Working Paper No. 808

Heterogeneity in the Relationship between Unemployment and Subjective Well-Being: A Quantile Approach*

by

Martin Binder**
Levy Economics Institute of Bard College

Alex Coad
Science and Technology Policy Research Unit, University of Sussex

June 2014

* Thanks to Christopher Boyce, Matias Ramirez, Rose Cairns, Ben Martin, Paul Nightingale, Tommaso Ciarli, Ohid Yaqub, Satoko Yasuda, and two anonymous referees for their helpful comments. This research was funded by the ESRC-TSB-BIS-NESTA as part of the ES/J008427/1 grant on Skills, Knowledge, Innovation, Policy and Practice (SKIPPY). 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. While we are not really very happy about it, as ever, any remaining errors are ours alone.
** To correspond with author: binder@uni-kassel.de

Levy Economics Institute
P.O. Box 5000
Annandale-on-Hudson, NY 12504-5000
http://www.levyinstitute.org

ISSN 1547-366X

Abstract

Unemployment has been robustly shown to strongly decrease subjective well-being (or "happiness"). In the present paper, we use panel quantile regression techniques in order to analyze to what extent the negative impact of unemployment varies along the subjective well--being distribution. In our analysis of British Household Panel Survey data (1996–2008) we find that, over the quantiles of our subjective well-being variable, individuals with high well-being suffer less from becoming unemployed. A similar but stronger effect of unemployment is found for a broad mental well-being variable (GHQ-12). For happy and mentally stable individuals, it seems their higher well-being acts like a safety net when they become unemployed. We explore these findings by examining the heterogeneous unemployment effects over the quantiles of satisfaction with various life domains.

Keywords: Subjective Well-being; Unemployment; Quantile Analysis; Heterogeneity; British Household Panel Survey; Domain Satisfaction

JEL Classifications: I31, J01, J64

1 INTRODUCTION

Becoming unemployed is a harrowing life experience for many people. For one, becoming unemployed often means losing one's primary source of income (which might be only incompletely replaced by unemployment benefits, if at all). But becoming unemployed also has non-monetary, psychological costs (e.g., Layard et al., 2012), which include one's potential loss of meaning in life, impairment of personal identity and the loss of self-esteem one draws from one's job. There may also be social stigma, arising from being unemployed in a society where the norm is to work for one's living. These negative effects can be compounded by the loss of social life and contacts one enjoyed at the work place. Taking these factors together, it is hardly surprising to note that unemployment is one of the main drivers of unhappiness in modern societies.

Given its importance for human well-being, the effect of unemployment on the subjective well-being of the unemployed has been well-researched. From the early contributions of Clark and Oswald (1994) and Winkelmann and Winkelmann (1998) onwards, unemployment has been shown to consistently and strongly depress subjective well-being. Causality here runs mainly from unemployment to subjective well-being, as research with panel data has shown (Winkelmann and Winkelmann, 1998; Lucas et al., 2004): selection effects, viz. the unhappy being more likely to self-select into unemployment, cannot explain the association between unemployment and subjective well-being (while causality might run in both directions, the stronger effects are from unemployment to subjective well-being). Nevertheless, some questions remain.

The present paper explores an issue that has so far been neglected in the literature. Research into subjective well-being mostly focuses on the average effect of life events on subjective well-being by employing multivariate regressions that focus on the conditional mean of the dependent variable. As has been argued in Binder and Coad (2011), focus on the average effects neglects potentially interesting heterogeneity across the subjective wellbeing distribution. Does unemployment impact happy individuals more than unhappy ones, or vice versa? These differential effects across the well-being distribution are averaged out in traditional analyses and can lead to misleading inferences. A case in point is the association between education and subjective well-being (Binder and Coad, 2011): the average absence of an association between both variables turns out to be caused by two countervailing effects in the extremes of the well-being distribution, where a significantly positive association for unhappy individuals and a significantly negative association for happy individuals average out to a null-effect in a traditional multivariate regression. In order to better understand this heterogeneity in the relationship between unemployment and subjective well-being over the full well-being distribution, in the present paper we use the panel quantile regression approach introduced by Canay (2011). As such, our paper connects to other approaches that explore the heterogeneity of subjective well-being and its determinants, for example by looking into heterogeneous effects on different domain satisfactions (van Praag et al., 2003), different concepts of well-being (Knabe et al., 2010; Krueger and Mueller, 2012) as well as differences in effects based on personality differences (Boyce et al., 2010).

