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Going Beyond Average Joe's Happiness: Using Quantile Regressions to Analyze the Full Subjective Well-Being Distribution☆

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Abstract

Standard regression techniques are only able to give an incomplete picture of the relationship between subjective well-being and its determinants since the very idea of conventional estimators such as OLS is the averaging out over the whole distribution: studies based on such regression techniques thus are implicitly only interested in Average Joe's happiness. Using cross-sectional data from the British Household Panel Survey (BHPS) for the year 2006, we apply quantile regressions to analyze effects of a set of explanatory variables on different quantiles of the happiness distribution and compare these results with an ordinary least squares regression. We also analyze some reversed relationships, where happiness enters the regression equation as an explanatory variable (e.g., the effects of happiness on individual's financial success). Among our results we observe a decreasing importance of income, health status and social factors with increasing quantiles of happiness. Another finding is that education has a positive association with happiness at the lower quantiles but a negative association at the upper quantiles.

Key words: quantile regressions, subjective well-being, happiness, life satisfaction, mental well-being, BHPS
JEL-classification: I20, I31, C31

1. Introduction

Research into the causes and correlates of human happiness (or synonymously: subjective well-being) has gained momentum in the past years and attracted attention in disciplines such as economics and psychology alike (see recent reviews, e.g. Easterlin, 2003; Frey and Stutzer, 2005; Dolan et al., 2008). With an increase in interest of researchers from various disciplines, happiness research progressed to a point where many of the initial findings are becoming increasingly qualified, theories become more refined and the statistical tools to

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analyze the complex relationships between happiness and its determinants become ever more sophisticated. One major theme during the last years was, for example, the introduction of panel data techniques that allow to more reliably identify individual responses to changes in external conditions (via accounting for time-invariant individual-specific components, "fixed effects", e.g. Ferrer-i Carbonell and Frijters, 2004).

What has been neglected so far is the information that is contained in happiness distributions. Thus, what we want to argue for in the present paper is that happiness research should now also start being less concerned with the mean effects of the explanatory variables on happiness but with their effects on different parts of the happiness distribution. Ordinary least squares regression techniques with their focus on the conditional mean of the dependent variable are only able to give an incomplete picture of the relationship between subjective well-being and its determinants since the very idea of OLS regressions is the averaging out of coefficient estimates over the conditional distribution of the dependent variable: studies based on such regression techniques thus are implicitly only interested in the happiness of "Average Joe", but remain silent on the question of the effects that explanatory variables have on the happiness levels of "Miserable Jane" or "Cheerful John".[1] While average effects certainly are an important feature to examine, from a policy perspective it is often more interesting to understand what happens at the extremes of a distribution. For example, are increases in income as relevant for the happiness of the happiest individuals in a population as they are for the most miserable individuals? Similarly, going beyond the mean is important with regard to individual-specific rates of hedonic adaptation (Diener et al., 2006, p. 311): as recent research on the hedonic treadmill shows, policy makers do have levers to permanently alter individuals' happiness levels but this seems not to be the case uniformly along the happiness distribution. This type of analysis is long known in welfare economics, where scholars are interested in the *distribution* of well-being and not just the average (e.g. when analyzing income inequality). This allows to more comprehensively assess policies, where for instance a policy might be ethically acceptable if it has a small positive effect on everyone's well-being, but it would be no longer acceptable, in ethical terms, if some individuals' gains are counterbalanced by large losses for a minority. In these types of considerations, the focus is no longer on the average effect, but on the full distribution of well-being. We argue that this line of reasoning needs to be extended to happiness research.

These considerations become more urgent when one takes into account the findings that happiness distributions are empirically quite skewed: most individuals have positive happiness values, with a mean of 6.33 on a 0 (most unhappy) to 10 (most happy) scale for a sample of 43 nations (Diener and Diener, 1996; Diener et al., 2006). In heterogeneous distributions, regression methodologies that focus on means might seriously under- or overestimate effects or even fail to identify effects at all (Cade and Noon, 2003). A solution to this lacuna is to extend happiness measurement from ordinary least square regressions to quantile regressions (Koenker and Bassett, 1978; Koenker and Hallock, 2001). Quantile regression enables the econometrician to analyze effects of the explanatory variables on different quantiles of the

[1] To be more precise, longitudinal research reveals that at the beginning of adult life, it would be more appropriate to label Janes (i.e. females) as cheerful and Johns (i.e. males) as miserable, while with increasing age, this relationship gradually reverses itself (Plagnol and Easterlin, 2008). To be fair: overall, there is still considerable uncertainty about gender effects in happiness research (Dolan et al., 2008).

happiness distribution as opposed to a (incomplete) focus on the mean of the distribution. It is a pragmatic tool for analyzing extreme effects in the happiness distribution and thus gives the researcher a more complete picture of the effects of the explanatory variables on the dependent variable (in our case happiness). While quantile regressions are starting to be recognized as a helpful technique in the case of skewed (non-normal) distributions in other economic sub-disciplines,[2] we are to our knowledge among the first to explore and demonstrate their use in happiness research.[3]

In order to motivate the usefulness of happiness quantile regressions, the paper proceeds in the following way. Section 2 gives an overview over some relevant knowledge in happiness research in order to justify the later selection of explanatory variables. Section 3 then gives an introduction to quantile regressions and relates them to the standard ordinary least squares regressions. In Section 4 we then apply quantile regressions to a fairly standard set of explanatory variables (and their effect on happiness) and compare these results with an ordinary least squares regression. We also analyze some reversed relationships, where happiness enters the regression equation as an explanatory variable (e.g., the effects of happiness on individual's financial success). This is motivated by recent research that shows how happy individuals systematically score higher in important life domains (Lyubomirsky et al., 2005; Binder and Coad, 2010a). We explore these relationships by using data from the British Household Panel Survey (BHPS), an extensive data set that covers information on many important life domains of a representative sample of the British populace. Section 5 concludes.

2. Theoretical background

The literature on subjective well-being (synonymously called "happiness" in this paper) has vastly increased over the last few years (see recent reviews, e.g. Easterlin, 2003; Frey and Stutzer, 2005; Dolan et al., 2008). While we can broadly distinguish between affective and cognitive layers of well-being, most of the (empirical) literature seems to be centred on a cognitive interpretation of subjective well-being. This is reflected in the notion of subjective well-being understood as "life satisfaction": the interest lies in the cognitive aspect, making well-being a cognitive judgement-cum-endorsement, i.e. an attitude which one holds towards one's life (see, e.g., Frey and Stutzer, 2002). Very similar to this tradition is research using the "satisfaction with life scale" (SWLS, Diener et al., 1985). Although the proponents of this scale argue that both cognitive and affective components together build the psychological construct "well-being", the cognitive components seem to dominate their scale.[4]

[2]For example, Buchinsky (1994) applies quantile regression to analyze the US wage structure, while Coad and Rao (2008) use quantile regression to distinguish between average firms and high-growth firms.

[3]Hohl (2009) discusses the methodological differences between ordinary least squares regressions and quantile regressions and their application in the social sciences, using the life satisfaction-income relationship as an example. We are less interested in providing a toolkit about when to use quantile regressions but more with the additional insights quantile regressions allow for happiness research. Moreover, we investigate the wider interrelationships between happiness, income, health, social relations and education (using BHPS data), not only focussing on the life satisfaction-income relationship.

[4]A third distinction is made by Veenhoven, who differentiates between affective and cognitive concepts of well-being, calling them "happiness" and "contentment", respectively (Veenhoven, 1991).

Depending on data availability and the concrete theory of happiness one subscribes to, subjective well-being is empirically captured by diverse mental well-being, happiness or life satisfaction measures (Ryff and Keyes, 1995; Easterlin, 2002; Frey and Stutzer, 2002; Diener and Seligman, 2004). While one might, in the face of the many different concepts, be critical of the validity of such constructs and ask whether these surveys really elicit anything useful at all, these doubts seem not to be justified. An impressive psychological literature exists that establishes the reliability and validity of such subjective well-being constructs (Diener et al., 1999), showing that there is a strong correlation between such well-being constructs and emotional expressions like smiling (Fernandez-Dols and Ruiz-Belda, 1995) and brain activity (Shizgal, 1999). Moreover, individuals tend to discontinue unsatisfactory behaviors (Kahneman et al., 1993; Shiv and Huber, 2000), thus also relating low satisfaction scores to choice behavior. Lastly, studies found that individuals are to a certain extent able to (ordinally) compare and assess other individuals' levels of satisfaction or happiness (Sandvik et al., 1993; Diener and Lucas, 1999). While there are certainly difficulties related to the practical elicitation of subjective well-being measures, a broad consensus emerged within the literature that these quite reliably measure the intended individual well-being. Research here extends also to the intertemporal context: psychological research shows that well-being is partly stable and fixed over time since it is determined to some extent by genes (Lykken and Tellegen, 1996) and by quite stable psychological personality traits (Diener et al., 1999). But it is also variable to a certain extent, being influenced permanently by such life events as repeated unemployment, marriage or child birth (Headey, 2010). Note also that 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), which is lower than some other economic variables' reliability, but nevertheless in a range that allows meaningful analysis.

So far it has been established that an individual's happiness depends on a complex vector of factors, ranging from individual determinants (e.g., self-esteem, optimism) to socio-demographic (such as gender, age, education, or marital status), economic (such as income, status, or unemployment), situational (such as health, social relationships), and even institutional factors (Frey and Stutzer, 2002, pp. 10-1).[5] The areas of research that have probably received the most attention so far are the relationship between happiness and income, happiness and health as well as happiness and the social domain (with marriage and divorce maybe the most prominent covariates). Another well-researched area concerns the effects of unemployment on happiness. With the exception of the latter domain, we will later analyse all other relevant domains, i.e. income, health and social relations. Therefore, some discussion of previous findings in these domains is in order.

