify behavior accordingly.

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 have therefore repeated the analysis with a broader concept of "mental well-being"[21] and the results are largely similar. Future work might fruitfully replicate our analysis with yet other well-being indicators. Further work might also attempt to 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 for example a patient who pursues a less stressful lifestyle after a heart attack). In our analysis, we focus on the expected changes in well-being following the onset of health problems (as implied in our title).

5. Conclusion

In this paper, we have offered an econometric account of the causal impact of health on subjective well-being. We found that the effect is quite considerable for the general decrease in health ($-.49$ if subjective health decreases by more than one category) and extends over a longer time period. More puzzling, we could not find 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 have analyzed the causal impact related to a set of different health conditions (impairments, mostly) on happiness. This extends the usual analyses that focus on the relationship between a more general (self-assessed) health status of individuals and happiness. Focussing on specific health conditions allows a more comprehensive picture of when and how ill-health decreases well-being and to what extent. Causal effects of these conditions on subjective well-being are quite varied (from $-.41$ for arm problems to -1.38 with 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 findings have a high political relevance when it comes to giving different priorities in health care policies to different health conditions. When budgets for health care are limited and trade-offs have to be made between what conditions to treat with priority, 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 to be normatively more urgent to treat than conditions where adaptation is quick and strong (Dolan and 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 far from clear that this happens very quickly and completely so that the mitigation of this bad impact can also be the target of public policies

[21]That is, 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 and so on (on this measure, see more extensively Gardner and Oswald, 2007).

(Graham, 2008, p. 77). Moreover, findings such as ours are needed to better assess the impact of different health conditions on individuals' well-being. Other methods that directly elicit individuals' evaluations may suffer from many focussing effects and biases that can be avoided via the indirect measurement through happiness regressions in big household panel surveys (Dolan, 2011, pp. 7-8).

Different health conditions have widely diverging causal impacts on individual's subjective well-being. With this paper we hope to have furthered our understanding of these complex impacts, even if the different health conditions still constitute "bad news" for the individuals experiencing them, in terms of health as well as happiness.

Date: May 13, 2012

1. Appendix

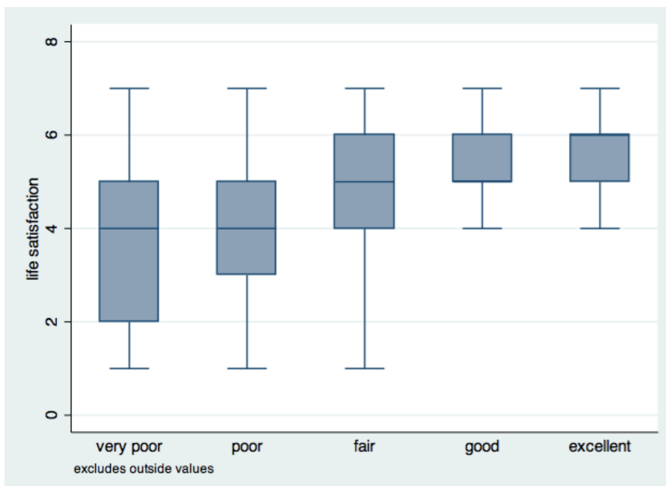

Figure A.1: Boxplot of life satisfaction by subjective health assessment.

Table A.1: Contemporaneous correlations

	life satisfaction	subj. health	log(income)	disabled	unemployed	employed	education	age	gender
life satisfaction	1.0000								
subj. health	0.3304*	1.0000							
log(income)	0.0741*	0.1385*	1.0000						
disabled	-0.1472*	-0.3679*	-0.0762*	1.0000					
unemployed	-0.0882*	-0.0255*	-0.1156*	-0.0238*	1.0000				
employed	0.0067	0.2264*	0.3006*	-0.2525*	-0.1890*	1.0000			
education	-0.0063	0.2026*	0.3092*	-0.1701*	-0.0542*	0.2763*	1.0000		
age	0.0881*	-0.1910*	-0.0409*	0.2512*	-0.1103*	-0.3841*	-0.2717*	1.0000	
gender	-0.0039	-0.0658*	-0.0647*	0.0041	-0.0487*	-0.0739*	-0.0607*	0.0317*	1.0000

Notes: Observations pooled over years: 100,278 observations. Key to significance levels: * $p < 0.01$.