The paper is organized as follows. In Section 2 we present the literature relevant to our analysis. We then discuss the quantile regression methodology, our data set and the results of our empirical exercise in Section 3. Our analysis consists of a set of baseline regressions as well as quantile regressions for life satisfaction and mental well-being variables. We then explore the heterogeneity found in our main analysis, by looking into how unemployment impacts a number of domain satisfactions. As in the main case, the effects of unemployment vary strongly over the domain satisfaction quantiles and vary strongly for different domain satisfactions. We can also show that mentally stable individuals are much less impacted by their loss of employment in terms of life satisfaction, probably due to their being able to psychologically cope more successfully with employment loss by focusing their life on other domains apart from their job, and better adapting to their new circumstances. Section 4 concludes by noting that our results show the need for analyzing the effect of life events on life satisfaction not only for the average case but taking into account the heterogeneity of reactions to these events over the full well-being distribution.

2 LITERATURE BACKGROUND

Subjective well-being (SWB, or synonymously “happiness”) has been intensively studied across the world in recent years and is linked to a range of determinants that seem to reliably influence it (Graham, 2009; Layard et al., 2012).[1]Among these life domains influencing subjective well-being, unemployment is one of the most robust negative influences and comparatively well-researched (e.g., Clark and Oswald, 1994; Di Tella et al., 2001; Helliwell, 2003): "The estimated effect is typically as large as the effect of bereavement or separation, and the unemployed share with these other experiences the characteristic of ceasing to be needed" (Layard et al., 2012, p. 66). This negative effect is not limited to cross-sectional data but also extends to the panel context (Winkelmann and Winkelmann, 1998; Lucas et al., 2004; Kassenboehmer and Haisken-De New, 2009), showing that the self-selection of unhappy individuals into unemployment is not the main driver for the empirically measured association between the two variables. While unhappiness can cause unemployment (or failure at work in general), the main arrow of causality seems to run from unemployment to subjective well-being. Moreover it seems that individuals have difficulties getting used to unemployment over time. While many determinants of subjective well-being fade in their hedonic intensity over time (a phenomenon called "hedonic adaptation," which is very domain-specific and inadequately understood as of yet (Frederick and Loewenstein, 1999), hedonic adaptation to unemployment seems to be quite restricted. Even when a new job is found, recovery from unemployment in terms of lost life satisfaction seems to be incomplete (Lucas et al., 2004; Clark et al., 2008a; Clark and Georgellis, 2012, p. 11).[2] From a dynamic perspective, it also seems that the years before and after becoming unemployed matter, and these leads and lags of subjective well-being have been analyzed (Clark et al., 2008a; Clark and Georgellis, 2012): in contrast to other life events, however, the years before unemployment show less pronounced anticipation effects, probably because becoming unemployed is less easy to anticipate than becoming married or divorced, for example.[3] Typical effect sizes of being unemployed in a fixed-effect regression framework with life satisfaction as dependent variable (on a 7 point Likert scale) for the British Household Panel Survey data set are around -0.22 (-0.33 in a cross-sectional analysis), compared to effect sizes of -0.34 (-0.60) for being separated and 1.04 (1.94) of being in "excellent" (as opposed to "very poor") health (Layard et al., 2012, pp. 84-85).