The relationship between happiness and income is a complex one, even when considering that it has been researched since Easterlin's seminal article on the paradox of happiness (Easterlin, 1974).[6] Initial findings purported that well-being has not increased substantially in the last decades even though incomes have risen strongly. For example, in the US, real

[5] See also Dolan et al. (2008).

[6] The paradox refers to the finding that although higher incomes are associated with higher happiness in cross-sections, in longitudinal studies, rising incomes seem not to translate into rising happiness. See also Keely (2005).

incomes have risen from 11,000 USD to 27,100 USD from 1946 to 1991 (measured in 1996 dollars, Frey and Stutzer, 2002, pp. 76-7), while happiness levels have dropped from 2.4 to 2.2 (average happiness on a three-point scale). Similar findings were presented by Oswald (1997, pp. 1818-20), who reports a slight increase in happiness with increasing income over time for the US and Europe. In a recent study, these findings have been qualified by Stevenson and Wolfers (2008), who have reappraised the data and were able to assess longer time horizons for the different countries. Based on a comprehensive data set, their main finding is that the paradox of happiness cannot be corroborated for European countries and Japan, while the US data confirms the previous analyses.[7] What can be concluded from recent reviews of the literature on this relationship is that there seems to be some positive association but diminishing effects with increasing income (see Clark et al., 2008b; Dolan et al., 2008). Some of the effects might also be explained by the positive influence happiness has on an individual's performance (Graham et al., 2004) or by individual personality traits, since accounting for fixed effects does diminish the relationship between both variables (Ferrer-i Carbonell and Frijters, 2004). What also seems to have an effect on happiness is relative income or income aspirations (Solnick and Hemenway, 1998; Stutzer, 2004; Ferrer-i Carbonell, 2005).

The happiness-health relationship is less contested and the literature does agree on a generally quite strong positive relationship between happiness and health. This is less surprising, for instance, for the GHQ measure of mental well-being that incorporates some (mental) health aspects (see below). But the relationship also holds when using life satisfaction as the dependent variable in the regressions. What is less certain is "which way the causal arrow runs: from health to life satisfaction or from life satisfaction to health" (Easterlin, 2003, p. 11177). A high level of well-being seems certainly relevant also for subsequent good health (Lyubomirsky et al., 2005), with significant positive effects of well-being on health being observed two or three years later (Binder and Coad, 2010a), but most certainly there are also effects the other way round: for example, acute or chronic illness decreases well-being as well as disability (Easterlin, 2003; Shields and Wheatley Price, 2005; Oswald and Powdthavee, 2008). Moreover, over time, hedonic adaptation to chronic pain or disability also seems limited, setting some limits for set point theories of happiness (Frederick and Loewenstein, 1999; Oswald and Powdthavee, 2008).[8]

What seems to be equally well understood today is that happiness is associated with fulfilling social relations (e.g., Myers, 1999; Bruni and Stanca, 2008; Becchetti et al., 2008), with marriage being the most important. Being separated, divorced or widowed (or just alone) is associated with lower levels of well-being than being in a fulfilling, stable partnership (Helliwell, 2003; Lucas, 2005; Stutzer and Frey, 2006). However, it seems that the increase in well-being after marriage might turn out not to be lasting (Lucas and Clark, 2006; Clark et al., 2008a). Other social relationships, for example with family and friends, are also positively associated with happiness (Lelkes, 2006; Pichler, 2006; Baker et al., 2005); nevertheless, the causal arrow might run in the other direction as well, insofar as happy

[7] The reason for the divergence of findings is that the original findings did not account for breaks in the data, where the wording of the life satisfaction and happiness questions had been changed and thus led to different results.

[8] A more extensive account of the intertemporal development of such subjective well-being constructs is given in Binder (2010), pp. 174-86.

individuals might be socially more agreeable and thus have more friends and socially more fulfilling relationships. The evidence for having children is more mixed and seems to depend on factors such as whether the parent is bringing up the children alone or not (Frey and Stutzer, 2000). A stronger positive relationship between children and happiness is found when using an equivalised income measure to correct for household size (Lelkes, 2006).

3. Quantile regression

Conventional least squares regression techniques provide summary point estimates that calculate the average effect of the explanatory variables for the "average individual". However, this focus on the average may hide important features of the underlying relationship. As Mosteller and Tukey explain in an oft-cited passage:

> "What the regression curve does is give a grand summary for the averages of the distributions corresponding to the set of x's. We could go further and compute several regression curves corresponding to the various percentage points of the distributions and thus get a more complete picture of the set. Ordinarily this is not done, and so regression often gives a rather incomplete picture. Just as the mean gives an incomplete picture of a single distribution, so the regression curve gives a correspondingly incomplete picture for a set of distributions" (Mosteller and Tukey, 1977, p. 266).

Quantile regression techniques can therefore help us obtain a more complete picture of the factors affecting individual well-being. While conventional regressions focus on the mean, quantile regressions are able to describe the entire conditional distribution of the dependent variable. Indeed, focusing on the average effects may under- or overestimate the relevant coefficient estimates, or may even fail to detect important relationships. A focus on the average is therefore unsuitable for the analysis of complex interactions of variables in distributions containing heterogeneous individuals (Cade and Noon, 2003).

In the context of this study, extreme cases of happiness are of interest in their own right, and instead of dismissing these cases as "outliers" we believe it would be worthwhile to study them in some detail. This can be done by calculating coefficient estimates at various quantiles of the conditional happiness distribution (i.e. conditional on the explanatory variables). Furthermore, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Relaxing this assumption allows us to acknowledge individual heterogeneity and consider the possibility that estimated slope parameters vary at different quantiles of the conditional happiness distribution.

The quantile regression model, first introduced in the seminal contribution by Koenker and Bassett (1978), can be written as:

$$y_{it} = x'_{it}\beta_\theta + u_{\theta it} \qquad \text{with} \qquad \mathrm{Quant}_\theta(y_{it}|x_{it}) = x'_{it}\beta_\theta \tag{1}$$

where y_{it} is the dependent variable, x is a vector of regressors, β is the vector of parameters to be estimated, and u is a vector of residuals. $Quant_\theta(y_{it}|x_{it})$ denotes the θ^{th} conditional quantile of y_{it} given x_{it}. The θ^{th} regression quantile, $0 < \theta < 1$, solves the following problem:

$$\min_{\beta} \frac{1}{n} \left\{ \sum_{i,t:y_{it} \geq x'_{it}\beta} \theta |y_{it} - x'_{it}\beta| + \sum_{i,t:y_{it} < x'_{it}\beta} (1-\theta)|y_{it} - x'_{it}\beta| \right\} = \min_{\beta} \frac{1}{n} \sum_{i=1}^{n} \rho_\theta(u_{\theta it}) \quad (2)$$

where $\rho_\theta(.)$, which is known as the "check function", is defined as:

$$\rho_\theta(u_{\theta it}) = \left\{ \begin{array}{ll} \theta u_{\theta it} & \text{if } u_{\theta it} \geq 0 \\ (\theta - 1)u_{\theta it} & \text{if } u_{\theta it} < 0 \end{array} \right\} \quad (3)$$

Equation (2) is then solved by linear programming methods. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y, conditional on x (Buchinsky, 1998).[9] For more accurate results, we base our statistical inference on bootstrapped standard errors, in both the results tables and also the quantile regression plots.[10]

Quantile regression was originally introduced, over 30 years ago, as a cross-sectional estimator (Koenker and Bassett, 1978). Only very recently, however, have some researchers focused on the econometric theory of applying quantile regression to panel data contexts (e.g., Koenker, 2004; Abrevaya and Dahl, 2008; Galvao, 2009; Canay, 2010).[11] In this paper we apply quantile regression as a cross-sectional estimator, even though panel data is available in our dataset. As a consequence, our paper implicitly focuses on the heterogeneity of individuals, and our results relate to comparisons across a cross-sectional distribution.[12]

Our cross-sectional regressions provide coefficient estimates that report the associations between variables, where other influences are controlled for in a conventional multivariate regression setting. As such, our regression results correspond to *associations* between variables, and cannot be interpreted as *causal* effects in any strict sense. This will be particularly apparent when, in our analysis, one variable that appeared as a dependent variable subsequently enters as an explanatory variable. Although an accurate understanding of causal relations is important for e.g. estimating macroeconomic responses to exogenous policy stimuli, in this paper we merely seek to report descriptive associations between variables and to improve our understanding of what certain life events actually entail.

4. Data and findings

4.1. Data set and indicator selection

The British Household Panel Survey (BHPS) is a longitudinal survey of private households in Great Britain, undertaken by the ESRC UK Longitudinal Studies Centre with the

[9] More on quantile regression techniques can be found in the surveys by Buchinsky (1998), Koenker and Hallock (2001) and Cade and Noon (2003).

[10] Our econometric investigations are performed in Stata 11. Boobstrapped quantile regression is performed using the sqreg command, and the quantile regression plots are produced using the external grqreg command (Azevedo, 2004).

[11] A further obstacle is that these theoretical developments in panel data quantile regression have not yet been incorporated into conventional software packages such as Stata.

[12] We do not control for individual-specific time-invariant effects by performing the "within transformation" usually done in panel data fixed effects models. If we had done so, our quantile regression results would relate to heterogeneity *within* individual responses, rather than *across* individuals.