Table A.2: Fixed effect regressions. Subgroup analysis for different personality traits: Extraversion; Neuroticism; Openness; Conscientiousness and Agreeableness.

	(1) E: high	(2) E: low	(3) N: high	(4) N: low	(5) A: high	(6) A: low	(7) O: high	(8) O: low	(9) C: high	(10) C: low
subj. health	0.1927***	0.1639***	0.2284***	0.1225***	0.2081***	0.1747***	0.1828***	0.1616***	0.1685***	0.1974***
	(13.03)	(12.05)	(15.20)	(9.68)	(10.84)	(12.80)	(11.95)	(11.41)	(11.78)	(15.45)
doc visits	-0.0023	-0.0268**	-0.0042	-0.0171	-0.0054	-0.0218*	-0.0112	-0.0245**	-0.0067	-0.0155
	(-0.22)	(-2.87)	(-0.41)	(-1.94)	(-0.39)	(-2.25)	(-1.01)	(-2.61)	(-0.65)	(-1.80)
accidents	-0.0351	-0.0381	-0.0094	-0.0411*	0.0028	-0.0440*	-0.0474*	-0.0073	0.0067	-0.0158
	(-1.69)	(-1.73)	(-0.41)	(-2.33)	(0.09)	(-2.14)	(-2.11)	(-0.32)	(0.31)	(-0.84)
log(hosp. days)	0.0418*	-0.0187	-0.0139	-0.0102	-0.0006	0.0078	0.0112	-0.0036	-0.0121	-0.0029
	(2.18)	(-1.21)	(-0.80)	(-0.65)	(-0.03)	(0.44)	(0.59)	(-0.25)	(-0.62)	(-0.20)
disabled	-0.1959**	-0.1875***	-0.1680***	-0.0705	-0.0795	-0.1552**	-0.1330*	-0.1195**	-0.1658**	-0.1463***
	(-3.22)	(-4.47)	(-3.32)	(-1.65)	(-1.30)	(-3.28)	(-2.35)	(-2.70)	(-3.20)	(-3.52)
no. cigarettes	-0.0048	-0.0022	-0.0042	-0.0001	-0.0025	-0.0042	-0.0047	-0.0001	-0.0001	-0.0031
	(-1.76)	(-0.92)	(-1.56)	(-0.06)	(-0.68)	(-1.92)	(-1.59)	(-0.05)	(-0.02)	(-1.58)
Health condition dummies										
arms	-0.0120	-0.0180	-0.0183	-0.0144	-0.0665*	0.0035	-0.0296	-0.0178	-0.0282	-0.0451*
	(-0.46)	(-0.82)	(-0.71)	(-0.68)	(-2.09)	(0.14)	(-0.98)	(-0.74)	(-1.17)	(-2.02)
sight	-0.0752	-0.0356	-0.0430	-0.0465	-0.0635	-0.0076	-0.0531	-0.0799	-0.0706	-0.0033
	(-1.43)	(-0.86)	(-0.85)	(-1.08)	(-0.98)	(-0.16)	(-0.92)	(-1.86)	(-1.26)	(-0.09)
hearing	-0.1050*	-0.0186	-0.0182	-0.1211***	-0.0558	-0.0211	-0.1744**	-0.0125	-0.1113*	-0.0165
	(-2.14)	(-0.47)	(-0.36)	(-3.29)	(-0.95)	(-0.52)	(-3.22)	(-0.31)	(-2.46)	(-0.44)
allergy	-0.0749*	-0.0641*	-0.0802*	-0.0035	-0.0718	-0.0255	-0.0945**	0.0172	-0.0316	-0.0131
