PAPERS on Economics & Evolution

1115

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Martin Binder
Alex Coad

The *Papers on Economics and Evolution* are edited by the Evolutionary Economics Group, MPI Jena. For editorial correspondence, please contact: evopapers@econ.mpg.de

ISSN 1430-4716

Max Planck Institute of Economics
Evolutionary Economics Group
Kahlaische Str. 10
07745 Jena, Germany
Fax: ++49-3641-686868

"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]

[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

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, diabetes and cancer. We also take into account differences in "Big Five" personality traits. 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, 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); 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., 2010; Veenhoven, 2010).

[☆]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, Maria Savona, Nick von Tunzelman, Michael Hopkins, Juan Mateos Garcia and other participants at a SPRU seminar 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 repeated cross-sections or 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 argue that the estimation of the *causal* impact of different life events on happiness constitutes a logical extension and should now receive more attention by researchers.

The aim of our paper is thus fourfold. 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 propensity score matching estimators (Rubin, 1974; Imbens, 2004; Caliendo and Kopeinig, 2008). Propensity score 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, propensity score matching is a technique that 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 obscures information on the distribution of covariates in the treatment versus control groups (presumably, the researcher is interested in comparing individuals that have the same values for all covariates). Unless there is substantial overlap in the two 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.

Second, we are interested in analysing 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) health status of individuals and happiness (see also Shields and Wheatley Price, 2005; Graham et al., 2010). 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.

A 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 hypothesised domain specificity of hedonic adaption to different life events (Frederick and Loewenstein, 1999; Clark et al., 2008a).

A fourth contribution of our paper lies in examining whether different health conditions impact subjective well-being differently for individuals that differ with respect to personality traits, as measured via the "Big Five" personality domains (McCrae and Costa, 2003; Benet-Martinez and John, 1998; Gosling et al., 2003). While personality inventories are usually taken only for smaller specialised data sets, a short version of the Big Five personality inventory has recently been added to the British Household Panel Survey (BHPS), a large-scale, nationally representative sample of the British populace. We use these responses to identify the individuals that score highly (or lowly) in the corresponding personality dimensions and examine whether these (stable) personality traits influence how health impacts on subjective well-being (Clark and Georgellis, 2010, have similarly analyzed the impact personality traits have on subjective well-being when getting unemployed or divorced).

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 happiness

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). Psychological research has established the reliability and validity of such subjective well-being constructs (Diener et al., 1999; Helliwell, 2006), showing that these measures capture indeed what they claim to do. The test-retest reliability of subjective well-being constructs lies between 0.5 and 0.7 (over two weeks, both for cognitive and affective measures, see Krueger and Schkade, 2008).[1]

The areas of research that have probably received the most attention so far are the relationship between happiness and income (e.g., Oswald, 1997; Easterlin, 2001; Stevenson and Wolfers, 2008; Clark and Senik, 2010), happiness and health as well as happiness and the social domain (with marriage and divorce maybe the most prominent covariates, see, e.g.

[1] The use of such psychological concepts in economics has rightly seen a recent upsurge, considering the limits a psychology-free economics faces when trying to explain human behaviour (on this, see Ng, 1997; Layard, 2006; Bruni and Sugden, 2007).

Plagnol and Easterlin, 2008). Another well-researched area concerns the effects of unemployment on happiness (see, e.g., Clark and Oswald, 1994; Lucas et al., 2004; Kassenboehmer and Haisken-De New, 2009). While personality traits, belonging to the category of individual determinants, 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), most empirical analyses neglect this insight, a possible source of omitted variable bias. The reason personality traits are usually not covered in these analyses, it can be conjectured, is that large-scale data sets, such as the BHPS (or the German Socio-Economic Panel, SOEP) only very recently incorporated personality trait scales into the survey questionnaires.

The happiness-health relationship 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 broader "mental well-being" measures 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). It seems that causality in this domain runs in both directions: a high level of well-being seems certainly 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). 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).[2]

The much stronger relationship seems to run from health to happiness. Healthier individuals tend to be happier. For example, acute or chronic illness decreases well-being and so does disability (Easterlin, 2003; Shields and Wheatley Price, 2005). Important in this context is the time dimension as individuals can adapt differently to different health conditions. While there is indeed reason to believe that some adaptation occurs, it is 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. If hedonic adaptation to adverse health would be complete, people should —over their life cycle— self-report a similar level of health. Although age objectively decreases health, this should not show in self-reports if the above contention were true. This is not borne out by empirical data: self-reported health declines with age (Easterlin, 2003, finds this effect for US data). Those whose health declines also report lower happiness levels.

As opposed to disability, which allows for cognitive adaptation (such as adaptive preference formation) to happen, 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). Studies in this field are complicated by the progressive nature of some of the diseases (Dolan and Kahneman, 2008, pp. 218-9).[3] In sum, acute or chronic illness decreases well-being as well as disability. Moreover, over time, hedonic adaptation to chronic

[2] A causal relationship from subjective well-being to health could play an important role for preventive healthcare (Veenhoven, 2010).

[3] Similar problems of adaptation pertain to cases of loss and bereavement. Adaptation in terms of regaining previous levels of well-being after the loss of a loved one can take a decade or, if measured by depression rates, even up to two decades. Here adaptation seems to work very slowly (Carnelley et al., 2006).

pain or disability seems limited (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). It is still debated to what extent happiness can be permanently influenced by life events. Set point theory of happiness argues that the stability is more predominant and events like illness, marriage, income shifts only have transitory influence. Headey (2010) gives a useful discussion of the limits of this theory and presents convincing evidence that set point theory is wrong if it argues for full adaptation. In line with many other studies on hedonic adaptation, he shows that adaptation is very domain-specific and adaptation in some domains is complete after some time, and in others not. He also shows that depending on the definition of set points, 14% to 33% of the individuals in the German Socio-Economic Panel (SOEP) data set have major changes in their set point of happiness over the long 20 year time horizon (Headey, 2010, p. 14). Longitudinal data reveals that some domains have effects on happiness that are lasting, which are marriages (Zimmermann and Easterlin, 2006), children (Kohler et al., 2005) and unemployment (the latter especially for males, see Clark et al., 2008a).

Nevertheless, it is plausible that subjective well-being is also partly fixed and stable, having trait-like *and* state-like characteristics (Diener et al., 1999, p. 280), since it is determined to some extent by genes (Lykken and Tellegen, 1996) and by quite stable psychological personality traits (Diener and Lucas, 1999). The influence of genes is only moderate at specific points in time and it is quite natural that the long-term average of subjective well-being should be more likely to be influenced by stable factors such as genes or personality. While this is not the place to discuss the extent of genetic determination and the associated difficulties with heritability studies (but see the discussion in Diener et al., 1999, pp. 279-80), we want to point out the unique opportunity the BHPS offers researchers in analysing how personality traits affect subjective well-being. As Dolan et al. (2008) lament (p. 94), despite extensive psychological research in this field, few studies use large scale survey data to examine the happiness-personality relationship. This is unfortunate since empirical evidence points to the important role that personality traits play for subjective well-being (DeNeve and Cooper, 1998; Gutiérrez et al., 2005). With surveys now starting to include personality inventories, we are able to make use of respondents' self-ratings along the "Big Five" personality dimensions of "Extraversion", "Agreeableness", "Conscientiousness", "Neuroticism" and "Openness" (Digman, 1990; McCrae and Costa, 2003; Gosling et al., 2003).[4] These "[f]ive dimensions represent personality at the broadest level of abstraction, and each dimension includes a large number of distinct, more specific personality characteristics" (Benet-Martinez and John, 1998, p. 730). Extraversion refers to sociability, assertiveness, activity, positive emotions (etc.), while Agreeableness refers to one's quality of interpersonal relations, describing traits such as altruism, trust, cooperation and such. Conscientiousness describes goal-directed task behaviour and socially mandated impulse control. Neuroticism relates to emotional instability, anxiety and irritability and Openness details traits related to creativ-

[4]We capitalise these traits when referring to their specific meaning as a "Big Five" personality trait.

ity, flexibility, or the extent of one's experiences more general. The latter trait is probably the most vaguely described and controversial (DeNeve and Cooper, 1998, p. 199). Despite the fact that personality traits could be further disaggregated within the five dimensions, the "Big Five" are widely recognised as an empirically driven and useful characterisation of personality. Their high level of abstraction (and a certain vagueness about the many subtraits contained in each dimension) also facilitates their robust use across different cultural contexts (Benet-Martinez and John, 1998). While it cannot be denied that personality can evolve over time especially when young or over long time horizons (for evidence from the BHPS, see Donnellan and Lucas, 2008), 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 (Hampson and Goldberg, 2006).[5] It is also believed these personality traits are partly inheritable (Jang et al., 1996).