Table 1: Summary statistics of variables

Variable	Mean	Std. Dev.	Min.	Max.	N
life satisfaction	5.216	1.252	1	7	11591
mental well-being	25.801	5.557	1	37	11591
log(income)	9.965	0.611	-0.441	12.14	11591
health	0.015	1.334	-7.793	1.623	11591
social	0	1.119	-5.468	1.868	11591
d_cohabiting	0.643	0.479	0	1	11591
d_married	0.532	0.499	0	1	11591
d_separated	0.02	0.14	0	1	11591
d_widowed	0.077	0.266	0	1	11591
d_divorced	0.082	0.274	0	1	11591
d_employed	0.506	0.5	0	1	11591
d_unemployed	0.03	0.169	0	1	11591
d_selfemployed	0.072	0.258	0	1	11591
d_retired	0.221	0.415	0	1	11591
d_studyschool	0.058	0.233	0	1	11591
d_maternityleave	0.004	0.066	0	1	11591
d_longtermsick	0.043	0.203	0	1	11591
d_familycare	0.059	0.235	0	1	11591
d_other	0.008	0.086	0	1	11591
d_disabled	0.102	0.302	0	1	11591
gender	1.533	0.499	1	2	11591
age	46.514	18.572	15	99	11591
(age-mean age)^2	344.916	370.077	0.127	2741.125	11591
education	3.224	1.765	1	7	11591
number of children	0.579	0.949	0	7	11591

Institute for Social and Economic Research at the University of Essex, UK (BHPS, 2009). Its aim is to track social and economic change in a representative sample of the British population (for the following and more information on the data set, see Taylor et al., 2009). The BHPS started as a nationally representative sample of 5,000 households, where adults (being of age sixteen and over) were interviewed and tracked over the years. The sample comprises about 15,000 individual interviews. Starting in 1991, up to now, there have been 17 waves of data collected with the aim of tracking the individuals of the first wave over time (there is a percentage of rotation as some individuals drop out of the sample over time and others are included, but attrition is quite low, see Taylor et al., 2009). The BHPS data contains information on various areas of the respondents' lives, ranging from income to jobs, household consumption, education, health, but also social and political values. We will now discuss the main explanatory variables chosen for our analysis, as well as control variables. Table 1 gives an overview of the descriptive statistics. Note that we are only using the 2006 wave (wave 16/p) of the data set. For our analysis, we have a total of $11,591$ observations after cleaning the data set.

Our main variables of interest are an individual's life satisfaction and a broader version of mental well-being that encompasses more affective parts of individual well-being (see also, e.g., Clark and Georgellis, 2010; Binder and Coad, 2010a,b). In the main model, we analyze how life satisfaction is influenced by variables such as income, health, social factors, as well as a large number of other well-known factors from the literature on subjective well-being. In line with our theoretical discussion, we also reverse this relationship and make health, income and social factors the dependent variables, thus also analyzing how these variables are associated with the well-being variables. We check on the robustness of our results for life satisfaction by examining the same relationships with the mental well-being variable. Before discussing these regressions, we turn to a short exposition of our indicators of interest.

To examine an individual's life satisfaction, we use the BHPS's life satisfaction question. It covers the response to the question "How dissatisfied or satisfied are you with your life overall?" It is effectively tracking an individual's life satisfaction ordinally on a seven point Likert scale, ranging from "not satisfied at all" (1) to "completely satisfied" (7). While comparatively more studies on the BHPS center on the GHQ-12 measure to be discussed below, recent work took up using the life satisfaction question too (Clark and Georgellis, 2010; Powdthavee, 2009). A histogram showing the distribution of life satisfaction is shown in Figure 1.

To assess mental well-being, we have decided on using the well-known GHQ-12 measure as a proxy of a broader notion of happiness or subjective well-being. This concept of mental well-being is relatively similar to the better known measures such as the life satisfaction question above (the contemporaneous correlation is $r = 0.5717$). It is, however, more encompassing as it also relates to mental health. It is an index from the "General Health Questionnaire" of the BHPS, composed of the answers to 12 questions that assess happiness, mental distress (such as existence of depression or anguish) and well-being. This subjective assessment is measured on a Likert scale from 0 to 36.[13] This proxy is widely used in the psychological literature (for more details on this indicator see, e.g., Gardner and Oswald, 2007; Shields

[13] We have recoded this to values of one (lowest well-being) to 37 (highest scores in mental well-being).

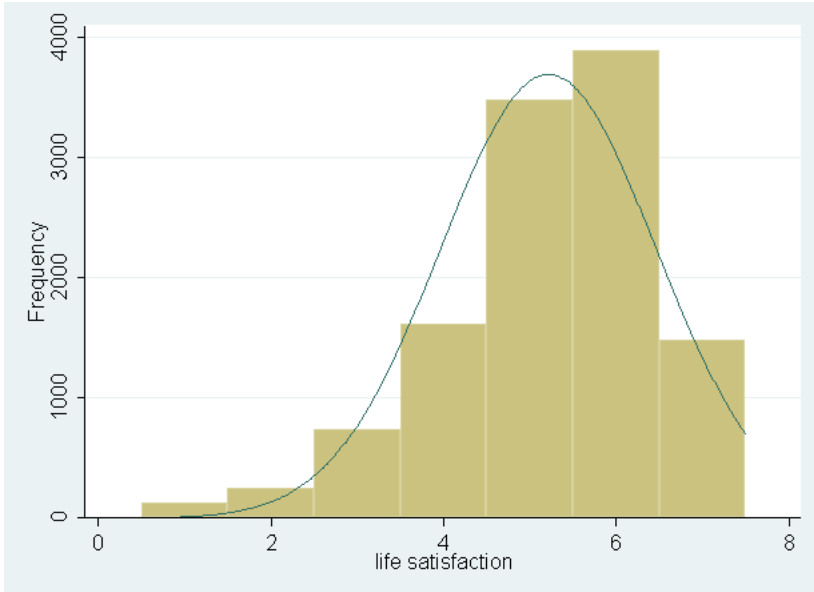


Figure 1: Histogram for life satisfaction variable, overlaid with a best-fit Gaussian density (fitted to the empirical mean and standard deviation).

and Wheatley Price, 2005; Clark and Oswald, 2002). Note that we implicitly interpret this well-being measure as cardinal in using an OLS regression. This is justified for two reasons. First, such an interpretation is common in the psychological literature on well-being, and it has been shown that there are no substantial differences between both approaches in terms of the results they generate (Ferrer-i Carbonell and Frijters, 2004).[14] Second, as this measure of well-being has 37 outcomes, the supposition of a cardinal underlying latent variable does not really seem problematic.

Turning to our measure of income, we have decided to 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). Such an income measure has been extensively discussed in our context of the BHPS (Burchardt, 2005; Kuklys, 2005). In accordance with recent consensus in the literature, 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.

To measure individuals' health, we have chosen to use a mixture of subjective and objective indicators of health. For the former, we focus on an individual's subjective assessment of health (during the last 12 months). This is ordinally scaled on a five point Likert scale, ranging from "excellent" (five) to "very poor" (one).[15] Subjective assessments of health seem

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

[15] As in the case of well-being, we have reversed the numerical order of the Likert scale to consistently use higher values for higher "achievement" in these domains. The original coding in the BHPS codes a value of one to be excellent health and five to be very poor health.

to predict objective health quite well in some cases (e.g., regarding morbidity). Whether objective health is sufficiently well captured by subjective health assessments is still debated (Johnston et al., 2009). In order to account for more objective aspects of individual health, we also included the 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 2).

While the aggregation of different indicators into one comprehensive measure is by no means trivial, we have opted for a simple Principal Component Analysis (PCA) for the aggregation exercise. Using this type of analysis is very convenient in our context, as this data reduction tool allows the data to determine the weights when aggregating the indicators, thus not forcing us to stipulate *ad hoc* some artificial weighting scheme about which indicators should be given which weight. Via PCA, we can summarize the information of different indicators into one measure that constitutes a summary representation of the common variance shared by related variables, while removing the idiosyncratic "noise" component contained in each variable when taken individually.[16] The overall health index is thus a continuous variable, derived from PCA. With this measure, we can account for $\rho = 45.16\%$ of the underlying indicators' variance. To further explore its goodness of fit, we calculated the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for the indicator (0.6297), which is acceptable.

Table 2: Summary statistics of variables in PCA (BHPS variable name in brackets)

Variable	Mean	Std. Dev.	Min.	Max.	N
health	0.015	1.334	-7.793	1.623	11591
health status over last 12 months (phlstat)	3.851	0.946	1	5	11591
no. of visits to gp since 1.9.2005 (phl2gp)	3.618	1.199	1	5	11591
no. of serious accidents since 1.9.2005 (pnxdts)	4.882	0.384	1	5	11591
log(days in hospital)	0.17	0.595	0	5.771	11591
social	0	1.119	-5.468	1.868	11591
satisfaction with: social life (plfsat6)	4.918	1.449	1	7	11591
frequency of talking to neighbours (pfrna)	4.053	1.003	1	5	11591
frequency of meeting people (pfrnb)	4.287	0.777	1	5	11591

The final other main variable we look at is an individual's social relations. We use an individual's satisfaction with her social relations as an indicator for this variable, as well as two questions regarding the amount of contact to family, friends and neighbours (an index based on similar questions is used by Lelli, 2001; Ramos and Silber, 2005). The former is

[16]While we are aware of possible drawbacks of such a procedure, viz. neglecting parts of the variance inherent in the indicators, we feel justified on ignoring these concerns in the present context. The main aim of our paper lies elsewhere, and we allow ourselves to remain agnostic on the concrete aggregation of indicators. Other measures might be equally appropriate, something which merits future research. There is also some discussion in the literature to what extent standard Principal Component Analysis provides flawed estimates for discrete proxy variables. This is based on the contention that a Pearson correlation matrix, as is used in standard PCA, would not make much econometric sense when it comes to binary or ordinal variables, hence different types of variables necessitate different types of correlation matrices to be used in PCA. We follow the reasoning of Kolenikov and Angeles (2009), who argue that this is unnecessary in the case of ordinal variables, especially when the number of ordinal categories is five or more. Empirically, there tend to be only small differences between using PCA with polychoric correlations and just treating ordinal variables as cardinal in PCA. We therefore did the calculations with standard (Pearson) PCA.

measured on a seven point Likert scale, where 1 denotes "not satisfied at all" and 7 denotes the individual is "completely satisfied". The latter are ordinal scaled variables regarding the "frequency of talking to neighbours" and the "frequency of meeting people" (0 to 5, ranging from "never" to "on most days"). Our overall measure is again computed via PCA and accounts for $\rho = 41.72\%$ of the indicators' variance. It yields an acceptable KMO measure of 0.5484.