	(-2.17)	(-2.06)	(-2.31)	(-0.11)	(-1.44)	(-0.78)	(-2.82)	(0.48)	(-0.85)	(-0.45)
chest	0.0452	-0.0497	-0.0060	0.0186	0.0462	-0.0126	0.0124	-0.0268	-0.0456	0.0009
	(1.09)	(-1.27)	(-0.15)	(0.49)	(1.01)	(-0.32)	(0.30)	(-0.69)	(-1.15)	(0.03)
heart	-0.0524	0.0197	-0.0112	-0.0546	0.0640	-0.0056	-0.0167	-0.0042	0.0073	-0.0126
	(-1.25)	(0.66)	(-0.30)	(-1.80)	(1.42)	(-0.16)	(-0.43)	(-0.13)	(0.21)	(-0.42)
stomach	-0.0644	-0.0245	0.0135	0.0100	-0.0579	-0.0093	0.0033	-0.0556	-0.0717	0.0149
	(-1.50)	(-0.76)	(0.37)	(0.28)	(-1.13)	(-0.24)	(0.08)	(-1.53)	(-1.78)	(0.47)
diabetes	0.1599	0.0267	-0.1951	0.0851	-0.1139	0.0725	-0.0829	0.0052	-0.0348	0.0097
	(1.49)	(0.39)	(-1.45)	(1.03)	(-0.96)	(0.95)	(-0.68)	(0.07)	(-0.40)	(0.12)
anxiety	-0.4500***	-0.3780***	-0.3888***	-0.4798***	-0.3067***	-0.4473***	-0.4436***	-0.3292***	-0.4605***	-0.3583***
	(-7.87)	(-8.82)	(-11.07)	(-6.12)	(-5.11)	(-9.28)	(-8.51)	(-7.34)	(-9.26)	(-8.67)
drugs	-0.4274	-0.4351**	-0.0934	-0.7132	-0.4686	-0.2987*	0.0959	-0.2295	0.3037	-0.2896*
	(-1.26)	(-3.17)	(-0.63)	(-1.60)	(-1.78)	(-2.17)	(0.38)	(-1.51)	(1.19)	(-2.18)
epilepsy	0.0688	-0.3386*	-0.0813	-0.0838	0.2416	0.0465	0.0629	0.0738	0.2117	-0.0057
	(0.38)	(-2.25)	(-0.48)	(-0.44)	(1.22)	(0.34)	(0.28)	(0.47)	(1.26)	(-0.04)
migraine	0.0027	-0.0488	-0.0108	-0.0501	0.0113	-0.0623	0.0619	-0.1316**	-0.0610	-0.0795
	(0.06)	(-1.24)	(-0.27)	(-1.05)	(0.18)	(-1.47)	(1.55)	(-3.00)	(-1.47)	(-1.91)
other	0.0164	-0.1031*	-0.0333	-0.0336	0.0080	-0.0364	-0.0444	-0.1101*	-0.0173	-0.0492
	(0.36)	(-2.35)	(-0.79)	(-0.79)	(0.13)	(-0.86)	(-0.94)	(-2.55)	(-0.38)	(-1.30)
log(income)	0.0057	0.0300	0.0531**	0.0353*	0.0406	0.0380	0.0521**	0.0377	0.0313	0.0337*
	(0.30)	(1.51)	(2.67)	(2.08)	(1.37)	(1.94)	(2.61)	(1.82)	(1.50)	(2.00)
age	0.0178	-0.0153	-0.0251	0.0058	-0.0081	-0.0157	-0.0139	0.0132	0.0168	-0.0268
	(0.55)	(-0.57)	(-0.80)	(0.21)	(-0.19)	(-0.54)	(-0.43)	(0.46)	(0.52)	(-1.12)
(age-mean age)^2	0.0001	-0.0000	-0.0000	-0.0000	-0.0003**	0.0000	0.0000	0.0001	0.0001	0.0000