In the context of subjective well-being, it is not surprising that personality traits should play a significant role when one thinks about how these traits impact on individuals' lives and their experiences in important life domains. Psychological research suggests that especially Extraversion and Neuroticism should influence subjective well-being (DeNeve and Cooper, 1998). There is less theoretical conviction and empirical evidence for the other three dimensions, although it has been suggested that Agreeableness and Conscientiousness might also have a positive bearing on SWB through facilitating positive experiences and social interactions (see, e.g., Hayes and Joseph, 2003). Since Openness would facilitate positive as well as negative experiences, no expectations seem *prima facie* reasonable. Large scale evidence so far found moderate relationships between personality traits and subjective well-being (Helliwell, 2006). 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). Using also BHPS data, Clark and Georgellis (2010) found that regarding their subjective well-being, extroverts suffered less over time from unemployment.

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 randomised 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 randomisation process in clinical trials ensures that there are no systematic differences between the control group and the treatment group – that is why randomised experiments are considered to be positioned at the top of the hierarchy of empirical techniques (Imbens, 2010). Randomised trials can be expected to yield treatment and control groups that are comparable

[5] See Srivastava et al. (2003) on how schooling, parental background but also job and social environment can affect personality traits beyond childhood stages.

in terms of both observable and unobserved characteristics. However, establishing a counterfactual is much harder when the researcher is not dealing with randomised 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 randomised laboratory experiment in which half the participants are subjected to long-term ill-health, this would be morally unacceptable. As such, a randomised trial is not feasible here, and so the best we can do is aim to recreate the conditions of a randomised 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 (life satisfaction) and participation in the treatment (i.e. experience of the bad health condition) are independent for individuals with the same set of exogenous characteristics. Under this assumption, we have:

$$Y(D=0), Y(D=1) \perp D|X, \tag{1}$$

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 as being 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:

$$0 < P(D=1|X) < 1 \tag{2}$$

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. First, we apply the nearest-neighbour matching estimator outlined in Abadie et al. (2004), which finds the nearest neighbour from the control group for each of the dimensions of X. If we have many matching covariates X, however, it becomes prohibitively difficult to find good matches for individuals in all dimensions simultaneously. On the one hand, it has been argued that omitting important variables can seriously increase bias in the resulting estimates (Heckman et al., 1997; Dehejia and Wahba, 1999). On the other hand, however, including too many variables should also be avoided, because it becomes more difficult to find suitable matches, and the variance of the estimates increases. 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.

We complement our multidimensional matching with propensity score matching, which does not suffer from dimensionality problems when a large number of matching covariates are considered. 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 neighbour matching, which is:

$$Y(0), Y(1) \perp D | P(X) \tag{3}$$

where $P(X)$ is the propensity score given the observed covariates X.

3.2. Data set and indicator selection

The British Household Panel Survey (BHPS), comprising about 15,000 individual interviews, is a longitudinal survey of private households in Great Britain that contains rich information on diverse areas of the respondents' lives.[6]

We are using unbalanced panel data from 1996 to 2008 (waves f to p) and have a total of $100,237$ 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), leaving us with a total of 9 waves. Our variables are depicted in Table 1. While our main analysis will focus on the matching methodology described above, a benchmark will be a set of preliminary regressions, where we analyze the impact of different health conditions on life satisfaction.

From the 1996 wave onwards, the BHPS offers a life satisfaction question which is going to be 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). Note that we will later on implicitly interpret this well-being measure as cardinal in our OLS regressions. Such an interpretation is common in the psychological literature on well-being, and it has been shown that there are no substantial

[6]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).

	(1)			
	mean	sd	min	max
life satisfaction	5.2263	1.2936	1	7
subj. health	3.8031	0.9494	1	5
doc visits	2.4196	1.2003	1	5
accidents	0.1197	0.3879	0	4
log(hosp. days)	0.1827	0.6134	0	5.9026
no. cigarettes	3.9455	7.9391	0	80
d_hp_arms	0.2846	0.4512	0	1
d_hp_sight	0.0516	0.2211	0	1
d_hp_hearing	0.0868	0.2815	0	1
d_hp_allergy	0.1213	0.3265	0	1
d_hp_chest	0.1375	0.3444	0	1
d_hp_heart	0.1720	0.3774	0	1
d_hp_stomach	0.0806	0.2722	0	1
d_hp_diabetes	0.0366	0.1878	0	1
d_hp_anxiety	0.0822	0.2747	0	1
d_hp_drugs	0.0053	0.0727	0	1
d_hp_epilepsy	0.0083	0.0908	0	1
d_hp_migraine	0.0827	0.2754	0	1
d_hp_other	0.0490	0.2158	0	1
d_hp_cancer	0.0088	0.0936	0	1
d_hp_stroke	0.0074	0.0855	0	1
Extraversion	13.3741	3.5399	3	21
Agreeableness	16.3053	3.0000	3	21
Openness	13.3112	3.6482	3	21
Neuroticism	10.9366	3.9452	3	21
Conscientiousness	15.8603	3.2417	3	21
log(income)	9.9181	0.6235	-0.4406	13.641
d_cohabiting	0.6407	0.4798	0	1
d_married	0.5349	0.4988	0	1
d_separated	0.0212	0.1441	0	1
d_widowed	0.0814	0.2734	0	1
d_divorced	0.0830	0.2759	0	1
d_employed	0.5092	0.4999	0	1
d_unemployed	0.0333	0.1794	0	1
d_selfemployed	0.0680	0.2518	0	1
d_retired	0.2136	0.4099	0	1
d_studyschool	0.0520	0.2221	0	1
d_maternityleave	0.0043	0.0654	0	1
d_longtermsick	0.0440	0.2050	0	1
d_familycare	0.0695	0.2543	0	1
d_other	0.0061	0.0776	0	1
d_disabled	0.0896	0.2856	0	1
gender	0.5328	0.4989	0	1
age	45.8385	18.5201	15	99
education	4.8515	2.9022	1	9
no. kids	0.5983	0.9714	0	9
Observations	100237			

Table 1: Summary statistics. Observations pooled over years.

differences between both approaches in terms of the results they generate (Ferrer-i-Carbonell and Frijters, 2004).[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. It is still debated whether objective health is sufficiently well measured by subjective health assessments (Johnston et al., 2009). Especially in the context of accounting for per-

[7]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).

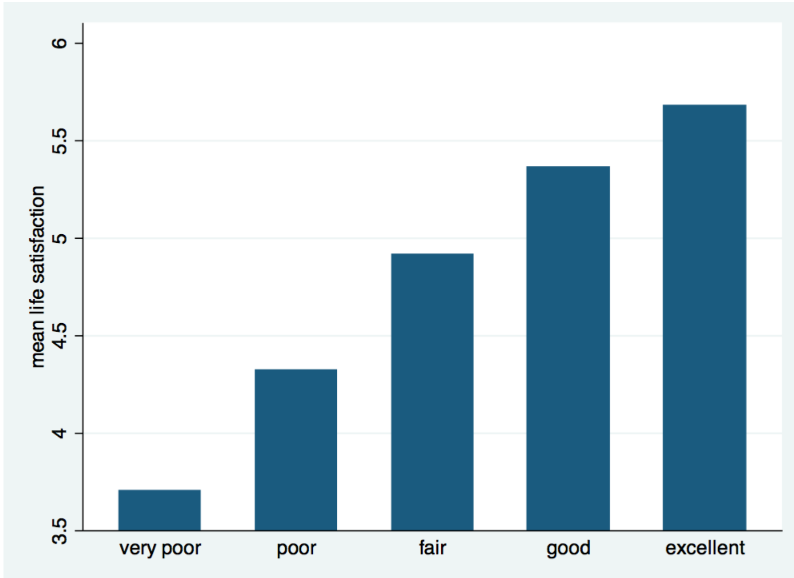

Figure 1: Mean life satisfaction by subjective health assessment (1="very poor" health . . . 5="excellent" health).

sonality traits, one should be aware that Neuroticism seems to be a personality trait that influences both self-reported health and subjective well-being (Okun and George, 1984). In the BHPS, an individual's subjective assessment of health (during the last 12 months) is ordinally scaled on a five point Likert scale, ranging from "excellent" (five) to "very poor" (one).[8] 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).[9] The large effect of health on life satisfaction can be seen in Figure 1, where mean life satisfaction in our sample is plotted according to the five different health categories (from "poor" (1) to "excellent" (5)). The evidence in Figure 1 suggests an approximately linear relationship between health and life satisfaction. Figure 2 shows changes in life satisfaction resulting from changes in subjective health status.