As mentioned in the introduction, there are a number of explanations why unemployment would depress individuals' subjective well-being. Besides losing one's main source of income, the psychological costs seem much worse: losing an important source of meaning in life, having to revise one's self-image and the accompanying impairment of self-identity, loss of self-esteem, social stigma and loss of social contacts and structure of one's daytime activities are all stipulated explanations for the loss in well-being incurred (see more extensively Jahoda, 1981, 1988; Darity and Goldsmith, 1996; Layard et al., 2012, and the sources cited therein).[4]

Recent research has also analyzed the composition of the negative impact unemployment has on subjective well-being, finding that the negative effect of losing one's job is somewhat mitigated by the fact that the unemployed can spend more time in pleasurable leisure activities, hence not decreasing affective well-being (Knabe et al., 2010; Powdthavee, 2012). A second study, however, has provided evidence that despite more leisure activities to pursue, the unemployed remain worse off, when measuring their well-being via negative emotions (Krueger and Mueller, 2012). This points to the question whether unemployment impacts differently on different measures of well-being such as life satisfaction, emotional well-being or mental well-being. It also raises the question whether unemployment has different impacts on different domain satisfactions.

An important complication neglected in the unemployment-happiness relationship can be conjectured to lie in the econometric methodology employed in the studies discussed above. These analyses all primarily deal with average effects, i.e., the association between unemployment and the conditional mean of the subjective well-being variable. Typical multivariate ordinary least squares regression techniques focus on the conditional mean of the dependent variable and average out coefficient estimates over the conditional distribution of the dependent variable (in essence analyzing the effect of unemployment on subjective well-being for "Average Joe," but not "Miserable Jane" or "Cheerful John"). As has been argued in Binder and Coad (2011), such a focus neglects important information about the extremes of the subjective well-being distribution: especially 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). Quantile regressions have only recently been introduced to subjective well-being research (Binder and Coad, 2011; Binder and Freytag, 2012) and provide evidence for considerable heterogeneity over the well-being distribution. As discussed in the introduction, this heterogeneity can account for the absence of an (average) association typically found between education and subjective well-being. Typical determinants of subjective well-being (income, social life and health) vary over the subjective well-being distribution as well, and all are less strongly associated with subjective well-being for the happiest quantiles (with considerable heterogeneity also between explanatory variables: for example, the social life variable was still positively associated with subjective well-being for the happiest individuals, while income was not, see Binder and Coad, 2011, p. 285). In a different study, a positive association (on average) between volunteering and subjective well-being turned out to be driven solely by the association found for the unhappiest individuals in the subjective well-being distribution (Binder and Freytag, 2012). It can be conjectured that unemployment will also have a heterogeneous impact over the well-being distribution. In order to assess this, we use a recent panel quantile regression methodology (Canay, 2011) that allows us to examine effects of unemployment on different quantiles of the subjective well-being distribution within a panel data context. As such, our paper relates to efforts of dealing with heterogeneity in the subjective well-being literature, such as the ones that explore differential impacts of life events on different well-being measures or domain satisfaction measures (van Praag et al., 2003; Knabe et al., 2010; Krueger and Mueller, 2012) or approaches that look into how different personality traits moderate effects of life events on subjective well-being (Boyce et al., 2010).

3 EMPIRICAL ANALYSIS

3.1. Quantile Regressions in a Panel Context

We begin our analysis of the effect of unemployment on well-being with Fixed-Effect panel regressions of the following equation:

$$\mathcal{Y}_{it} = \grave{x}_{it} + u_i + \varepsilon_{it} \tag{1}$$

Where $\mathcal{Y}_{it}$ is our dependent variable, well-being, for individual i in year t, $\grave{x}_{it}$ is our set of control variables, and ε_{it} is the usual error term. u_i corresponds to a vector of time-invariant individual-specific effects—the "fixed effects."