	(0.50)	(-0.36)	(-0.31)	(-0.39)	(-2.67)	(0.20)	(0.15)	(0.75)	(0.57)	(0.46)
no. children	-0.0213	0.0171	-0.0034	0.0023	0.0498	-0.0366	0.0072	0.0071	0.0077	-0.0034
	(-1.02)	(0.96)	(-0.16)	(0.14)	(1.74)	(-1.93)	(0.34)	(0.37)	(0.40)	(-0.19)
Education dummies										
elementary	-0.0214	-0.1701	-0.1389	0.0875	-0.0446	0.0588	-0.2965	-0.1773	0.3455	-0.2501
	(-0.07)	(-0.38)	(-0.33)	(0.39)	(-0.12)	(0.27)	(-0.96)	(-0.66)	(1.33)	(-0.99)
basic voc.	0.0126	0.0005	-0.0991	-0.2577	-0.1595	-0.2159	-0.1288	-0.1231	0.1643	-0.2561
	(0.04)	(0.00)	(-0.32)	(-1.44)	(-0.60)	(-1.33)	(-0.51)	(-0.77)	(0.92)	(-1.54)
middle gen.	0.3944	0.2638	0.1006	0.3106	0.0764	0.2715	0.3297	0.2079	0.4335*	0.2235
	(1.57)	(1.38)	(0.36)	(1.63)	(0.36)	(1.83)	(1.67)	(0.97)	(2.10)	(1.28)
middle voc.	0.8080**	0.3266	0.3799	0.5638*	-0.1372	1.1674***	0.7730**	0.1863	0.4358	0.3991
	(2.77)	(1.01)	(0.95)	(2.33)	(-0.55)	(3.46)	(3.25)	(0.50)	(1.19)	(1.33)
gen: hi gen.	0.4634	0.3115	0.1621	0.4054*	-0.0122	0.3967**	0.4478*	0.1381	0.5127*	0.3201
	(1.86)	(1.55)	(0.56)	(2.08)	(-0.05)	(2.58)	(2.28)	(0.59)	(2.48)	(1.77)
voc: hi voc.	0.2629	0.1042	0.0271	0.3181	-0.4442	0.1897	0.1131	0.0141	0.5031	0.1090
	(1.01)	(0.48)	(0.08)	(1.62)	(-1.66)	(1.18)	(0.52)	(0.05)	(1.89)	(0.56)
low tert.	0.2905	0.4409*	0.1913	0.2209	-0.1611	0.5228**	0.3865	0.1602	0.3775	0.4058*
	(1.15)	(2.22)	(0.62)	(1.01)	(-0.60)	(3.26)	(1.85)	(0.68)	(1.47)	(2.07)
high tert.	0.3511	0.3034	0.0409	0.1319	-0.2548	0.3275	0.2523	0.0064	0.3227	0.1793
	(1.36)	(1.45)	(0.13)	(0.64)	(-0.87)	(1.88)	(1.17)	(0.03)	(1.35)	(0.91)
Marital status dummies										
never married	-0.0688	-0.0450	-0.0260	-0.0494	0.2409**	-0.0021	-0.1148	-0.0222	0.0299	-0.0219
	(-1.21)	(-0.82)	(-0.44)	(-1.00)	(3.12)	(-0.04)	(-1.94)	(-0.39)	(0.48)	(-0.45)
separated	-0.1033	-0.1087	-0.1012	-0.2377**	-0.0400	-0.0894	-0.0784	-0.0077	-0.1683*	-0.0196
	(-1.18)	(-1.16)	(-1.06)	(-3.01)	(-0.28)	(-0.99)	(-0.79)	(-0.09)	(-2.01)	(-0.25)