The last category of variables concerns the (mostly individual) control variables (see Table 1). These comprise gender, age, and age^2 (note that we use the squared difference between age and mean-age instead of age^2 in order to avoid problems of multicollinearity) as well as some dummies regarding disability, various employment dummies (being employed, unemployed, self-employed, retired, etc.) and also marital status dummies (e.g., cohabiting, being married, being separated, divorced or widowed). We have also added a regional control variable (which we do not report, however). Of our sample, 53.27% were female. The mean age is 46.514 years (s.d. 18.572) 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. This is measured ordinally, ranging from one ("none of these") to seven ("higher degree"), giving intermediate values to the middle education levels.[17]

Table 3: Contemporaneous correlations

Variables	life satisfaction	mental well-being	log(income)	health	social	education	age	gender
life satisfaction	1.0000							
obs.								
mental well-being	0.5717	1.0000						
	(0.0000)							
obs.	11591							
log(income)	0.0861	0.0733	1.0000					
	(0.0000)	(0.0000)						
obs.	11591	11591						
health	0.2804	0.3507	0.0997	1.0000				
	(0.0000)	(0.0000)	(0.0000)					
obs.	11591	11591	11591					
social	0.3909	0.2487	-0.0457	0.0772	1.0000			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
obs.	11591	11591	11591	11591				
education	0.0120	0.0773	0.2569	0.1954	-0.1330	1.0000		
	(0.1974)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
obs.	11591	11591	11591	11591	11591			
age	0.0659	-0.0553	0.0518	-0.1991	0.0517	-0.3118	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
obs.	11591	11591	11591	11591	11591	11591		
gender	-0.0150	-0.1298	-0.0394	-0.1177	0.0546	-0.0562	0.0193	1.0000
	(0.1056)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0376)	
obs.	11591	11591	11591	11591	11591	11591	11591	

In Table 3, we report pairwise correlations between our main variables of interest. The correlations of most of our indicators are highly statistically significant. We find positive correlation between life satisfaction and log equivalised income ($r = 0.0861$), our health variable ($r = 0.2804$), the social variable ($r = 0.3909$), as well as education ($r = 0.0120$)

[17]For more information see Taylor et al. (2009), App. 2, pp. 18-9.

and age ($r = 0.0659$; while there is negative correlation between the gender variable and life satisfaction, this correlation is not statistically significant). Correlations of measures of well-being and income are generally low in intra-country cross-sections (Bechtel, 2007). The low correlation of log equivalised income with some of the other variables (except education) shows that these other dimensions of well-being do indeed capture important information on individuals' well-being that cannot be captured by income variables. Such low correlation also suggests that income might not be very important for being happy, healthy and sociable.

On the other hand, the high correlations between the social and health domains and life satisfaction point to the important role the former domains play for the latter and vice versa. Also of note is the high correlation between life satisfaction and mental well-being ($r = 0.5717$). While both concepts vary in the same direction, the less than perfect correlation nevertheless shows that they both do capture somewhat different underlying constructs of well-being, making it seem worthwhile to further analyze the differences between both concepts (see Section 4.3). The correlation between mental well-being and health is also quite high ($r = 0.3507$), possibly due to the incorporation of some (mental) health aspects in the concept of mental well-being.[18] Due to the simplistic nature of this correlation analysis, this can be only a first approximation and one should probably not put too much emphasis on these correlations. For instance, these simple correlations do not include the relevant control variables.

4.2. Findings and discussion

We now turn to a discussion of our regression exercise and our findings. Our main regression equation takes the form:

$$LifeSat_i = \gamma + \alpha_1 LogIncome_i + \alpha_2 Social_i + \alpha_3 Health_i + \alpha_4 Education_i + \beta X_i + \varepsilon_i \quad (4)$$

where the dependent variable $LifeSat_i$ corresponds to the life satisfaction score for individual i, α_1 - α_4 correspond to the coefficient estimates for the main variables of interest, and β is the vector of coefficient estimates that correspond to the matrix of individual-specific control variables. ε_i is the usual error term. We do not restrict our analysis to just one dependent variable, however, given that it has been shown that happiness, income, health and social relations are all interdependent and mutually determined (Binder and Coad, 2010a). Therefore, the regression equation shown above relates to column 1 in Table 4, while for the other columns in Table 4 different dependent variables are used.

Our main findings are reported in Table 4 and Table 5. In Table 4, we report a standard regression as is customary for cross-sectional analyses in happiness research. It can be read as follows: each column is a different regression model where the independent variable can be found in the column title. Rows specify the independent variables. For example, the first column, model 1, contains the coefficients for a model where we regress our list of explanatory variables (from log income to number of children, see Table 1) on life satisfaction. The second

[18]A somewhat puzzling high negative correlation in that table is between education and age ($r = -0.3118$). An explanation why age is negatively associated with education could be that the sample contains a large proportion of older individuals who do not hold as many high academic degrees as might be usual today.

Table 4: Regression analysis; dependent variables (life satisfaction, log(income), social & health index in columns); ordered probit regression for life satisfaction, robust OLS for social, health and income.

	life sat.	log(income)	social	health
	(1)	(2)	(3)	(4)
life satisfaction		.0273***	.3489***	.2268***
		(.0046)	(.0089)	(.0105)
log-inc	.0905***		-.0133	.0443*
	(.0179)		(.0172)	(.0189)
social	.3860***	-.0040		.0038
	(.0099)	(.0052)		(.0105)
health	.1973***	.0107*	.0031	
	(.0093)	(.0045)	(.0084)	
education	.0034	.0739***	-.0725***	.0406***
	(.0063)	(.0030)	(.0061)	(.0066)
age	.0032**	.0026***	-.0049***	.0016
	(.0011)	(.0006)	(.0010)	(.0012)
d-cohabiting	.2998***	.0809***	-.1438***	-.1595***
	(.0350)	(.0188)	(.0352)	(.0365)
d-married	.0192	.0468*	.0580	-.0473
	(.0378)	(.0202)	(.0379)	(.0398)
d-separated	-.0327	-.0604	-.0038	-.1377
	(.0736)	(.0352)	(.0688)	(.0793)
d-widowed	-.0070	.0734**	.0378	-.1552*
	(.0578)	(.0259)	(.0496)	(.0619)
d-divorced	-.0808	-.0140	.0534	-.1734***
	(.0453)	(.0230)	(.0435)	(.0506)
d-employed	.1391	-.0628	-.0187	1.7358***
	(.1203)	(.0523)	(.1280)	(.1901)
d-unemployed	-.2749*	-.4493***	.1086	1.5538***
	(.1358)	(.0619)	(.1410)	(.2022)
d-selfemployed	.1686	-.2251***	.0990	1.7912***
	(.1243)	(.0608)	(.1327)	(.1933)
d-retired	.2556*	-.3129***	.3684**	1.3210***
	(.1271)	(.0559)	(.1331)	(.1966)
d-studyschool	.2828*	-.5181***	.1510	1.8816***
	(.1267)	(.0665)	(.1354)	(.1950)
d-maternityleave	.8734***			
	(.1908)			
d-longtermsick	-.1617	-.3537***	.1248	.4206*
	(.1354)	(.0576)	(.1405)	(.2075)
d-familycare	.0498	-.3832***	.1333	1.4341***
	(.1272)	(.0559)	(.1323)	(.1959)
d-other		-.3588***	.3325*	1.5913***
		(.0709)	(.1649)	(.2328)
d-disabled	-.2016***	.0666***	-.1179**	-1.0528***
	(.0453)	(.0189)	(.0398)	(.0547)
gender	.0133	.0110	.0882***	-.2164***
	(.0206)	(.0108)	(.0199)	(.0217)
(age-mean age)^2	.0003***	-.00006**	-.00004	-.0003***
	(.00005)	(.00002)	(.00004)	(.00005)
number of children	-.0565***	-.0983***	.0311**	.0407***
	(.0118)	(.0063)	(.0117)	(.0122)
Obs.	11591	11591	11591	11591
R^2		.1925	.1994	.2962
Pseudo-R^2	.0962			

column, model 2, contains coefficients for a model where we regress life satisfaction and other variables on log income. And so on. As life satisfaction is an ordinal variable, model 1 reports the results of an ordered probit regression. In contrast, the other three dependent variables are all continuous and we thus report OLS coefficients in these cases.