To explore heterogeneity in the responses of well-being to unemployment across the quantiles θ, we apply quantile regression techniques to our panel dataset. Koenker and Bassett (1978) developed the first quantile regression estimator, for cross-sectional data, while Koenker (2004) was the first to extend quantile regression to the context of panel datasets. Canay (2011) introduces an alternative estimator for panel quantile regression, which models fixed effects as pure location shifts. Canay's two-step estimator performs better with large matrices and is less computationally intensive than the estimator in Koenker (2004), and also performs as well as Koenker (2004) in Monte Carlo simulations (see Canay, 2011). In this paper, we therefore apply Canay's two-step estimator.

In the first stage, we estimate the unobserved fixed effects. Consider the conditional mean equation represented by equation (1), where $E(\varepsilon_{ij}|x_i,\ u_i) = 0$. This formulation implies that the individual fixed effect u_i is present in the conditional mean of $\mathcal{Y}_{it}$. We define the estimated fixed effect $\hat{u}_i$ as $\hat{u}_i \equiv E_T\left(\mathcal{Y}_{it} - \grave{x}_{it}\hat{\beta}(\theta\mu)\right)$, where $\hat{\beta}(\theta_\mu)$ is a $\sqrt{nT}$-consistent estimator of $\beta(\theta\mu)$. The second step proceeds with standard quantile regressions (following Koenker and Bassett, 1978) using a new transformed dependent variable, $\hat{\mathcal{Y}}_{it} = \mathcal{Y}_{it} - \hat{\mathcal{U}}_i,$ regressed on $\grave{x}_{it}$. The two-step estimator $\hat{\beta}(\theta)$ solves the following minimization problem.

$$min\, \beta E_{nT}\left[\rho\theta\left(\hat{\mathcal{Y}}_{ij} - \grave{x_{ij}}\beta(\theta)\right)\right] \tag{2}$$

This estimator is consistent and asymptotically normal under certain regularity conditions (details can be found in Canay, 2011). Finally, Canay (2011) suggests that inference proceeds using bootstrapped standard errors.

3.2. Data Set and Indicator Selection

We use the well-known British Household Panel Survey (BHPS) data set that offers detailed information on employment status for a representative sample of the British populace. The BHPS is a longitudinal survey of private households in Great Britain that contains information on various areas of the respondents' lives, ranging from income to household consumption, education, health, and also social and political values. The survey is undertaken by the Economic and Social Research Council (ESRC) UK Longitudinal Studies Centre with the 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 more information on the data set, see Taylor, 2009). The sample comprises about 15,000 individual interviews. 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 (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, 2009). The BHPS has now been replaced with the "Understanding Society" Survey that continues and expands on the topics from the BHPS.

For the analysis we focus on those years where life satisfaction, mental well-being and domain satisfaction data are available, which limits us to the years 1996 to 2008 (waves f to r), with a gap in wave i due to different coding of the health status variable and a gap in wave k due to lack of satisfaction variables. We drop cases where our main variables are missing and effectively have an unbalanced panel with a total of 116, 865 observations at our disposal after cleaning the data set. In this section we will describe our two dependent variables as well as the main variables which we use in our analysis. These variables are depicted in Table 1, where we give descriptive statistics for the full sample, as well as for the subsample of unemployed and employed individuals.

Our main dependent variables are a typical life satisfaction question as well as the General Health Questionnaire (GHQ)-12 measure of mental well-being, both of which are often used in subjective well-being research.[5] In order to explore our results further, we use the information in a range of different domain satisfactions, namely satisfaction with health, income, house, spouse (where applicable), job (where applicable), social life, amount and use of leisure time. Similar to the life satisfaction question in the BHPS, the domain satisfaction questions cover the response to the question "How dissatisfied or satisfied are you with. . . ?" It is tracking an individual's domain satisfaction ordinally on a seven-point Likert scale, ranging from "not satisfied at all (1)" to "completely satisfied (7)."[6] We interpret these measures as cardinal in our regression exercises for ease of interpretation and exposition. It has been shown that the difference in results between using cardinal OLS versus the econometrically more appropriate ordered choice models is negligible (Ferrer-i-Carbonell and Frijters, 2004).