divorced	0.1127	-0.0695	-0.0590	0.0940	0.1348	-0.0392	0.0735	-0.0103	0.0590	-0.0291
	(1.58)	(-0.81)	(-0.71)	(1.41)	(1.31)	(-0.51)	(0.95)	(-0.13)	(0.82)	(-0.40)
widowed	-0.1132	-0.3215**	-0.2927	-0.1724	-0.1808	-0.3206**	-0.0487	-0.1827	-0.2806*	-0.1369
	(-0.92)	(-2.61)	(-1.85)	(-1.75)	(-1.39)	(-2.77)	(-0.29)	(-1.56)	(-2.40)	(-1.29)
Labour market status dummies										
unemployed	-0.2101**	-0.4123***	-0.2837***	-0.2391***	-0.2106*	-0.3084***	-0.3111***	-0.2857***	-0.2271**	-0.3316***
	(-2.98)	(-6.56)	(-4.51)	(-3.83)	(-2.22)	(-5.33)	(-4.65)	(-4.31)	(-3.14)	(-6.31)
self-employed	-0.0300	-0.0210	-0.0250	0.0124	-0.1554*	-0.0002	0.0456	0.0497	0.0011	-0.0121
	(-0.63)	(-0.42)	(-0.38)	(0.31)	(-2.25)	(-0.00)	(0.99)	(0.87)	(0.02)	(-0.25)
retired	0.0333	0.0123	-0.0521	0.1129**	-0.0445	0.0827	0.1287*	-0.0138	0.0225	0.0811
	(0.57)	(0.26)	(-0.80)	(2.72)	(-0.72)	(1.70)	(2.15)	(-0.28)	(0.44)	(1.81)
study school	0.0901	-0.0262	0.0093	0.0854	-0.0017	-0.0037	0.0628	0.0514	-0.0371	0.0422
	(1.39)	(-0.36)	(0.14)	(1.45)	(-0.02)	(-0.06)	(0.96)	(0.68)	(-0.47)	(0.82)
maternity leave	0.2441**	0.4398***	0.4524***	0.2079*	0.3603**	0.5592***	0.2156*	0.3745***	0.2697***	0.3442***
	(3.29)	(4.21)	(5.56)	(2.23)	(2.96)	(5.00)	(2.22)	(4.68)	(3.40)	(4.04)
long-term sick	-0.2840**	-0.3117***	-0.3353***	-0.2050*	-0.1858*	-0.3091***	-0.1679	-0.2788***	-0.1795*	-0.3008***
	(-2.73)	(-4.66)	(-4.67)	(-2.32)	(-2.10)	(-3.87)	(-1.73)	(-4.21)	(-2.16)	(-4.37)
family care	-0.0316	-0.0586	-0.1054*	0.0201	-0.0850	-0.0410	0.0417	-0.0428	0.0074	-0.0685
	(-0.62)	(-1.17)	(-1.98)	(0.42)	(-1.44)	(-0.71)	(0.74)	(-0.89)	(0.14)	(-1.51)
other	0.0503	-0.1330	-0.0755	0.0411	0.0543	-0.1963	0.0291	-0.0878	0.0550	-0.1769
	(0.46)	(-0.96)	(-0.56)	(0.39)	(0.40)	(-1.85)	(0.29)	(-0.69)	(0.42)	(-1.73)
Region dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	15098	23256	18756	20622	11285	20091	14826	22667	17763	25508
R^2 (overall)	0.0841	0.0257	0.0295	0.0354	0.0081	0.0236	0.0109	0.1349	0.0846	0.0214