Apart from these measures of individual health, 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)", "Difficulty in seeing (other than needing glasses to read

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

[9] Hospital days are given as (log) days, while 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.

	coefficient (standard error)
-2 or more	-0.4317
	(0.0333)
-1	-0.1579
	(0.0120)
no health change	-0.0041
	(0.0061)
+1	0.1421
	(0.0117)
+2 or more	0.3656
	(0.0358)
Observations	57579

Table 2: Transition matrix: mean change in (7 point scale) life satisfaction between two years for different changes in subjective health.

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" (in Table 1, these are coded as "d_hp_xxx"). Individuals can solely answer whether 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. Apart from these conditions, 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 hypothesised to play a major role in influencing individuals' well-being through various complicated 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. 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).[10] Three questions supposedly capture each of the five traits (each is answered on a 7-point Likert scale from "Does not apply" to "Applies perfectly"). How valid and reliable can these answers measure an individual's personality trait? Psychological research has assessed this question for quite some time. While we take as given the existence of the five broad and abstract personality traits here, it is useful to explore whether a fifteen question inventory can really adequately measure them. Usual inventories in psychological questionnaires use much larger inventories with 44 or more questions (e.g. the "Big Five Inventory", BFI, John et al., 1991). These have been established to robustly capture the Big Five personality traits over different cultural and inter-temporal contexts (Benet-Martinez and John, 1998; McCrae and Costa, 1997). Empirically, a standard measure to judge the internal consistency of the scale and the items used to measure it is Cronbach's alpha. Big Five inventories here usually reach the threshold value of 0.7 that denotes satisfactory consistency and scale reliability. This is not the case for shorter versions (Gosling et al., 2003; Donnellan and

[10] A full list is provided, e.g., by Clark and Georgellis (2010).

Lucas, 2008), and our calculations show indeed that $\alpha < 0.70$ for our traits as measured by the short inventory (Openness: $\alpha = 0.6739$, Conscientiousness: $\alpha = 0.5056$, Extraversion: $\alpha = 0.5557$, Agreeableness: $\alpha = 0.5218$, Neuroticism: $\alpha = 0.6786$). This need not necessarily invalidate the measures, however, for several reasons. First, shorter inventories were used and analyzed in several studies and have proven to be reliable despite lower alphas (Gosling et al., 2003; Gerlitz and Schupp, 2005). Second, one has to be aware of the fact that higher alphas are generally reached just by increasing the number of items for a construct, so that larger inventories imply higher alphas (Cortina, 1993). This caveat has prompted an analysis of a similar short inventory in terms of different measure of goodness of fit and a comparison between the short and long version for the German Socio-Economic Panel data set (SOEP), which proved to be satisfactory despite similarly low alphas as in the BHPS case (Gerlitz and Schupp, 2005). A last rationale is pragmatic: eliciting personality traits in large-scale repeated surveys via long inventories is simply impractical and quicker (more dirty) inventories are needed if one wants to measure personality traits on such a large scale. This clearly means one has to make trade-offs between very high scale reliability and availability of any measures at all.

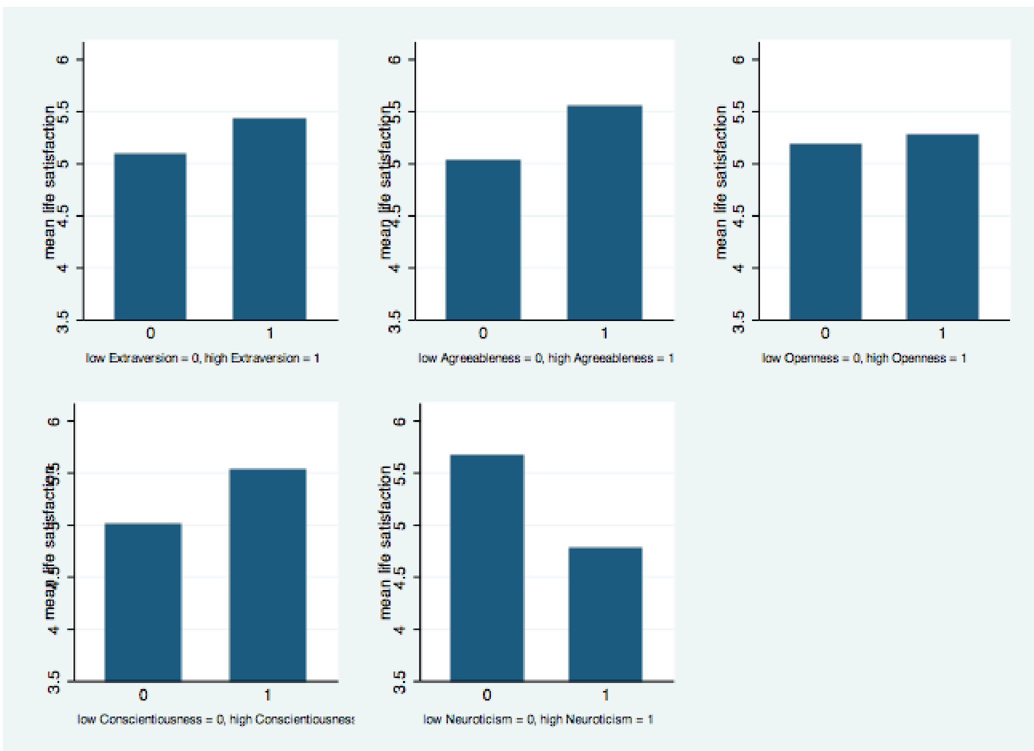

Figure 2: Comparison of mean life satisfaction for high and low personality trait expressions (1="high" vs. 0="low" personality trait).

In Table 1 we present means and standard deviations for the Big Five, which are in the range of 10.94 (Neuroticism) to 16.31 (Agreeableness). These variables were coded by adding up the ordinal responses to the three questions relating to each personality trait.[11]

[11]Some questions had to be reverse-coded, as they negatively measure the trait. It is still an open question

Figure 2 shows a comparison of mean life satisfaction for high versus low personality traits. All differences of means are highly significant (Levene's test for unequal variances of the pairs was conducted in each case, prompting to use t-tests with unequal variances for this exercise).

A final caveat should be noted here as regards our assumption of stable personality traits over our sample horizon. As detailed in Section 2, there is some controversy about how stable the Big Five personality traits are in adults. While the high level of abstraction and great degree of heritability gives a plausible case that personality is quite stable over the short run, it has become disputed that these traits are completely invariant. Some evidence points to the fact that personality is subject to change also if one is over thirty years (*pace* Costa and McCrae, 1994). This is not altogether implausible if one considers how important or scarring life events can alter the trajectories of human (well-) being (Srivastava et al., 2003). What also seems clear is that stability of personality traits is increasing in age: test-retest reliability in childhood ranges between 0.22-0.53 and increases to 0.70-0.79 for adults (Hampson and Goldberg, 2006; Roberts et al., 2006; Roberts and DelVecchio, 2000). Since the Big Five were only asked in the BHPS once so far, we are forced by data limitations to consider personality traits to be fixed in the individuals over the course of our sample horizon. It would be certainly desirable to have further waves of the BHPS to include the Big Five inventory again, in order to get a better understanding of the plausibility of our implicit assumption.

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. This assumption of a decreasing marginal utility of income, has been found to be well-corroborated and quite similar in a wide range of countries, and although the functional form of the happiness-income relationship is slightly more concave than implied by the logarithm, using log(income) seems to be a reasonable approximation (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

whether one would best add up these components are use averages (Heineck, 2011). Clark and Georgellis (2010) interpret values of greater than five for each question as expression of a high prevalence of the personality trait and values below 3 as low. As the personality distributions are quite skewed in some cases (especially for Agreeableness and Conscientiousness), this coding scheme would lead to very small sample sizes for the low-personality trait groups so that 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 more appropriate.

marital status dummies (e.g., cohabiting, being 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, 53.28% were female (the gender variable is one if female, zero if male). The mean age is 45.84 years (s.d. 18.52) with maximum age at 99 years and minimum age at 15 (younger individuals were not interviewed in the BHPS). 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.