Our main focus, however, is on model 1, where life satisfaction is the dependent variable. But as we have seen in section 2, in many cases, it is not clear how the causal arrow runs in the relationship between happiness and other variables. In order to also explore the effects happiness has on other important life domains, we will also highlight some of the findings from these other three models. A first observation is that our data bear out many of the relationships discussed in section 2: log equivalised income has a small, positive but highly significant effect on life satisfaction. Good health and social relations (as captured by our health and social indices) also positively affect life satisfaction. Apart from social relationships, cohabiting has a strongly positive effect (the effect of being married is not significant, though, probably because of the cohabitation dummy capturing all of the relevant variance. Similarly, the dummies for divorce, separation and widowhood are not significant.) Job related dummies also do not exhibit surprising new results: being unemployed has a negative effect on life satisfaction (highly significant). Being retired, studying or on maternity leave all positively influence life satisfaction. Being disabled has a strongly negative influence on life satisfaction. What is surprising is that the number of children does have a negative effect on life satisfaction, even though we use a measure of income that accounts for household composition (this is at odds with Lelkes, 2006). While we find no gender or education effects in our sample year, age has a positive relationship with life satisfaction, also in its quadratic component.

In model 2, where log equivalised income is the dependent variable, we see that positive health and high well-being are associated with increased income. Significant are also an inverted-U-shape of the age-income relationship, possibly capturing the increasing income of individuals after studies and the subsequent decreasing income after retirement. Model 3 also bears out expectations from the discussion of the pertinent literature. Higher life satisfaction is associated with higher performance in our social variable. Gender is positively related with social accomplishment, suggesting that females are more successful in social matters (gender is coded 1 for males and 2 for females). We find puzzling that age and education both are negatively related with our social variable (highly significant). Why higher age or higher education decreases social achievement is not so clear from a theoretical perspective. In the case of age, we might conjecture that the frequency of talking to neighbours and friends decreases because of lowered mobility of the elderly. This and a high proportion of elderly in our sample could be an explanation for the negative age effect at least. Lastly, when health is the dependent variable, we find positive associations with income and life satisfaction. Being widowed or divorced leads to lower health and being better educated increases health, a finding well-known from health economics (Grossman, 2005).

These findings by themselves are fairly unsurprising and have been reported in other studies. We will now turn to a quantile regression analysis with the same data, providing evidence for our claim that the above results only provide an incomplete picture about the causes and correlates of happiness (and the other variables). By looking at the full distribution, previously overlooked modifications to the above results come to the fore. Comparable to Table 4, in Table 5 we provide estimates of a quantile regression for the same four models

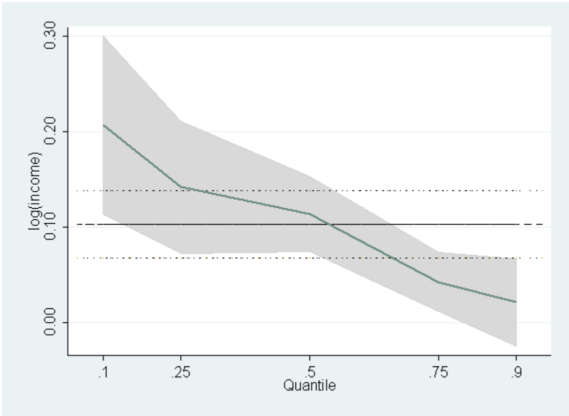
Table 5: Quantile regression table (bootstrapped, 100 replications)

	(1) life satisfaction		(2) log(income)		(3) social		(4) health	
q10								
life satisfaction			0.0193**	(2.63)	0.429***	(24.55)	0.335***	(12.75)
log(income)	0.207***	(3.96)			0.00126	(0.03)	0.122*	(2.35)
social	0.513***	(32.62)	0.00535	(0.63)			-0.0409*	(-1.98)
health	0.326***	(15.75)	0.00541	(0.76)	0.0391	(1.80)		
education	0.0380**	(2.76)	0.0519***	(9.16)	-0.0796***	(-6.26)	0.0839***	(4.78)
age	0.00428	(1.82)	0.00266*	(2.42)	-0.00522*	(-1.97)	0.00212	(0.69)
q25								
life satisfaction			0.0218***	(4.51)	0.388***	(26.27)	0.266***	(19.37)
log(income)	0.142***	(4.75)			0.00728	(0.29)	0.0512	(1.54)
social	0.460***	(28.19)	-0.00214	(-0.36)			0.00270	(0.18)
health	0.255***	(16.16)	0.00478	(1.12)	0.00460	(0.35)		
education	0.0371***	(3.58)	0.0716***	(18.41)	-0.0777***	(-7.29)	0.0466***	(4.64)
age	0.00248	(1.55)	0.00199***	(3.40)	-0.00377	(-1.95)	-0.0000387	(-0.02)
q50								
life satisfaction			0.0283***	(6.42)	0.350***	(32.49)	0.216***	(20.58)
log(income)	0.114***	(5.26)			-0.0213	(-0.87)	0.0199	(0.97)
social	0.390***	(42.31)	-0.00599	(-1.32)			0.0145	(1.18)
health	0.203***	(19.53)	0.00929**	(2.67)	0.00191	(0.17)		
education	0.0144*	(1.97)	0.0814***	(29.96)	-0.0829***	(-10.31)	0.0338***	(4.75)
age	0.00239*	(2.21)	0.00172***	(3.87)	-0.00731***	(-5.56)	0.000806	(0.70)
q75								
life satisfaction			0.0290***	(5.67)	0.333***	(30.34)	0.161***	(15.07)
log(income)	0.0427*	(2.06)			-0.0405*	(-2.14)	0.0268	(1.44)
social	0.293***	(20.73)	-0.0119*	(-2.10)			0.0263*	(2.49)
health	0.168***	(16.29)	0.0110*	(2.35)	-0.00674	(-0.57)		
education	-0.00875	(-1.23)	0.0862***	(25.10)	-0.0688***	(-8.73)	0.0266***	(4.42)
age	0.00301**	(2.68)	0.00162**	(2.60)	-0.00404***	(-3.35)	0.000790	(0.77)
q90								
life satisfaction			0.0375***	(5.89)	0.288***	(32.54)	0.151***	(14.37)
log(income)	0.0213	(0.93)			-0.0312	(-1.92)	0.0471***	(3.75)
social	0.265***	(22.79)	-0.0174*	(-2.27)			0.0114	(1.16)
health	0.115***	(10.58)	0.0118	(1.65)	0.00697	(1.08)		
education	-0.0465***	(-5.53)	0.0875***	(18.96)	-0.0450***	(-5.58)	0.0128*	(2.20)
age	0.00200	(1.45)	0.00252***	(3.43)	-0.00244*	(-2.04)	-0.000298	(-0.28)
Observations	11591		11591		11591		11591	
0.10 Pseudo R2	.2168		.1211		.1227		.2143	
0.25 Pseudo R2	.1864		.1328		.1117		.1982	
0.50 Pseudo R2	.1463		.1633		.1063		.1532	
0.75 Pseudo R2	.0524		.1639		.1089		.1086	
0.90 Pseudo R2	.114		.1563		.1219		.109	

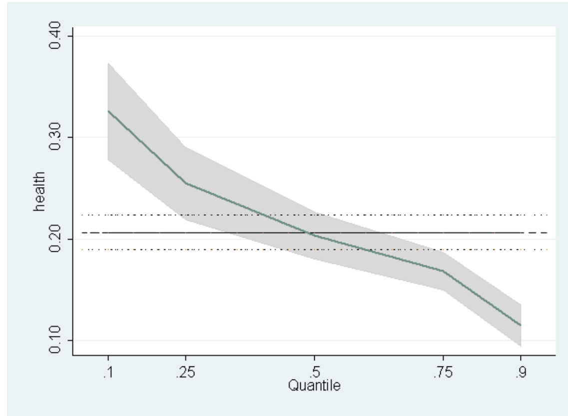
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(i.e. including our set of control variables). In Table 5, however, the rows are displaying only the coefficients for our main variables life satisfaction, income, health, social as well as education and age. These coefficients are provided for the .10, .25, .50, .75 and .90 quantiles of the distribution of the dependent variable (with the Pseudo-R^2 for every quantile provided at the bottom of the table). For the model where life satisfaction is the dependent variable, the .10 quantile thus refers to the least happy 10% of the sample (conditional on the explanatory variables), and so on. Bootstrapped standard errors are applied here to provide a more reliable basis for statistical inference.