The broad GHQ-12 "mental well-being" variable 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), and wellbeing, each on a four-point ordinal scale. GHQ-12 assessments are often just added up and measured on a Likert scale from 0 to 36, which we have recoded so that high values denote high mental well-being. The GHQ-12 measure of mental well-being is a remarkably valid instrument that is widely used in the medical literature (see, e.g., Goldberg et al., 1997; Gardner and Oswald, 2007, and the references therein): validity and reliability have been established for many different contexts, languages and so on. In our case, Cronbach's α for the 12 questions is 0.90 and well above the usual threshold values for α.

Table 1 Summary Statistics

Summary statistics

	(1) full sample		(2) employed		(3) unemployed	
	mean	sd	mean	sd	mean	sd
Well-being						
subjective well-being	5.22	1.27	5.24	1.11	4.60	1.55
mental well-being (GHQ-12)	24.79	5.48	25.28	5.04	23.04	6.78
Domain satisfactions						
health	4.94	1.59	5.18	1.37	4.76	1.68
income of hhold	4.57	1.58	4.63	1.41	3.42	1.76
house/flat	5.41	1.42	5.30	1.33	4.83	1.73
spouse/partner	4.46	2.99	4.96	2.70	3.39	3.14
job	3.17	2.66	4.95	1.46	0.51	1.49
social life	4.93	1.48	4.93	1.34	4.52	1.68
amount of leisure time	4.81	1.62	4.46	1.47	4.92	1.72
use of leisure time	4.88	1.53	4.77	1.40	4.56	1.71
Health						
health==very poor	0.02	0.14	0.01	0.08	0.02	0.12
health==poor	0.07	0.26	0.04	0.19	0.10	0.30
health==fair	0.21	0.41	0.17	0.38	0.26	0.44
health==good	0.46	0.50	0.50	0.50	0.44	0.50
health==excellent	0.23	0.42	0.28	0.45	0.19	0.39
docvisits: 1-2	0.37	0.48	0.40	0.49	0.32	0.47
docvisits: 3-5	0.21	0.41	0.19	0.39	0.21	0.41
docvisits: 6+	0.18	0.38	0.11	0.32	0.21	0.41
accidents: 1	0.09	0.29	0.09	0.29	0.11	0.31
accidents: 2	0.01	0.09	0.01	0.09	0.02	0.12
accidents: 3+	0.00	0.06	0.00	0.05	0.01	0.07
log(hosp. days+1)	0.17	0.59	0.10	0.40	0.14	0.50
d_longtermsick	0.04	0.20				
Income						
log(income)	9.97	0.62	10.15	0.50	9.58	0.65
Social						
d_nevermarried	0.28	0.45	0.31	0.46	0.57	0.50
d_married	0.54	0.50	0.57	0.50	0.27	0.45
d_separated	0.02	0.14	0.02	0.15	0.04	0.18
d_widowed	0.08	0.26	0.01	0.12	0.01	0.10
d_divorced	0.08	0.28	0.09	0.28	0.12	0.32
Job						
d_employed	0.52	0.50				
d_unemployed	0.03	0.18				
d_selfemployed	0.07	0.25				
d_retired	0.20	0.40				
d_studyschool	0.05	0.22				
d_maternityleave	0.00	0.07				
d_familycare	0.07	0.25				
d_other	0.01	0.08				
Education (CASMIN)						
1a none	0.21	0.41	0.11	0.31	0.27	0.45
1b elementary	0.04	0.19	0.04	0.20	0.09	0.29
1c basic vocational	0.09	0.28	0.08	0.26	0.10	0.29
2b middle general	0.16	0.37	0.17	0.38	0.19	0.39
2a middle vocational	0.05	0.23	0.07	0.25	0.04	0.20
2c high general	0.08	0.26	0.07	0.26	0.06	0.25
2c hi vocational	0.05	0.23	0.07	0.26	0.05	0.21
3a low tertiary	0.18	0.39	0.21	0.41	0.11	0.31
3b high tertiary	0.13	0.34	0.18	0.39	0.09	0.29
Other						
gender	0.53	0.50	0.50	0.50	0.40	0.49
age	45.51	18.30	39.09	12.19	34.49	13.48
children: 1	0.15	0.36	0.19	0.39	0.19	0.39
children: 2	0.14	0.34	0.17	0.37	0.13	0.33
children: 3+	0.05	0.23	0.05	0.23	0.08	0.28
Observations	116865		61093		3750	

Source: Authors' calculations.