To get a first impression of our data, Table 3 reports pairwise correlations between the variables of interest. The correlations of most of our indicators are highly statistically significant and we can find no problems of multicollinearity. It is also instructive to see how personality traits are correlated with some of our variables (see Table 6 in the Appendix). While Openness is only very weakly correlated with life satisfaction ($r = 0.0308$), there is stronger correlation between life satisfaction and Agreeableness ($r = 0.1273$), Extraversion ($r = 0.1028$) and Conscientiousness ($r = 0.1673$). Neuroticism is strongly negatively related with life satisfaction ($r = -0.2826$), in line with the psychological findings discussed in Section 2. Also of note are the high correlation between the level of education and the trait of Openness ($r = 0.2743$), while the other traits only weakly correlate with education (of course, this correlation begs the question whether open-minded individuals are more likely to seek more education or whether higher levels of education lead to more open-mindedness). While Neuroticism is strongly related to gender ($r = 0.2555$; to being female, the way gender is coded), the opposite holds for the Openness trait and gender ($r = -0.0759$). Finally, Conscientiousness is highly correlated with Agreeableness ($r = 0.3890$, but also with Extraversion, $r = 0.1973$, and Openness, $r = 0.2532$). In sum this correlation analysis can only be a first approximation and one should probably not put too much emphasis on these correlations (since no relevant control variables are included here).

4. Results

Our results are grouped in three parts. A preliminary baseline regression exercise is depicted in Table 4. These regressions are repeated for high trait characteristics in Table 7 in the Appendix, and then we give the estimates of the causal impact of different health impairments in Table 5. The BHPS dataset offers unique and comprehensive information on individual characteristics, which help in finding a suitable twin for each individual suffering from certain illnesses, and thus recreate an appropriate control group in our analysis of how strong the decrease in life satisfaction is which is associated with this ailment.

4.1. Regressions

Table 4 presents six different models that give an orientation of the life satisfaction health relationship. Models (1) and (2) are ordered probit regressions that pool the data over all waves and treat the observations as one large cross-section (standard errors are clustered on the individual though). This does, of course, neglect important structural facts about the data, such as individual-specific time-invariant components and the like. Nevertheless, it

	life satisfaction	subj. health	log(income)	d_disabled	d_unemployed	d_employed	education	age	gender
life satisfaction	1.0000								
subj. health	0.3304***	1.0000							
	(0.0000)								
log(income)	0.0741***	0.1386***	1.0000						
	(0.0000)	(0.0000)							
d_disabled	-0.1472***	-0.3678***	-0.0763***	1.0000					
	(0.0000)	(0.0000)	(0.0000)						
d_unemployed	-0.0882***	-0.0254***	-0.1156***	-0.0237***	1.0000				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
d_employed	0.0067*	0.2264***	0.3007***	-0.2525***	-0.1890***	1.0000			
	(0.0344)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
education	-0.0064*	0.2027***	0.3092***	-0.1702***	-0.0541***	0.2764***	1.0000		
	(0.0425)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
age	0.0883***	-0.1908***	-0.0409***	0.2512***	-0.1102***	-0.3843***	-0.2719***	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
gender	-0.0039	-0.0658***	-0.0646***	0.0040	-0.0486***	-0.0741***	-0.0607***	0.0316***	1.0000
	(0.2226)	(0.0000)	(0.0000)	(0.2040)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Observations	100237								

P-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Contemporaneous correlations. Observations pooled over years.

serves as a baseline and also allows us to underline the contention that including personality traits (Model 2) improves the model fit (Pseudo-R^2 of 0.088 in Model 2 versus 0.068 in Model 1). Otherwise, there are largely the same significant coefficients (also, inclusion of personality traits decreases many in size, as variance is capture by the personality traits). In accordance with findings in the literature (see Section 2), we find a strong positive association between life satisfaction and subjective health, cohabitation, retirement and maternity leave. Coefficient size for (log equivalised) income and self-employment is still positive but much smaller. In the pooled analysis, life satisfaction is positively related to being female, something we have not observed in our correlations, but much more important: something that is usually not corroborated in the literature (Plagnol and Easterlin, 2008; Binder and Coad, 2011). A t-test cannot reject the null hypothesis of equal means for males and females in our data set, so we would be careful about this association. A slight negative association is observable for life satisfaction and education, but again, this effect has been shown to be rather unstable in the literature (Dolan et al., 2008; Binder and Coad, 2011). We find strong negative associations between life satisfaction and unemployment and separation. With regard to our health variables, we can observe strong negative associations for disability and two health conditions, viz. problems relating to anxiety and stroke. Several other conditions seem associated with smaller decreases in life satisfaction, such as problems with arms, sight, hearing, allergies, stomach, migraine and other health problems.[12] For our personality variables, we can see that Agreeableness, Extraversion and Conscientiousness are positively associated with life satisfaction, while Neuroticism and Openness (the latter very weakly) show a negative association. These associations bear out the expectations discussed in Section 2.

[12] A strong negative association between drug related health problems disappears when adding the personality controls into the regression equation.