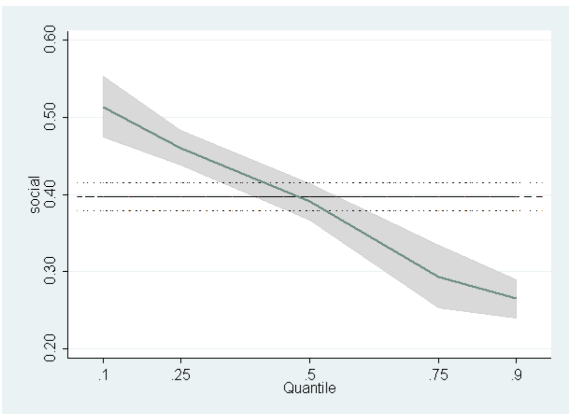
We begin by considering the quantile regressions for model 1, where we regress income, health and the social index on life satisfaction (although we only report the mentioned variables and age and education for the quantiles, we have included all the same variables in the



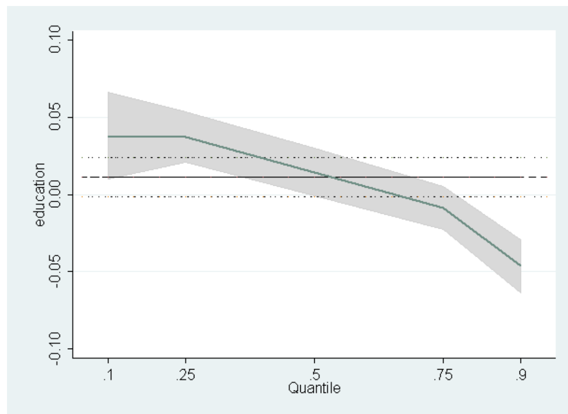
(a) log(income)



(b) health



(c) social



(d) education

Figure 2: Quantile regression with life satisfaction as dependent variable (vertical axes show coefficient estimates of named explanatory variable over the life satisfaction distribution; horizontal axes depict the quantiles of the dependent variable). Quantile regression error bars correspond to bootstrapped 95% confidence intervals (100 bootstrap replications).

analysis as above, controlling thus for the employment status, marriage status and so on).[19] We can clearly see how income plays a different role in the reported quantiles. While the effect is significant for the the .10, .25, .50 and .75 quantiles in the life satisfaction distribution, the effect can no longer be found for the .90 quantile. We find thus that while money buys you happiness if you belong to the lower parts of the happiness distribution, this isn't the case any more for the happiest individuals in our sample. The happiest ten percent of individuals in our sample are satisfied independent of their income, which means that truly happy individuals, it seems, do not depend on money for their happiness (to be more precise: while we find consistent significant effects for the less happy individuals, no significant effect can be shown for the happiest individuals). This effect can only be clearly seen in quantile regressions and is glossed over in a standard regression framework because the strong effect on income in the lower quantiles of the distribution compensates this in the average values.

[19]The authors will provide the full regression results on request.

The declining relationship can also be clearly seen in Figure 2(a), where we plot the bootstrapped coefficient for the whole life satisfaction distribution. In these quantile regression diagrams the grey-shaded area depicts the 95% confidence bands of the estimated quantile regression coefficient. The small horizontal black line depicts the OLS coefficient estimates (with small dotted black lines referring to the OLS confidence bands). If we can observe for a variable that the quantile regression estimates lie outside the confidence intervals of the OLS regression, this shows that effects of this variable are not constant across the conditional distribution of the independent variable (Koenker and Hallock, 2001, p. 151). We see that in the upper part of the life satisfaction distribution, the income coefficient is close to zero, while it is much higher in the lower parts of the distribution. From Table 5 we can also see that the Pseudo-R^2 decreases strongly with increasing quantiles (although its minimum is at the .75 quantile). In quantile regressions, the Pseudo-R^2 can be interpreted in a similar fashion as the R^2 in regular regressions (Hao and Naiman, 2007).

We do find similar, decreasing coefficient estimates over the conditional happiness distribution for health, our social index and education (see Figures 2(b), 2(c) and 2(d), respectively). Health influences life satisfaction more strongly in the lower quantiles, similar to income. The effect is still positive for the upper quantiles, although it is diminished in magnitude. Similar results obtain for the social index, although here, the coefficient is still higher in the upper quantiles: even for the happiest in the distribution, a functioning social life does explain parts of their high happiness. Nevertheless, this effect is much more pronounced for the lower parts of the distribution, where the coefficient is nearly twice as high. With education, we find a nice example how the averaging out in standard regressions can effectively mask an effect: while education is not a significant influence on life satisfaction in the standard ordered probit model (see Table 4) we find clearly significant effects in our quantile regression (see Table 5). For the lower quantiles, education has a positive (significant) effect on life satisfaction (i.e., if you are less happy, a better education does benefit well-being). This effect is then reversed for the upper quantiles, where the coefficient estimate turns (significantly) negative. Those who are the most happy are negatively influenced by education. Education therefore plays a stabilizing role by decreasing the likelihood of extremes in well-being. In a certain sense, education can provide consolation to unhappy individuals, while it has a sobering effect at the upper end of the happiness distribution. In each of the four cases shown in Figure 2, we observe that the regression coefficients are closer to zero at the upper quantiles. This suggests that, for unhappy individuals, there is much that they can do to improve their well-being. The secret to experiencing the highest levels of happiness, however, is relatively unrelated to the four main factors investigated here.

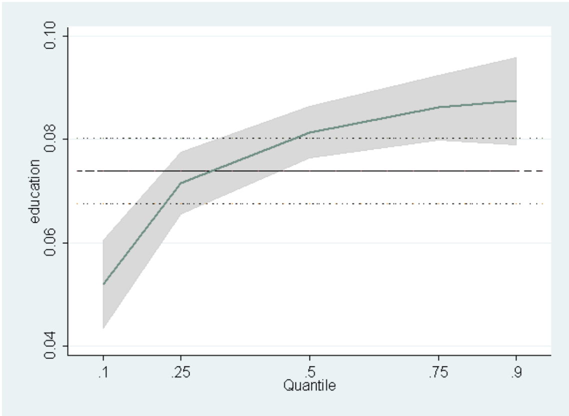
Our models 2 to 4 also offer new insights about non-constant effects of our variables of interest (see Table 5 and Figure 3). Pertaining to model (2), where we analyze the effects of our explanatory variables on log(income), we find that the effect of education is much more pronounced for those who have higher incomes: if you have a high income, your education contributes much more to this income than if you have a low income (Figure 3(a)). The greater importance of education for income at the upper end of the income distribution might be a cause for concern, if low-income parents pass on to their children the notion that education is not important for income (i.e., this might be a channel through which children inherit the low socio-economic status of their parents). Noteworthy as well is that for the high income quantiles, the social index has a negative effect on income, while this effect is absent in the lower quantiles. It seems that high incomes are bought at the cost of a less fulfilling social life, or for that matter, perhaps, less time to allot to friends and family. Another finding is the role life satisfaction plays for income. Graham et al. (2004) find for a Russian data set that happiness matters more for future income of the poor than for the rich, which they explain in the following way: for example for workers in the service sector, "in the absence of income, a good attitude can make a difference to one's future earnings" (p. 334). In our data set, we find that this relationship is rather the opposite: having higher incomes, the effect of happiness on income is much stronger. Note, however, that our analysis is not concerned with individuals' future incomes, so that both effects might even be compatible.

Concerning our social index as the dependent variable, we find a persistent negative influence of education on social relations. While this pertains to all quantiles of the distribution of the social index, we can observe that less sociable individuals are more strongly negatively influenced by education, which is reminiscent of the popular stereotype of the "antisocial egg-head." One might conjecture that, as with income, higher education means that individuals have demanding jobs that decrease the leisure time that is needed to pursue fulfilling social relations. Another possible explanation is that more educated individuals might consider social relations to be a trivial part of life, and prefer to direct their attention to more intellectually challenging tasks.

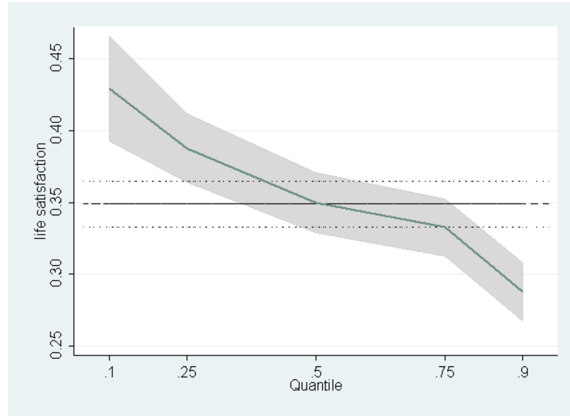
Secondly, we find that the high correlation between life satisfaction and social achievements is also declining towards the higher quantiles of the distribution: while life satisfaction plays a lessened role for those individuals already having fulfilling social lives, it is highly effective for individuals where this is not the case (see Figure 3(b)). A similarly declining role for life satisfaction is also found when we examine health as the dependent variable (see Table 5, model (4)). A higher life satisfaction seems thus of a much higher relevance for those who are ill, than for those who show high levels of health. When health is taken as the dependent variable, such a declining effect also is found for education (see Figure 3(c)). The individuals that have low levels of health benefit much more from higher education levels than individuals who are healthy (although still significant, the coefficient size for the healthiest individuals is closer to zero). Finally, we also find that income seems to influence health differently along the distribution (see Figure 3(d)). Those individuals in the lowest quantile of the health distribution benefit from increases in income, as do those in the highest quantile (although in comparison, the magnitude of the effect for the highest quantile is only one-third), while we find no significant effects of income on health in the middle parts of the distribution. Taken together, these last results are encouraging in that there seem to be several ways in which problems associated with poor health can be alleviated — through higher income, education, or through higher life satisfaction more generally.