Notes: High trait expression refers to the upper quartile, while low trait expression refers to the lower quartile.

References

Abadie, A., Drukker, D., Herr, J. L., and Imbens, G. W. (2004). Implementing matching estimators for average treatment effects in Stata. *The Stata Journal*, 4(3):290–311.

Almus, M. and Czarnitzki, D. (2003). The Effects of Public R&D Subsidies on Firms' Innovation Activities. *Journal of Business and Economic Statistics*, 21(2):226–236.

Arrow, J. (1996). Estimating the influence of health as a risk factor on unemployment: A survival analysis of employment durations for workers surveyed in the German Socio-Economic Panel (1984-1990). *Social Science & Medicine*, 42(12):1651–1659.

BHPS (2010). British Household Panel Survey. http://www.iser.essex.ac.uk/ulsc/bhps/.

Binder, M. and Coad, A. (2010). An examination of the dynamics of well-being and life events using vector autoregressions. *Journal of Economic Behavior & Organization*, 76(2):352–371.

Binder, M. and Coad, A. (2012). Life satisfaction and self-employment: A matching approach. forthcoming in: *Small Business Economics*, DOI 10.1007/s11187-011-9413-9.

Binder, M. and Coad, A. (2011). From Average Joe's happiness to Miserable Jane and Cheerful John: using quantile regressions to analyze the full subjective well-being distribution. *Journal of Economic Behavior & Organization*, 79(3):275–290.

Blanchflower, D. G. and Oswald, A. J. (2008). Hypertension and happiness across nations. *Journal of Health Economics*, 27(2):218 – 233.

Böckerman, P. and Ilmakunnas, P. (2009). Unemployment and self-assessed health: Evidence from panel data. *Health Economics*, 18:161–179.

Boyce, C. J., Wood, A. M., and Powdthavee, N. (2012). Is personality fixed? personality changes as much as "variable" economic factors and more strongly predicts changes to life satisfaction. *Social Indicators Research*. doi: 10.1007/s11205-012-0006-z.

Brickman, P. E., Coates, D., Janoff-Bulman, R., 1978. Lottery winners and accident victims: Is happiness relative? *Journal of Personality and Social Psychology*, 36:917–927.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.

Clark, A. E., Diener, E., Georgellis, Y., and Lucas, R. E. (2008a). Lags and leads in life satisfaction: A test of the baseline hypothesis. *The Economic Journal*, 118:F222–F243.

Clark, A. E., Frijters, P., and Shields, M. A. (2008b). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*, 46(1):95–144.

Clark, A. E. and Georgellis, Y. (2010). Back to baseline in Britain: Adaptation in the BHPS. Mimeo.

Contoyannis, P. and Jones, A. M. (2004). Socio-economic status, health and lifestyle. *Journal of Health Economics*, 23:965–995.

Contoyannis, P., Jones, A. M., and Rice, N. (2004). The dynamics of health in the British Household Panel Survey. *Journal of Applied Econometrics*, 19:473–503.

Costa, P. T. J. and McCrae, R. R. (1994). Set like plaster?: Evidence for the stability of adult personality. In Heatherton, T. F. and Weinberger, J. L., editors, *Can personality change?*, pages 21–40. American Psychological Association, Washington, D.C.

D'Agostino, R. B. (1998). Propensity score methods for bias reduction in the comparison of a treatment to a non-randomized control group. *Statistics in Medicine*, 17(19):2265–2281.

Dehejia, R. H. and Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94(448):pp. 1053–1062.

DeNeve, K. M. and Cooper, H. (1998). The happy personality: A meta-analysis of 137 personality traits and subjective well-being. *Psychological Bulletin*, 124:197–229.

Diener, E. and Lucas, R. E. (1999). Personality and subjective well-being. In Kahneman et al. (1999), chapter 11, pages 213–229.

Diener, E., Suh, E., Lucas, R. E., and Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, 125(2):276–302.

Di Tella, R., MacCulloch, R., and Oswald, A. (2003). The macroeconomics of happiness. *The Review of Economics and Statistics*, 85(4):809–827.

Dolan, P. and Kahneman, D. (2008). Interpretations of utility and their implications for the valuation of health. *The Economic Journal*, 118:215–234.

Dolan, P., Peasgood, T., and White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, 29:94–122.