	(1) life sat. (pooled)		(2) life sat. (pooled, B5)		(3) life sat. (FE)		(4) life sat. (FE, no subj.health)		(5) life sat. (male)		(6) life sat. (female)	
main												
subj. health	0.3265***	(50.87)	0.2916***	(37.82)	0.1838***	(28.54)			0.1694***	(18.67)	0.1951***	(21.58)
doc visits	0.0059	(1.24)	0.0014	(0.24)	-0.0082	(-1.85)	-0.0412***	(-9.38)	-0.0189**	(-2.89)	-0.0007	(-0.11)
accidents	0.0073	(0.74)	-0.0093	(-0.79)	-0.0196*	(-2.02)	-0.0247*	(-2.50)	-0.0260*	(-2.09)	-0.0127	(-0.83)
log(hosp. days)	0.0028	(0.37)	0.0060	(0.63)	-0.0125	(-1.65)	-0.0407***	(-5.38)	-0.0251*	(-2.10)	-0.0034	(-0.35)
d_disabled	-0.1507***	(-6.95)	-0.1684***	(-6.20)	-0.1481***	(-6.64)	-0.1725***	(-7.64)	-0.1380***	(-4.51)	-0.1536***	(-4.82)
no. cigarettes	-0.0063***	(-8.54)	-0.0063***	(-7.04)	-0.0025*	(-2.11)	-0.0026*	(-2.21)	-0.0028	(-1.84)	-0.0021	(-1.13)
d_hp_arms	-0.0521***	(-4.26)	-0.0473**	(-3.28)	-0.0304**	(-2.68)	-0.0624***	(-5.46)	-0.0133	(-0.85)	-0.0465**	(-2.85)
d_hp_sight	-0.0967***	(-4.34)	-0.0803**	(-2.86)	-0.0485*	(-2.24)	-0.0578**	(-2.64)	-0.0347	(-1.07)	-0.0593*	(-2.05)
d_hp_hearing	-0.0601**	(-2.92)	-0.0340	(-1.34)	-0.0543**	(-2.63)	-0.0551**	(-2.64)	-0.0529*	(-1.97)	-0.0568	(-1.78)
d_hp_allergy	-0.0460**	(-3.21)	-0.0412*	(-2.39)	-0.0296	(-1.94)	-0.0323*	(-2.09)	-0.0255	(-1.10)	-0.0315	(-1.56)
d_hp_chest	-0.0058	(-0.37)	-0.0019	(-0.10)	0.0046	(0.25)	-0.0296	(-1.64)	0.0059	(0.24)	0.0034	(0.13)
d_hp_heart	0.0060	(0.38)	0.0087	(0.45)	-0.0013	(-0.08)	-0.0245	(-1.54)	-0.0046	(-0.21)	0.0033	(0.15)
d_hp_stomach	-0.0710***	(-4.01)	-0.0624**	(-2.89)	-0.0134	(-0.76)	-0.0484**	(-2.73)	-0.0140	(-0.54)	-0.0115	(-0.49)
d_hp_diabetes	0.0649*	(2.02)	0.0182	(0.48)	0.0281	(0.66)	-0.0050	(-0.12)	0.0227	(0.40)	0.0358	(0.55)
d_hp_anxiety	-0.5857***	(-30.86)	-0.4645***	(-19.80)	-0.3845***	(-17.80)	-0.4338***	(-19.77)	-0.4649***	(-12.33)	-0.3467***	(-13.18)
d_hp_drugs	-0.2337***	(-3.83)	-0.1161	(-1.50)	-0.1128	(-1.34)	-0.1430	(-1.69)	-0.1593	(-1.52)	-0.0050	(-0.04)
d_hp_epilepsy	-0.0819	(-1.32)	-0.0023	(-0.03)	-0.0665	(-0.77)	-0.0865	(-0.99)	-0.1581	(-1.13)	0.0194	(0.20)
d_hp_migraine	-0.0774***	(-4.35)	-0.0673**	(-3.13)	-0.0639**	(-3.27)	-0.0836***	(-4.23)	-0.0435	(-1.26)	-0.0710**	(-3.02)
d_hp_other	-0.0582**	(-2.91)	-0.0559*	(-2.37)	-0.0501*	(-2.52)	-0.1015***	(-5.07)	-0.0559	(-1.68)	-0.0480	(-1.94)
d_hp_cancer	-0.0088	(-0.17)	-0.0532	(-0.89)	0.0289	(0.59)	-0.0377	(-0.75)	-0.0577	(-0.79)	0.0908	(1.38)
d_hp_stroke	-0.2393***	(-3.72)	-0.2426**	(-3.18)	-0.1697**	(-2.70)	-0.1873**	(-2.97)	-0.1454	(-1.79)	-0.1955*	(-2.05)
log(income)	0.0584***	(7.23)	0.0674***	(6.61)	0.0231**	(2.64)	0.0236**	(2.67)	0.0301*	(2.51)	0.0173	(1.36)
age	0.0033***	(5.42)	0.0021**	(2.82)	-0.0134	(-0.99)	-0.0151	(-1.09)	0.0096	(0.53)	-0.0313	(-1.72)
(age-mean age)^2	0.0003***	(11.74)	0.0003***	(10.59)	-0.0000	(-0.40)	-0.0000	(-0.79)	0.0002*	(2.44)	-0.0001*	(-2.50)
no. kids	-0.0512***	(-8.38)	-0.0556***	(-7.66)	-0.0075	(-0.88)	-0.0077	(-0.89)	-0.0001	(-0.01)	-0.0147	(-1.17)
education	-0.0286***	(-12.47)	-0.0240***	(-8.44)	0.0080	(0.91)	0.0083	(0.93)	0.0005	(0.04)	0.0149	(1.17)
d_cohabiting	0.2595***	(15.23)	0.2641***	(12.73)	0.1930***	(8.10)	0.1915***	(7.96)	0.1780***	(5.36)	0.2106***	(6.20)
d_married	0.0249	(1.28)	0.0108	(0.46)	-0.0241	(-0.94)	-0.0222	(-0.85)	0.0243	(0.65)	-0.0694	(-1.94)
d_separated	-0.1365***	(-4.08)	-0.1758***	(-4.49)	-0.0459	(-1.00)	-0.0499	(-1.07)	-0.0586	(-0.89)	-0.0416	(-0.66)
d_divorced	-0.0495*	(-1.98)	-0.0616*	(-2.08)	0.0634	(1.56)	0.0659	(1.61)	0.1005	(1.70)	0.0284	(0.51)
d_widowed	-0.0030	(-0.09)	-0.0472	(-1.13)	-0.1017	(-1.67)	-0.0999	(-1.62)	-0.0135	(-0.14)	-0.1572*	(-2.01)
d_unemployed	-0.2194***	(-8.40)	-0.1998***	(-6.02)	-0.3099***	(-10.97)	-0.3141***	(-11.01)	-0.3398***	(-8.67)	-0.2826***	(-6.96)
d_selfemployed	0.0565**	(2.87)	0.0375	(1.66)	-0.0065	(-0.29)	-0.0020	(-0.09)	0.0124	(0.46)	-0.0411	(-1.02)
d_retired	0.2884***	(12.03)	0.3054***	(10.62)	0.0592*	(2.40)	0.0560*	(2.24)	0.0746*	(2.04)	0.0497	(1.50)
d_studyschool	0.1503***	(7.13)	0.1781***	(6.67)	0.0799**	(2.84)	0.0719*	(2.53)	0.0575	(1.37)	0.1009**	(2.66)
d_maternityleave	0.3382***	(7.07)	0.3939***	(7.33)	0.2814***	(6.48)	0.3313***	(7.51)	0.3457	(1.28)	0.2688***	(6.00)
d_longtermsick	-0.0186	(-0.59)	0.0058	(0.15)	-0.2882***	(-7.58)	-0.3394***	(-8.78)	-0.3318***	(-5.68)	-0.2473***	(-4.94)
d_familycare	0.0566*	(2.50)	0.1140***	(4.28)	-0.0576*	(-2.43)	-0.0607*	(-2.52)	-0.2128*	(-2.20)	-0.0491	(-1.92)
d_other	0.0575	(1.12)	0.0588	(0.99)	-0.0087	(-0.16)	-0.0178	(-0.33)	-0.1188	(-1.48)	0.0769	(1.08)
gender	0.0756***	(6.14)	0.0961***	(6.16)								
Neuroticism			-0.0505***	(-23.05)								
Openness			-0.0089***	(-3.65)								
Agreeableness			0.0309***	(10.90)								
Extraversion			0.0181***	(7.94)								
Conscientiousness			0.0284***	(10.79)								
Observations	100237		75798		100237		100237		46835		53402	
R^2					0.048		0.034		0.051		0.048	
Pseudo R^2	0.068		0.088									
r2_w					0.0478		0.0339		0.0508		0.0479	
r2_b					0.0533		0.0223		0.1825		0.0072	
r2_o					0.0484		0.0205		0.1517		0.0078	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Baseline regression analysis: Ordered Probit and Fixed-Effect (FE) regressions.

The middle two columns (models (3) and (4)) now repeat this analysis within a fixed-effects (FE) regression framework, controlling for time-invariant individual-specific components (standard errors are clustered on the individual). Accounting for fixed effects in happiness regressions does substantively alter regression results, a fact happiness researchers need to take into account (Ferrer-i-Carbonell and Frijters, 2004). But due to the fact that happiness is partly determined by genes and stable personality traits (Lykken and Tellegen, 1996; Diener et al., 1999), accounting for fixed effects is nevertheless the preferable model choice. Model (3) here depicts the FE-version of model (1) and model (4) is a robustness test where we exclude the subjective health measure. The idea behind model (4) 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 in model 4, coefficients of negative health conditions increase in size as opposed to the model where subjective health ratings are included.

We can observe that some of the associations for the cross-section disappear when controlling for individual-specific time-invariant effects in our regressions. This pertains, for example, to the relationship between education and life satisfaction, but also for age or the number of children (which showed only weak associations in the cross-section anyways). We also find no significant relationship for separation, widowhood, or being divorced which is surprising given usual results in the literature (being widowed is significant at the 10% level though). A relationship between self-employment and life satisfaction usually also does not bear out in such a context (see Andersson, 2008). 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 or stroke (it is interesting to note that the decrease of life satisfaction due to stroke seems to be driven by the effect on females, compare Models 5 and Model 6, which show a gender disaggregation). There are also less strong negative effects from problems with arms, sight, hearing, allergies, migraine and other health problems on life satisfaction. We find highly significant positive coefficients for cohabiting and also for maternity leave. For the latter, however, this effect seems solely restricted to females — no big surprise considering the negligible number of males being on paternity leave in this sample. Finally, there is also a significant effect of income on life satisfaction (smaller than in Models 1 and 2), which in the gender disaggregation seems to be driven by the male subsample.

4.2. Disaggregating by personality traits

We have also run regressions for subgroups grouped according to personality characteristics (results are given in Table 7 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. Extrovert individuals suffer more strongly from ill health and disability than their less extrovert peers. Similar to conscientious and open individuals, they suffer stronger from anxiety disorders than less extrovert, conscientious or open 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 cohabitation with a partner or 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 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 cohabitation and 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. For the latter, it is also important to note that cohabitation has a very large positive impact on subjective well-being, while being married on the other hand has an even as large negative coefficient. What specific characteristic about the formal bond of marriage causes this reversal might be fruitfully explored in future work.[13]

4.3. Matching estimates

While FE models are certainly preferable to simple pooled models for panel data, we may be "overcontrolling" and removing some slow-changing variables of interest. Furthermore, fixed-effect regression suffers from other drawbacks of regression models discussed above (in particular, lack of a common support for treatment and control groups). 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. multidimensional nearest-neighbour matching as well as propensity score matching. Nearest neighbour matching finds a match in many dimensions simultaneously while propensity score matching collapses all covariates into one composite variable (the so-called "propensity score"). For our nearest neighbour matching analysis, we matched individuals according to a smaller number of criteria, namely: previous change in life satisfaction, log(income), gender, age, number of children, education, personality trait scores, dummies for being disabled, being married or cohabiting, as well as for being unemployed or self-employed. Adding more criteria would have made it harder to get good matches in our context.