4.3. Robustness analysis

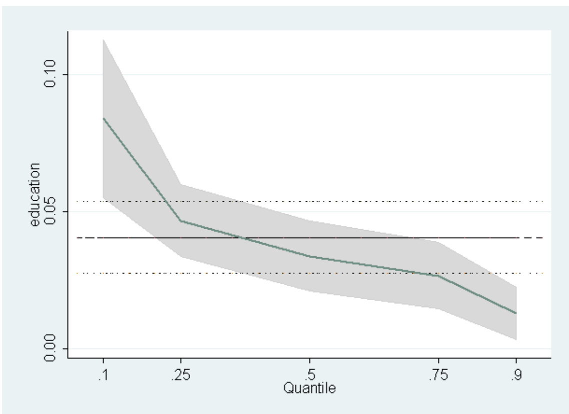
We have seen that subjective well-being can be captured by diverse well-being constructs (see Section 2). In order to further explore how robust the results are that we have obtained using the life satisfaction variable, we redid the analysis using the mental well-being concept of happiness. We report the full results for the quantile regression in Table 6 in the appendix and highlight some of the differences in this subsection. Overall the findings for both concepts of well-being are quite similar. The signs of the coefficients of the variables of interest largely coincide, although there are differences in the effect sizes. We do not want to go



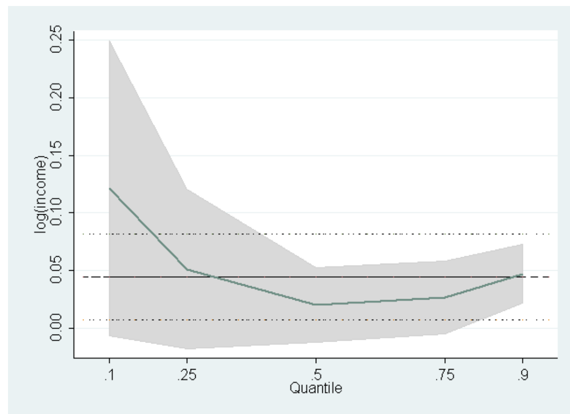
(a) effect of education on log(income)



(b) effect of life satisfaction on social index



(c) effect of education on health



(d) effect of income on health

Figure 3: Quantile regression for different models (vertical axes show coefficient estimates of named explanatory variable; horizontal axes depict the quantiles of the dependent variable). Quantile regression error bars correspond to bootstrapped 95% confidence intervals (100 bootstrap replications).

into all details here for want of space, but highlight some findings regarding mental well-being as the dependent variable. Over the quantiles of the mental well-being distribution, income coefficients are much more uniform than compared to the life satisfaction distribution (Figure 4(a), appendix). Also education's effects on mental well-being are more uniform and less strong than for life satisfaction (Figure 4(b)). On the other hand, age plays a more "stabilizing" role for mental well-being, exhibiting a positive role at the lower end of the mental well-being distribution and a negative one at the upper end (Figure 4(c)).

As a further investigation of the robustness of our results, we repeated our analysis on subsamples disaggregated according to gender (results in Tables 7 and 8 in the appendix). In most cases, similar results are obtained, although we did observe a few interesting results that can be briefly mentioned here. First, we observed that income has the strongest impact on life satisfaction at the 10% quantile for the male subsample (i.e. income has its strongest effect on happiness for the least happy males), while at the 10% quantile for females the coefficient is much lower and not statistically significant. Second, life satisfaction has a positive and significant impact on income for the poorest males (10% quantile) but the corresponding effect for females is smaller and not significant. Third, the negative effect of education on social relations is less pronounced for females (i.e. the coefficients are of lower magnitude). Fourth, social relations are, if anything, positively related to health for females, while for males the relationship is negative and highly significant at the 10% quantile of health (and insignificant at other quantiles). One speculative interpretation could be that men are more likely to associate social activity with unhealthy activities such as drinking, smoking, and dangerous sports. Note finally that our gender disaggregation provides us with only scant justification for distinguishing "Miserable Janes" from "Cheerful Johns": mean life satisfaction of males is 5.236 (s.d. of 1.21), while females are the tiniest bit less happy (mean 5.199 and s.d. 1.287).[20]

5. Conclusion

Research into the causes and correlates of human happiness (or synonymously in this paper: subjective well-being) has increased in momentum in the past years and progressed to a point where many of the initial findings are becoming increasingly qualified, theories become more refined and the statistical tools to analyze the complex relationships between happiness and its determinants become ever more sophisticated. What has been neglected so far is the information that is contained in happiness distributions.

We have argued that happiness research should start being more concerned with the effects of explanatory variables on different parts of the happiness distribution. While average effects certainly are an important feature to examine, it is also interesting to understand what happens at the extremes of a distribution. For example, are increases in income as relevant for the happiness of the happiest individuals in a population as they are for the most miserable individuals? If effects are not uniform along the distribution, a standard regression gives the researcher only an incomplete picture of the relationship between dependent and independent variable: in heterogeneous distributions, regression methodologies that focus on means might seriously under- or overestimate effects or even fail to identify effects at all (Cade and Noon, 2003). In this paper, we demonstrated how extending happiness measurement from ordinary least square regressions to quantile regressions can solve this problem (Koenker and Bassett, 1978; Koenker and Hallock, 2001). Quantile regression enables the analysis of effects of the explanatory variables on different quantiles of the happiness distribution as opposed to a (incomplete) focus on the mean of the distribution.

We have applied quantile regressions to a fairly standard set of explanatory variables (and their effect on happiness) and compared these results with an ordinary least squares regression. Since we were using cross-sectional data in this expositional exercise, we also analyzed some reversed relationships, where happiness enters the regression equation as an explanatory variable (e.g., the effects of happiness on an individual's income). This was motivated by recent research that shows how happy individuals systematically score higher in important life domains. We have explored these relationships by using data from the British Household Panel Survey (BHPS) for the year 2006, an extensive data set that covers information on many important life domains of a representative sample of the British populace. Among our results, we observed that income has a positive impact on life satisfaction, which

[20] Although our analysis focuses on the 2006 cross-section, we additionally repeated our analysis for a different year, 2004. Since we obtained similar results, we have chosen to omit this robustness test here.

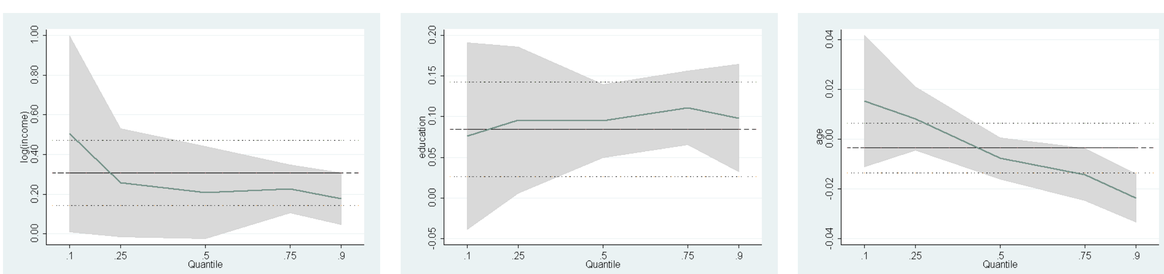
is strongest for the least happy individuals, but not significant for the happiest. Relatedly, social relations and health have their largest impacts for the least happy individuals, with their positive effects being much smaller at the upper end of the happiness distribution. Education increases happiness for the least happy individuals, while decreasing happiness for the happiest (thus, having a "stabilizing" role overall). Life satisfaction and education have their largest effects on income for the richest individuals, and these effects decrease steadily as income falls. For those individuals in the worst states of health, we observe a strong positive impact of both life satisfaction and education on health, while this effect fades as we move up the (conditional) health distribution.

The good news is that much can be done to alleviate the unhappiness of those individuals at the lower end of the distribution (i.e. the "Miserable Janes"). In contrast, with the factors explored in this study, we have not succeeded in finding the secrets of happiness for the truly happy individuals — at the upper tail of the distribution. These "Cheerful Johns", it seems, can be found in all situations in life, with little that links them together. Their happiness does not seem to be affected by the external factors identified here, but may come from other sources yet to be uncovered.

Future extensions of a quantile regression methodology in happiness research could test whether these relationships found in the present paper generalize to other countries and data sets. Another important step would constitute an application of fixed effects quantile regressions that would exploit the panel properties of a data set, thus being able to take into account time-invariant individual-specific effects. Fixed effects quantile regression would be a suitable tool for exploring differential effects for growth versus decline in happiness, where efforts are made to "homogenize" different individuals, and make them more comparable, by removing time-invariant fixed effects. As such, future work into happiness that applies fixed effect quantile regressions would likely provide an interesting extension to our current findings.

Date: August 3, 2010; ca. 8,900 words

Appendix



(a) income (b) education (c) age

Figure 4: Quantile regression for mental well-being as dependent variable (vertical axes show coefficient estimates of named explanatory variable; horizontal axes depict the quantiles of the dependent variable). Quantile regression error bars correspond to bootstrapped 95% confidence intervals (100 bootstrap replications).