Dolan, P. (2011). Using happiness to value health. Office of Health Economics Report.

Donnellan, M. B. and Lucas, R. E. (2008). Age differences in the Big Five across the life span: Evidence from two national samples. *Psychology and Aging*, 23(3):558–566.

Easterlin, R. A. (2001). Income and happiness: Towards a unified theory. *The Economic Journal*, 111:465–484.

Easterlin, R. A. (2003). Explaining happiness. *Proceedings of the National Academy of Sciences*, 100(19):11176–11183.

EuroQol Group (1990). EuroQol–a new facility for the measurement of health-related quality of life. The EuroQol group. *Health Policy*, 16(3):199–208.

Ferrer-i-Carbonell, A. and Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, 114:641–659.

Frederick, S. and Loewenstein, G. F. (1999). Hedonic adaptation. In Kahneman et al. (1999), pages 302–329.

Frey, B. S. and Stutzer, A. (2000). Happiness, economy and institutions. *The Economic Journal*, 110(466):918–938.

Fuchs, V. R. (2004). Reflections on the socio-economic correlates of health. *Journal of Health Economics*, 23:653–661.

Gardner, J. and Oswald, A. (2004). How is mortality affected by money, marriage, and stress? *Journal of Health Economics*, 23:1181–1207.

Gardner, J. and Oswald, A. J. (2007). Money and mental wellbeing: A longitudinal study of medium-sized lottery wins. *Journal of Health Economics*, 26:49–60.

Gerlitz, J.-Y. and Schupp, J. (2005). Zur Erhebung der Big-Five-basierten Persoenlichkeitsmerkmale im SOEP. DIW Berlin, Research Notes 4.

Gosling, S. D., Rentfrow, P. J., and Swann, W. B. J. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37:504–528.

Graham, C. (2008). Happiness and health: Lessons -and questions- for public policy. *Health Affairs*, 27(1):72–87.

Graham, C., Higuera, L., and Lora, E. (2011). Which health conditions cause the most unhappiness? *Health Economics*, 20:1431–1447.

Gutiérrez, J. L. G., Jiménez, B. M., Hernández, E. G., and Puente, C. P. (2005). Personality and subjective well-being: Big Five correlates and demographic variables. *Personality and Individual Differences*, 38(7):1561 – 1569.

Hampson, S. E. and Goldberg, L. R. (2006). A first large cohort study of personality trait stability over the 40 years between elementary school and midlife. *Journal of Personality and Social Psychology*, 91(4):763–779.

Headey, B. (2010). The set point theory of well-being has serious flaws: On the eve of a scientific revolution? *Social Indicators Research*, 97:7–21.

Heckman, J. J., Ichimura, H., Smith, J., and Todd, P. (1996). Sources of selection bias in evaluating social programs: An interpretation of conventional measures and evidence on the effectiveness of matching as a program evaluation method. *Proceedings of the National Academy of Sciences*, 93(23):13416–13420.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64(4):605–654.

Heineck, G. (2011). Does it pay to be nice? Personality and earnings in the UK. forthcoming in Industrial and Labor Relations Review.

Helliwell, J. F. (2006). Well-being, social capital and public policy: What's new? *Economic Journal*, 116:C34–C45.

Hirst, M. (2005). Carer distress: A prospective, population-based study. *Social Science & Medicine*, 61:697-708.

Ichino, A., Mealli, F., and Nannicini, T. (2008). From temporary help jobs to permanent employment: What can we learn from matching estimators and their sensitivity? *Journal of Applied Econometrics*, 23(3):305–327.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics*, 86(1):4–29.

Imbens, G. W. (2010). Better late than nothing: Some comments on Deaton (2009) and Heckman and Urzua (2009). *Journal of Economic Literature*, 48(2):399–423.

John, O. P., Donahue, E. M., and Kentle, R. L. (1991). The Big Five Inventory—Versions 4a and 54. Berkeley: University of California, Berkeley, Institute of Personality and Social Research.