For the propensity score matching, we did not have pressing concerns of dimensionality (since the matching covariates are collapsed into a synthetic propensity score, and matching is performed with reference to the propensity score only). Therefore with propensity score

[13]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, we matched individuals according to the above-mentioned factors but added also the following list of covariates: ethnicity dummies, year dummies, regional dummies for the different former Metropolitan counties and Inner and Outer London, dummies for being separated, divorced or widowed, a dummy being retired, still studying or in school, being on maternity leave or for family care and a quadratic age term.

	nearest neighbour matching				propensity score matching				transitions	
	t+1		t+2		t+1		t+2		t+1	t+2
	SATE		SATE		ATT		ATT		sick	sick
	z-stat	obs	z-stat	obs	t-stat	obs	t-stat	obs	healthy	healthy
Δ health > −1	-.4194***		-.4516**		-.4855***		-.5007**			
	(-8.20)	19004	(-2.66)	9687	(-9.60)	18955	(-3.00)	9079		
Δ health −1	-.1808***		-.1123**		-.2277***		-.1996***			
	(-9.74)	23661	(-2.96)	10894	(-11.47)	23661	(-5.17)	10864		
Δ health +1	.0013		.0081		-.0544**		-.0081			
	(0.07)	23785	(0.24)	11145	(-2.89)	23785	(-0.24)	11121		
Δ health > +1	.0298		.0160		-.0828		-.0527			
	(0.60)	18899	(0.17)	9795	(-1.75)	18885	(-0.64)	9705		
condition: arms	-.2895***		-.3929***		-.3959***		-.5095***		4560	1298
	(-9.61)	12013	(-5.69)	4771	(-12.23)	12008	(-7.73)	4677	17550	8803
condition: sight	-.3094***		-.1694		-.6064***		-.5789***		1617	305
	(-4.89)	10331	(-1.05)	4299	(-8.61)	10288	(-3.48)	3987	17550	8803
condition: hearing	-.3986***		-.1947		-.5433***		-.3463**		1532	434
	(-5.67)	10366	(-1.57)	4377	(-8.31)	10311	(-3.10)	4284	17550	8803
condition: allergy	-.3278***		-.1604		-.4591***		-.3502***		2445	594
	(-7.92)	10813	(-1.82)	4444	(-9.92)	10805	(-4.00)	4396	17550	8803
condition: chest	-.4460***		-.2758**		-.5815***		-.4124***		2000	490
	(-8.81)	10544	(-2.72)	4386	(-9.83)	10508	(-3.78)	4324	17550	8803
condition: heart	-.4757***		-.5470***		-.5903***		-.4452***		2656	934
	(-8.77)	10950	(-6.08)	4614	(-11.49)	10919	(-5.75)	4573	17550	8803
condition: stomach	-.5150***		-.4751***		-.6262***		-.6318***		2124	459
	(-9.86)	10663	(-3.94)	4379	(-9.83)	10631	(-5.93)	4302	17550	8803
condition: diabetes	-.7589***		-.7329***		-.6786***		-.7872***		358	178
	(-5.05)	9714	(-3.67)	4244	(-5.65)	9549	(-4.26)	4085	17550	8803
condition: anxiety	-1.0659***		-1.0581***		-1.0986***		-1.2133***		1984	451
	(-17.10)	10542	(-7.57)	4381	(-17.98)	10500	(-9.46)	4344	17550	8803
condition: drugs	-.9582***		-1.3862**		-1.3598***		-.9929*		141	19
	(-4.04)	9579	(-3.43)	4162	(-6.90)	8542	(-2.12)	775	17550	8803
condition: epilepsy	-.1626		-1.0446**		-.4411		-1.6430***		76	28
	(-0.61)	9545	(-2.79)	4167	(-1.86)	7267	(-3.68)	2516	17550	8803
condition: migraine	-.4613***		-.6934***		-.6275***		-.7708***		1681	360
	(-8.55)	10342	(-5.32)	4298	(-11.49)	10302	(-5.84)	4216	17550	8803
condition: cancer	-.7536***		-.2486		-.6728***		-.6178**		296	93
	(-4.63)	9694	(-1.06)	4209	(-4.93)	7443	(-2.96)	3401	17550	8803
condition: stroke	-.3339		-.5174		-.7558***		-.8318**		240	65
	(-1.65)	9657	(-1.19)	4190	(-4.31)	7578	(-2.48)	3085	17550	8803
condition: other	-.4330***		-.4724***		-.5555***		-.6741***		1892	293
	(-8.16)	10580	(-3.68)	4301	(-10.25)	10539	(-5.31)	4068	17550	8803

Table 5: Results for matching estimates. Sample Average Treatment Effects (SATEs) and Average Treatment effects for the Treated (ATTs), with z-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 shows the estimates obtained. In our interpretation we focus mostly on the propensity score estimates.[14] The causal impact of a two category decrease in subjective

[14]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

health assessment is highly significant ($-.4855^{***}$) and even a bit stronger after two years ($-.5007^{**}$). A slighter decrease in health (by one category) still affects subjective well-being quite strongly ($-.2277^{***}$ in $t+1$ and $-.1996^{***}$ in $t+2$). Surprisingly, we cannot find a reciprocal effect of increased subjective health rating – the effect is negative and in most 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 effect is in the category alcohol and drug abuse (-1.3598^{***}), followed by anxiety, depression and other mental illnesses (-1.0986^{***}), stroke ($-.7558^{***}$) and diabetes ($-.6786^{***}$) and cancer ($-.6728^{***}$). Migraines ($-.6275^{***}$), problems with sight ($-.6064^{***}$), stomach ($-.6262^{***}$), chest ($-.5815^{***}$), heart ($-.5903^{***}$), hearing ($-.5433^{***}$) and the heterogeneous catch-all "other" condition ($-.5555^{***}$) also depress subjective well-being. Smaller causal effects can be found for arm and allergy problems ($-.3959^{***}$ to $-.4591^{***}$). 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 28 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. (2010) 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. Even if personality traits mediate problems of bad health and their impact on individual life satisfaction, this is much less so the case 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).

It also should be noted that our estimates are conservative in the sense that they might underestimate the impact of these health impacts 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

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 provide these regression diagnostics on request.

has been shown not to affect response rates in the BHPS (Uhrig, 2008, p. 28).

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 cancer). Especially for cancer this seems to be surprising. The findings can be either due to attrition (the worst cases drop out quickly) or due to the fact that many cases of cancer are curable if diagnosed early these days. 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 (hearing, allergy, chest, heart and drug abuse). In other cases, however, the point estimates increase at the second lag (arms, diabetes, anxiety, epilepsy, migraine, stroke and other conditions), 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 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 when considering the nearest-neighbour-matching estimates. The most robust estimates seem to be the arms, chest, migraines and "other" condition, where the inter-temporal dynamics are the same over the different estimators.

Finally, we have examined to what extent individuals recover their lost life satisfaction after recovering from their health impairments (see Table 8 in the Appendix). In line with the asymmetric finding regarding positive (subjectively assessed) health changes, it is striking to observe 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, migraines but also strokes and arm or stomach problems). Overall it seems that "objective" physical conditions (problems with arms, sight etc.) have smaller negative impacts when occurring and 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. (2010) 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 behavioural 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 behaviour accordingly.

Our analysis is not without limitations, one of which is that we measure well-being in terms of life satisfaction. Knabe et al. (2010) show that alternative indicators of well-being are far from perfectly correlated. We have therefore repeated the analysis with a broader concept of "mental well-being" 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. The matching estimators applied in this paper have an advantage over multivariate regressions techniques that are widely used in the related literature. We found that the effect is quite considerable for the general decrease in health ($-.4855$ if subjective health decrease by more than one category) and extends over a longer time period. More puzzling, we could not find a significant effect 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. 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. Causal effects of these conditions on subjective well-being are quite varied (from $-.3959$ for arm problems to -1.3598 with drug abuse). 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, we see that hedonic adaptation is highly domain-specific that the impact of bad health conditions can increase with time (most likely due to the progressive nature of certain illnesses, as in the case of addictions). Moreover, we have examined whether different health conditions impact subjective well-being differently for individuals that differ with respect to personality traits, as measured via the "Big Five" personality domains. We have used these responses to identify the individuals that score highly in the corresponding personality dimensions and have examined whether these stable personality traits influence how health impacts on subjective well-being.

These 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 abolish than conditions where adaptation is quick and strong (Dolan and Kahneman, 2008). Of course, this is not to marginalise the negative impact of health conditions that are subject to adaptation and should in no way trivialise 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 as well be the target of public policies (Graham, 2008, p. 77).