Table 6: Robustness: Quantile regression table, mental well-being

	(1) mental well-being		(2) log(income)		(3) social		(4) health	
q10								
mental well-being			0.00444**	(2.96)	0.0579***	(12.57)	0.0697***	(14.18)
log(income)	0.505*	(2.37)			0.0464	(1.02)	0.129*	(2.47)
social	1.751***	(14.68)	0.00718	(0.97)			-0.0157	(-0.78)
health	2.202***	(17.95)	0.00503	(0.66)	0.0657***	(3.30)		
education	0.0758	(0.94)	0.0505***	(9.59)	-0.0788***	(-6.08)	0.0858***	(5.91)
age	0.0152	(1.24)	0.00254*	(2.48)	-0.00345	(-1.28)	0.00275	(0.94)
q25								
mental well-being			0.00389***	(3.79)	0.0560***	(16.68)	0.0692***	(18.34)
log(income)	0.259	(1.90)			0.0373	(1.47)	0.0733*	(2.31)
social	1.223***	(18.53)	0.000601	(0.12)			0.0365*	(2.51)
health	1.483***	(20.28)	0.00276	(0.60)	0.0496***	(3.30)		
education	0.0959*	(2.38)	0.0713***	(18.83)	-0.0882***	(-9.87)	0.0447***	(4.64)
age	0.00823	(1.27)	0.00207**	(2.95)	-0.00426*	(-2.50)	0.000816	(0.48)
q50								
mental well-being			0.00449***	(5.12)	0.0507***	(18.80)	0.0554***	(22.24)
log(income)	0.208	(1.95)			0.0142	(0.55)	0.0309	(1.57)
social	0.974***	(20.93)	0.0000951	(0.02)			0.0387***	(3.87)
health	1.045***	(23.37)	0.0115***	(3.58)	0.0234*	(2.27)		
education	0.0948**	(2.61)	0.0810***	(27.61)	-0.0872***	(-11.81)	0.0331***	(5.09)
age	-0.00776	(-1.51)	0.00176***	(3.35)	-0.00458***	(-3.42)	0.00140	(1.08)
q75								
mental well-being			0.00447***	(3.46)	0.0472***	(14.88)	0.0428***	(18.10)
log(income)	0.226***	(3.72)			-0.0162	(-0.85)	0.0120	(0.85)
social	0.747***	(18.00)	-0.00643	(-1.32)			0.0446***	(5.38)
health	0.684***	(20.74)	0.0143**	(2.95)	0.00742	(0.68)		
education	0.111***	(4.20)	0.0854***	(25.46)	-0.0745***	(-8.91)	0.0241***	(4.10)
age	-0.0142**	(-2.96)	0.00149*	(2.43)	-0.00373*	(-2.43)	0.00117	(1.00)
q90								
mental well-being			0.00350*	(2.27)	0.0362***	(13.71)	0.0347***	(16.52)
log(income)	0.176**	(3.12)			-0.0399	(-1.65)	0.0473***	(5.32)
social	0.510***	(11.45)	-0.00649	(-0.89)			0.0250*	(2.47)
health	0.334***	(9.79)	0.0143*	(2.31)	0.0170	(1.63)		
education	0.0984***	(3.40)	0.0892***	(20.63)	-0.0698***	(-8.70)	0.00897	(1.53)
age	-0.0237***	(-4.44)	0.00255***	(3.32)	-0.00139	(-1.02)	0.000349	(0.36)
Observations	11591		11591		11591		11591	
0.10 Pseudo R2	.1871		.1212		.075		.2217	
0.25 Pseudo R2	.1408		.1325		.0708		.2081	
0.50 Pseudo R2	.0995		.1626		.0645		.1629	
0.75 Pseudo R2	.0736		.1623		.0651		.1147	
0.90 Pseudo R2	.0422		.1534		.0699		.1122	

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

Table 7: Robustness: Quantile regression table, males

	(1) life satisfaction		(2) log(income)		(3) social		(4) health	
q10								
life satisfaction			0.0217*	(2.18)	0.450***	(15.39)	0.364***	(10.52)
log(income)	0.268***	(4.26)			-0.0207	(-0.38)	0.0804	(1.13)
social	0.497***	(19.83)	0.00296	(0.29)			-0.0980***	(-3.90)
health	0.331***	(11.85)	0.0159	(1.43)	0.0257	(0.76)		
education	0.0367	(1.63)	0.0569***	(7.38)	-0.0947***	(-5.73)	0.0946***	(4.32)
age	0.00584	(1.84)	0.00300*	(2.23)	-0.00473	(-1.59)	-0.00877**	(-2.63)
q25								
life satisfaction			0.0305***	(3.99)	0.402***	(16.01)	0.271***	(11.81)
log(income)	0.110**	(2.89)			-0.000906	(-0.02)	0.0248	(0.58)
social	0.423***	(18.07)	0.00432	(0.59)			-0.0152	(-0.82)
health	0.288***	(13.92)	0.00249	(0.27)	-0.0360	(-1.71)		
education	0.0288*	(2.25)	0.0715***	(12.85)	-0.101***	(-7.74)	0.0560***	(4.85)
age	0.00257	(1.12)	0.00168*	(2.04)	-0.00445	(-1.69)	-0.00722**	(-3.25)
q50								
life satisfaction			0.0291***	(4.43)	0.363***	(21.51)	0.231***	(14.60)
log(income)	0.106**	(2.89)			0.00734	(0.20)	0.00440	(0.18)
social	0.370***	(24.12)	-0.000645	(-0.11)			-0.00867	(-0.47)
health	0.224***	(9.84)	0.0104*	(1.96)	-0.0197	(-1.26)		
education	0.0141	(1.43)	0.0842***	(20.56)	-0.101***	(-9.72)	0.0296***	(3.33)
age	0.00267	(1.61)	0.00137	(1.88)	-0.00711***	(-3.46)	-0.00446	(-1.96)
q75								
life satisfaction			0.0287***	(3.39)	0.329***	(19.28)	0.177***	(9.82)
log(income)	0.00831	(0.29)			-0.00541	(-0.22)	0.00711	(0.34)
social	0.267***	(13.02)	-0.00938	(-1.17)			0.0125	(0.89)
health	0.173***	(12.24)	0.00633	(0.69)	-0.0160	(-1.02)		
education	-0.00717	(-0.96)	0.0915***	(21.11)	-0.0901***	(-7.83)	0.0271**	(2.93)
age	0.00466**	(2.62)	0.00136	(1.60)	-0.00242	(-1.38)	-0.00270	(-1.51)
q90								
life satisfaction			0.0339***	(3.52)	0.281***	(17.68)	0.128***	(5.21)
log(income)	0.0116	(0.38)			-0.0123	(-0.41)	0.0150	(0.81)
social	0.251***	(14.82)	0.00325	(0.35)			0.00609	(0.61)
health	0.127***	(7.70)	0.0109	(1.18)	-0.0137	(-0.99)		
education	-0.0396***	(-3.81)	0.0994***	(16.88)	-0.0662***	(-6.05)	0.00760	(1.18)
age	0.00191	(0.88)	0.00290**	(2.87)	-0.000617	(-0.34)	-0.00290*	(-2.10)
Observations	5417		5417		5417		5417	
0.10 Pseudo R2	.223		.1485		.1336		.2434	
0.25 Pseudo R2	.1732		.1405		.1186		.2115	
0.50 Pseudo R2	.1521		.1636		.116		.1438	
0.75 Pseudo R2	.0468		.1685		.1205		.103	
0.90 Pseudo R2	.134		.173		.1275		.0857	

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

Table 8: Robustness: Quantile regression table, females

	(1) life satisfaction		(2) log(income)		(3) social		(4) health	
q10								
life satisfaction			0.0120	(1.15)	0.429***	(17.24)	0.303***	(9.62)
log(income)	0.111	(1.58)			0.0302	(0.49)	0.152*	(2.57)
social	0.521***	(18.29)	0.00813	(0.74)			0.00754	(0.21)
health	0.300***	(10.12)	0.00140	(0.12)	0.0497	(1.79)		
education	0.0274	(1.42)	0.0535***	(6.41)	-0.0635***	(-3.69)	0.0734**	(2.93)
age	0.00141	(0.39)	0.00296	(1.73)	-0.00543	(-1.43)	0.0124**	(3.16)
q25								
life satisfaction			0.0140*	(2.17)	0.361***	(22.52)	0.255***	(10.22)
log(income)	0.161***	(3.66)			0.00324	(0.09)	0.0578	(1.13)
social	0.488***	(22.01)	-0.00394	(-0.51)			0.0537*	(2.08)
health	0.223***	(10.12)	0.00783	(1.22)	0.0261	(1.79)		
education	0.0386**	(2.84)	0.0693***	(12.40)	-0.0545***	(-4.95)	0.0506**	(3.07)
age	0.00305	(1.52)	0.00206*	(2.22)	-0.00271	(-1.23)	0.00926***	(4.11)
q50								
life satisfaction			0.0221***	(3.70)	0.340***	(25.27)	0.207***	(10.85)
log(income)	0.108**	(3.07)			-0.0510	(-1.52)	0.0477	(1.33)
social	0.413***	(24.69)	-0.00816	(-1.31)			0.0316*	(2.00)
health	0.198***	(12.24)	0.0126*	(2.34)	0.00354	(0.23)		
education	0.0161	(1.57)	0.0756***	(16.78)	-0.0586***	(-5.30)	0.0372***	(3.39)
age	0.00113	(0.62)	0.00209**	(3.27)	-0.00587**	(-3.22)	0.00410*	(2.28)
q75								
life satisfaction			0.0312***	(4.64)	0.325***	(27.45)	0.157***	(9.55)
log(income)	0.0598*	(2.32)			-0.0683*	(-2.26)	0.0374	(1.42)
social	0.328***	(17.49)	-0.0175*	(-2.43)			0.0486***	(3.54)
health	0.153***	(9.88)	0.0158*	(2.46)	0.0179	(1.42)		
education	-0.00794	(-0.86)	0.0804***	(18.32)	-0.0510***	(-4.86)	0.0318***	(3.61)
age	0.00212	(1.19)	0.00204**	(2.85)	-0.00678***	(-4.28)	0.00476**	(3.28)
q90								
life satisfaction			0.0396***	(4.57)	0.297***	(19.10)	0.135***	(9.19)
log(income)	0.0155	(0.50)			-0.0201	(-0.98)	0.0562**	(2.72)
social	0.277***	(17.09)	-0.0319**	(-3.16)			0.0214	(1.40)
health	0.101***	(6.63)	0.0206*	(2.51)	0.0118	(1.47)		
education	-0.0416***	(-3.83)	0.0783***	(11.33)	-0.0287**	(-2.65)	0.0115	(1.30)
age	0.00298	(1.51)	0.00247*	(2.50)	-0.00427*	(-2.49)	0.00550**	(2.74)
Observations	6174		6174		6174		6174	
0.10 Pseudo R2	.2164		.1065		.12		.1956	
0.25 Pseudo R2	.2004		.1322		.1094		.1865	
0.50 Pseudo R2	.1466		.1659		.1053		.1592	
0.75 Pseudo R2	.0635		.1662		.1092		.119	
0.90 Pseudo R2	.1063		.1523		.1199		.0879	

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

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