Johnston, D. W., Propper, C., and Shields, M. A. (2009). Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient. *Journal of Health Economics*, 28(3):504–552.

Jones, A. M., Koolman, X., and Rice, N. (2006). Health-related non-response in the British Household Panel Survey and European Community Household Panel: using inverse-probability-weighted estimators in non-linear models. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 169(3):543–569.

Kahneman, D., Diener, E., and Schwarz, N., editors (1999). *Well-Being: The Foundations of Hedonic Psychology*. Russell Sage Foundation, New York.

Krueger, A. B. and Schkade, D. (2008). The reliability of subjective well-being measures. *Journal of Public Economics*, 92:1833–1845.

Layard, R., Mayraz, G., and Nickell, S. (2008). The marginal utility of income. *Journal of Public Economics*, 92:1846–1857.

Levy, H. and Jenkins, S. P. (2008). Documentation for derived current and annual net household income variables, BHPS waves 1-16. Institute for Social and Economic Research, University of Essex, Colchester.

Lykken, D. and Tellegen, A. (1996). Happiness is a stochastic phenomenon. *Psychological Science*, 7(3):186–189.

Lyubomirsky, S., King, L., and Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin*, 131(6):803–855.

McClements, L. D. (1977). Equivalence scales for children. *Journal of Public Economics*, 8(2):191 – 210.

Oakes, J. M. and Kaufman, J. S. (2006). Propensity score matching for social epidemiology. In Oakes, J. M. and Kaufman, J. S., editors, *Methods in Social Epidemiology*, chapter 15, pages 364–386. Jossey-Bass/Wiley, San Francisco.

Okun, M. A. and George, L. K. (1984). Physician- and self-ratings of health, neuroticism and subjective well-being among men and women. *Personality and Individual Differences*, 5(5):533–539.

Oswald, A. J. and Powdthavee, N. (2008). Does happiness adapt? A longitudinal study of disability with implications for economists and judges. *Journal of Public Economics*, 92:1061–1077.

Plagnol, A. C. and Easterlin, R. A. (2008). Aspirations, attainments, and satisfaction: Life cycle differences between American women and men. *Journal of Happiness Studies*, 8:601–619.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5):688–701.

Shields, M. A. and Wheatley Price, S. (2005). Exploring the economic and social determinants of psychological well-being and perceived social support in England. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 168(3):513–537.

Smith, C. A. and Wallston, K. A. (1992). Adaptation in patients with chronic rheumatoid arthritis: Application of a general model. *Health Psychology*, 11(3):151–162.

Stevenson, B. and Wolfers, J. (2008). Economic growth and subjective well-being: Reassessing the Easterlin paradox. *Brookings Papers on Economic Activity*, Spring 2008.

Stewart, J. M. (2001). The impact of health status on the duration of unemployment spells and the implications for studies of the impact of unemployment on health status. *Journal of Health Economics*, 20:781–796.

Taylor, M. F. E. (2010). British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices. edited with John Brice, Nick Buck and Elaine Prentice-Lane. Colchester: University of Essex.

Uhrig, S. C. N. (2008). The nature and causes of attrition in the British Household Panel Survey. Mimeo.

Umberson, D. (1987). Family status and health behaviors: Social control as a dimension of social integration. *Journal of Health and Social Behavior*, 28:306–319.

van Praag, B. M. S. (1991). Ordinal and cardinal utility: An integration of the two dimensions of the welfare concept. *Journal of Econometrics*, 50(1-2):69–89.

Veenhoven, R. (2008). Healthy Happiness: Effects of Happiness on Physical Health and the Consequences for Preventive Health Care. *Journal of Happiness Studies*, 9(3):449–469.

Wilson, T. D. and Gilbert, D. T. (2005). Affective forecasting - knowing what to want. *Current Directions in Psychological Science*, 14(3):131–134.