Different health conditions have widely diverging causal impacts on individual's subjective well-being, often also mediated by a person's personality. 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: September 13, 2011

Appendix

	life satisfaction	Extraversion	Agreeableness	Openness	Neuroticism	Conscientiousness	subj. health	education	gender
life satisfaction	1.0000								
Extraversion	0.1028***	1.0000							
	(0.0000)								
Agreeableness	0.1273***	0.1496***	1.0000						
	(0.0000)	(0.0000)							
Openness	0.0308***	0.2975***	0.1917***	1.0000					
	(0.0000)	(0.0000)	(0.0000)						
Neuroticism	-0.2826***	-0.1585***	-0.0649***	-0.0896***	1.0000				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
Conscientiousness	0.1673***	0.1973***	0.3890***	0.2532***	-0.1549***	1.0000			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
subj. health	0.3304***	0.0663***	0.0144***	0.0871***	-0.2004***	0.1205***	1.0000		
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)			
education	-0.0064*	0.0544***	-0.0451***	0.2743***	-0.0318***	0.0479***	0.2027***	1.0000	
	(0.0425)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
gender	-0.0039	0.1015***	0.1594***	-0.0759***	0.2555***	0.0472***	-0.0658***	-0.0607***	1.0000
	(0.2226)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Observations	100237								

P-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Contemporaneous correlations of personality variables. Observations pooled over years.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	E: high	E: low	N: high	N: low	A: high	A: low	O: high	O: low	C: high	C: low
subj. health	0.1916***	0.1646***	0.2286***	0.1226***	0.2070***	0.1765***	0.1836***	0.1622***	0.1681***	0.1993***
	(12.95)	(12.09)	(15.19)	(9.64)	(10.78)	(12.91)	(12.02)	(11.43)	(11.76)	(15.55)
doc visits	-0.0025	-0.0279**	-0.0034	-0.0170	-0.0057	-0.0216*	-0.0110	-0.0242*	-0.0066	-0.0155
	(-0.24)	(-2.98)	(-0.33)	(-1.93)	(-0.41)	(-2.22)	(-0.99)	(-2.57)	(-0.63)	(-1.80)
accidents	-0.0346	-0.0360	-0.0103	-0.0411*	0.0010	-0.0427*	-0.0479*	-0.0057	0.0032	-0.0141
	(-1.67)	(-1.63)	(-0.46)	(-2.32)	(0.03)	(-2.08)	(-2.12)	(-0.25)	(0.15)	(-0.75)
log(hosp. days)	0.0416*	-0.0185	-0.0172	-0.0072	-0.0018	0.0084	0.0129	-0.0049	-0.0125	-0.0051
	(2.17)	(-1.21)	(-0.99)	(-0.46)	(-0.08)	(0.47)	(0.69)	(-0.34)	(-0.66)	(-0.36)
d_disabled	-0.1950**	-0.1786***	-0.1663***	-0.0626	-0.0781	-0.1529**	-0.1260*	-0.1180**	-0.1662**	-0.1507***
	(-3.20)	(-4.31)	(-3.32)	(-1.48)	(-1.30)	(-3.26)	(-2.23)	(-2.68)	(-3.26)	(-3.61)
no. cigarettes	-0.0047	-0.0021	-0.0038	-0.0002	-0.0020	-0.0040	-0.0045	-0.0000	-0.0004	-0.0028
	(-1.72)	(-0.90)	(-1.40)	(-0.09)	(-0.55)	(-1.81)	(-1.52)	(-0.00)	(-0.15)	(-1.40)
d_hp_arms	-0.0153	-0.0150	-0.0165	-0.0145	-0.0663*	0.0052	-0.0320	-0.0166	-0.0252	-0.0454*
	(-0.58)	(-0.68)	(-0.65)	(-0.68)	(-2.09)	(0.21)	(-1.06)	(-0.70)	(-1.05)	(-2.03)
d_hp_sight	-0.0760	-0.0378	-0.0463	-0.0443	-0.0658	-0.0043	-0.0470	-0.0795	-0.0742	-0.0026
	(-1.45)	(-0.92)	(-0.92)	(-1.04)	(-1.03)	(-0.09)	(-0.82)	(-1.85)	(-1.35)	(-0.07)
d_hp_hearing	-0.1014*	-0.0226	-0.0165	-0.1264***	-0.0604	-0.0212	-0.1766**	-0.0125	-0.1094*	-0.0149
	(-2.06)	(-0.57)	(-0.32)	(-3.48)	(-1.04)	(-0.52)	(-3.27)	(-0.31)	(-2.42)	(-0.40)
d_hp_allergy	-0.0761*	-0.0660*	-0.0852*	-0.0039	-0.0773	-0.0294	-0.0964**	0.0129	-0.0362	-0.0167
	(-2.21)	(-2.12)	(-2.45)	(-0.12)	(-1.55)	(-0.89)	(-2.88)	(0.36)	(-0.98)	(-0.57)
d_hp_chest	0.0457	-0.0491	-0.0061	0.0199	0.0446	-0.0093	0.0145	-0.0229	-0.0467	0.0037
	(1.10)	(-1.25)	(-0.15)	(0.52)	(0.98)	(-0.24)	(0.35)	(-0.59)	(-1.18)	(0.11)
d_hp_heart	-0.0499	0.0189	-0.0147	-0.0505	0.0644	-0.0046	-0.0107	-0.0041	0.0077	-0.0140
	(-1.19)	(0.63)	(-0.40)	(-1.66)	(1.43)	(-0.14)	(-0.28)	(-0.13)	(0.22)	(-0.46)
d_hp_stomach	-0.0646	-0.0255	0.0135	0.0099	-0.0556	-0.0109	-0.0005	-0.0564	-0.0720	0.0147
	(-1.51)	(-0.80)	(0.37)	(0.28)	(-1.09)	(-0.28)	(-0.01)	(-1.55)	(-1.79)	(0.47)
d_hp_diabetes	0.1617	0.0277	-0.1991	0.0828	-0.1136	0.0766	-0.0808	0.0071	-0.0402	0.0078
	(1.49)	(0.40)	(-1.50)	(1.00)	(-0.97)	(1.00)	(-0.66)	(0.10)	(-0.47)	(0.10)
d_hp_anxiety	-0.4478***	-0.3707***	-0.3816***	-0.4770***	-0.2880***	-0.4433***	-0.4397***	-0.3220***	-0.4525***	-0.3534***
	(-7.85)	(-8.70)	(-10.95)	(-6.18)	(-4.87)	(-9.22)	(-8.50)	(-7.20)	(-9.13)	(-8.57)
d_hp_drugs	-0.4211	-0.3888**	-0.0538	-0.6971	-0.3400	-0.2970*	0.0928	-0.2255	0.4281	-0.2943*
	(-1.25)	(-2.95)	(-0.38)	(-1.56)	(-1.43)	(-2.15)	(0.37)	(-1.49)	(1.87)	(-2.20)
d_hp_epilepsy	0.0576	-0.3147*	-0.0615	-0.0678	0.2506	0.0432	0.0652	0.0614	0.2022	-0.0134
	(0.31)	(-2.07)	(-0.37)	(-0.36)	(1.30)	(0.31)	(0.29)	(0.39)	(1.19)	(-0.10)
d_hp_migraine	0.0017	-0.0524	-0.0178	-0.0479	0.0067	-0.0668	0.0639	-0.1328**	-0.0626	-0.0823*
	(0.04)	(-1.33)	(-0.44)	(-1.01)	(0.11)	(-1.58)	(1.61)	(-3.02)	(-1.52)	(-1.97)
d_hp_other	0.0139	-0.1000*	-0.0315	-0.0353	0.0055	-0.0360	-0.0477	-0.1079*	-0.0182	-0.0464
	(0.31)	(-2.28)	(-0.75)	(-0.84)	(0.09)	(-0.86)	(-1.01)	(-2.51)	(-0.40)	(-1.23)
d_hp_cancer	-0.0363	0.2058**	0.2237	-0.0393	0.1542	0.1144	0.0722	0.0784	0.0762	0.1618*
	(-0.31)	(2.61)	(1.81)	(-0.45)	(0.97)	(1.24)	(0.83)	(0.94)	(0.56)	(2.11)
d_hp_stroke	-0.0581	-0.2846**	-0.1547	-0.2561*	-0.2138	-0.1871	-0.2497	-0.0672	-0.3223	0.0329
	(-0.38)	(-2.70)	(-0.80)	(-2.04)	(-1.18)	(-1.60)	(-1.38)	(-0.65)	(-1.59)	(0.36)
log(income)	-0.0028	0.0246	0.0445*	0.0273	0.0243	0.0319	0.0444*	0.0322	0.0221	0.0267
	(-0.14)	(1.24)	(2.27)	(1.60)	(0.83)	(1.64)	(2.23)	(1.56)	(1.06)	(1.59)
age	0.0149	-0.0131	-0.0259	0.0049	-0.0089	-0.0135	-0.0167	0.0162	0.0141	-0.0245
	(0.46)	(-0.49)	(-0.83)	(0.18)	(-0.21)	(-0.46)	(-0.52)	(0.57)	(0.43)	(-1.02)
(age-mean age)^2	0.0001	0.0000	0.0000	0.0000	-0.0003*	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.88)	(0.02)	(0.01)	(0.18)	(-2.28)	(0.58)	(0.56)	(1.07)	(1.10)	(0.68)
no. kids	-0.0254	0.0089	-0.0098	-0.0044	0.0459	-0.0411*	0.0018	0.0037	0.0016	-0.0085
	(-1.23)	(0.51)	(-0.45)	(-0.26)	(1.63)	(-2.18)	(0.09)	(0.20)	(0.08)	(-0.48)
education	-0.0010	0.0189	-0.0056	0.0007	-0.0485	0.0276	0.0019	-0.0104	0.0153	0.0171
	(-0.05)	(0.95)	(-0.27)	(0.03)	(-1.48)	(1.60)	(0.10)	(-0.41)	(0.60)	(0.97)
d_cohabiting	0.1748**	0.2526***	0.2714***	0.1718***	0.3597***	0.1843***	0.1906***	0.2412***	0.2492***	0.1928***
	(3.24)	(4.46)	(5.00)	(3.42)	(4.48)	(3.61)	(3.62)	(3.78)	(4.21)	(3.97)
d_married	0.0200	-0.0240	-0.0588	0.0036	-0.3809***	-0.0513	0.0616	-0.0493	-0.0818	-0.0451
	(0.34)	(-0.42)	(-0.97)	(0.07)	(-4.80)	(-0.98)	(1.02)	(-0.83)	(-1.28)	(-0.86)
d_separated	0.0227	0.0367	0.0266	-0.1324	-0.1980	-0.0187	0.0991	0.1070	-0.1049	0.0645
	(0.23)	(0.35)	(0.25)	(-1.47)	(-1.32)	(-0.19)	(0.89)	(1.10)	(-1.03)	(0.73)
d_divorced	0.2135*	0.0398	0.0357	0.1773*	-0.0569	-0.0028	0.2335*	0.0620	0.0969	0.0299
	(2.46)	(0.41)	(0.37)	(2.21)	(-0.48)	(-0.03)	(2.52)	(0.66)	(1.08)	(0.36)
d_widowed	0.0494	-0.1235	-0.1240	-0.0187	-0.2606	-0.2136	0.1673	-0.0230	-0.1586	-0.0209
	(0.36)	(-0.92)	(-0.75)	(-0.17)	(-1.76)	(-1.69)	(0.94)	(-0.18)	(-1.18)	(-0.18)
d_unemployed	-0.2018**	-0.4066***	-0.2804***	-0.2309***	-0.2031*	-0.3084***	-0.3095***	-0.2814***	-0.2273**	-0.3272***
	(-2.88)	(-6.49)	(-4.47)	(-3.69)	(-2.15)	(-5.34)	(-4.64)	(-4.24)	(-3.15)	(-6.21)
d_selfemployed	-0.0314	-0.0214	-0.0279	0.0127	-0.1634*	-0.0047	0.0449	0.0465	0.0013	-0.0166
	(-0.66)	(-0.43)	(-0.42)	(0.32)	(-2.37)	(-0.10)	(0.97)	(0.82)	(0.03)	(-0.35)
d_retired	0.0290	0.0109	-0.0551	0.1107**	-0.0516	0.0785	0.1284*	-0.0157	0.0207	0.0804
	(0.49)	(0.23)	(-0.86)	(2.67)	(-0.84)	(1.61)	(2.14)	(-0.32)	(0.41)	(1.79)
d_studyschool	0.1162	0.0118	0.0511	0.1357*	0.0346	0.0253	0.1032	0.0852	0.0352	0.0833
	(1.87)	(0.17)	(0.77)	(2.33)	(0.36)	(0.42)	(1.63)	(1.14)	(0.46)	(1.66)
d_maternityleave	0.2363**	0.4398***	0.4504***	0.1997*	0.3447**	0.5417***	0.2058*	0.3660***	0.2551**	0.3391***
	(3.17)	(4.25)	(5.61)	(2.11)	(2.85)	(4.87)	(2.12)	(4.61)	(3.24)	(3.99)
d_longtermsick	-0.2849**	-0.3115***	-0.3325***	-0.2032*	-0.1834*	-0.3127***	-0.1622	-0.2811***	-0.1816*	-0.2966***
	(-2.74)	(-4.69)	(-4.67)	(-2.31)	(-2.08)	(-3.93)	(-1.68)	(-4.27)	(-2.19)	(-4.31)
d_familycare	-0.0360	-0.0641	-0.1155*	0.0175	-0.1018	-0.0424	0.0354	-0.0463	-0.0006	-0.0706
	(-0.70)	(-1.29)	(-2.18)	(0.37)	(-1.75)	(-0.74)	(0.63)	(-0.96)	(-0.01)	(-1.56)
d_other	0.0604	-0.1286	-0.0678	0.0520	0.0521	-0.1869	0.0504	-0.0933	0.0631	-0.1706
	(0.56)	(-0.93)	(-0.51)	(0.50)	(0.38)	(-1.77)	(0.52)	(-0.74)	(0.48)	(-1.68)
Observations	15091	23243	18749	20610	11278	20088	14821	22660	17755	25499
R^2	0.056	0.057	0.071	0.032	0.048	0.060	0.055	0.048	0.048	0.056

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Subgroup analysis for different personality traits (high trait expression refers to the upper quartile, while low trait expression refers to the lower quartile). E = Extraversion; N = Neuroticism; O = Openness; C = Conscientiousness and A = Agreeableness.

	nearest neighbour matching				propensity score matching				transitions	
	t+1		t+2		t+1		t+2		t+1	t+2
	SATE		SATE		ATT		ATT		recovers	recovers
	z-stat	obs	z-stat	obs	t-stat	obs	t-stat	obs	sick	sick
condition: arms	.1799***		.2875***		.1409***		.2085***		4086	1508
	(4.79)	8853	(4.43)	4716	(4.04)	8851	(3.54)	3882	24443	21963
condition: sight	.1236		.1727		.1332		.1504		1518	684
	(1.66)	1521	(1.50)	696	(1.62)	1500	(1.03)	619	3650	2940
condition: hearing	-.0611		-.0368		-.1084		-.0568		1315	467
	(-0.97)	2585	-(0.35)	1364	(-1.69)	2577	(-0.54)	1133	7384	6642
condition: allergy	.0101		.0269		.0167		-.0322		2492	1066
	(0.24)	3726	(0.40)	1842	(0.38)	3722	(-0.43)	1488	9670	8151
condition: chest	-.0218		.0206		-.0157		-.0008		1917	758
	(-0.42)	3941	(0.24)	2171	(-0.30)	3939	(-0.01)	1798	11865	10719
condition: heart	.0181		.0590		-.0255		-.0859		2139	717
	(0.37)	5578	(0.63)	3019	(-0.52)	5564	(-0.92)	2557	15105	13870
condition: stomach	.1875***		.2660**		.1486**		.2476**		1990	926
	(3.24)	2419	(3.09)	1142	(2.44)	2406	(2.52)	979	6089	4955
condition: diabetes	.0494		-.0720		.0795		.0044		138	43
	(0.24)	1249	(-0.20)	760	(0.42)	1156	(0.01)	502	3533	3447
condition: anxiety	.6851***		.6994***		.5519***		.5142***		1885	816
	(10.75)	2427	(7.02)	1180	(8.11)	2424	(4.40)	1016	6359	5289
condition: drugs	.4783		.4067		-.2221		—-	—-	127	59
	(1.93)	150	(1.14)	75	(-0.58)	134	—-	44	405	333
condition: epilepsy	-.0455		-.5660		-.4288		—-	—-	66	25
	(-0.14)	264	(-1.46)	159	(-1.07)	217	—-	68	767	723
condition: migraine	.1730**		.2692**		.1167*		.1649		1895	810
	(3.07)	2482	(3.04)	1251	(2.01)	2475	(1.64)	965	6390	5277
condition: other	.0707		.0398		.0289		-.1930		1646	819
	(0.98)	1471	(0.37)	666	(0.35)	1461	(-1.30)	554	3261	2331
condition: cancer	.2318		.2732		.3218		.2663		206	118
	(1.43)	370	(1.32)	183	(1.81)	355	(0.89)	170	680	614
condition: stroke	.5998**		.5871		.4485*		.5227		173	71
	(3.12)	283	(1.93)	132	(2.05)	271	(1.06)	114	566	507

Table 8: Results for matching estimates: recovery. Sample Average Treatment Effects (SATEs) and Average Treatment effects for the Treated (ATTs), with z-statistics in parentheses.

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