Our main independent variable is becoming unemployed, which happens only for a small subsample. We also report other employment types for the full sample (ranging from being employed, to being self-employed, retired, studying or being in school, being on maternity leave, being long-term sick, being in family care or “other” employment status). Except for these different employment types, we control for some important individual characteristics in our analysis.

An important control variable is net equivalized 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 income in our analysis.

We also use a wide variety of health variables from subjectively self-assessed health status to more objective health indicators such as visits to a doctor, number of accidents, (log) number of hospital days (+1) and being on long-term sick-leave. Subjective health status is ordinally scaled on a five-point Likert scale, ranging from “excellent” (five) to “very poor” (one).[7]

Besides income and health, our control variables also comprise the usual set of gender, age, and age^2, number of children, as well as some dummies regarding marital status (e.g., being married as control category, never being married, being separated, divorced or widowed). We have also added a regional control variable, dummies for different ethnicities and years (which we do not report, however).
Also included is an educational control variable, viz. an individual’s highest level of education, as measured by the CASMIN scale, which we measure via dummies for the different educational achievements ranging from one (“none”) to nine (“higher tertiary”). Of our sample, 53% of those surveyed were female. The mean age is 45.51 years (s.d. 18.30) with maximum age at 100 years and minimum age at 15 (younger individuals were not interviewed in the BHPS).

Table 5 (in the Appendix) shows the contemporaneous correlations of our main variables. We find no problems of multicollinearity.

3.3. Baseline Regression

We group our results into three parts. In this section, we present baseline regression estimates using a standard multivariate FE regression framework, giving us a baseline of the typical average influence of our variables of interest on (subjective and mental) well-being. These estimates, however, are only the starting point for our quantile regression analysis (in Section 3.4), where we then analyze the extent of heterogeneity in the subjective well-being distribution when becoming unemployed. We further explore our main results in Section 3.5 in order to explore possible explanations for the heterogeneity found in our analysis.

Turning to our baseline regressions (see Table 2), we use standard fixed-effects multivariate regressions with robust standard errors clustered on the individual. We have computed two models which differ only in our choice of dependent variable. The first column in Table 2 has life satisfaction as dependent variable, whereas column (2) features the GHQ-12 measure as dependent variable. In order to allow comparing effect sizes between the different dependent variables, we have standardized the dependent variables as well as the non-dummy independent variables. Focusing on unemployment first, we find similar results as reported in the literature. The coefficient in the life satisfaction regression (-0.26^{***}) is strongly significant and comparable to being widowed (-0.22^{***}). It is of note that the association between unemployment and life satisfaction is less strong than in the case of mental well-being (-0.34^{***}). The GHQ-12 mental well-being variable incorporates aspects of bad mental health such as anxiety, distress and sleep problems, which can be conjectured to all be negatively influenced by unemployment, thus explaining the stronger association. For want of space, we refrain from discussing the other coefficients in our baseline regression exercise, which are quite well-aligned with typical findings in the literature (see, e.g., Dolan et al., 2008; Layard et al., 2012).

Table 2 FE Regressions, Standardized Coefficients

Baseline fixed effects regressions

	(1) life satisfaction		(2) mental well-being	
Job				
d_unemployed	-0.2587***	(-12.71)	-0.3375***	(-14.95)
d_selfemployed	-0.0107	(-0.68)	-0.0123	(-0.74)
d_retired	0.0415*	(2.39)	0.0331*	(1.98)
d_studyschool	0.0440*	(2.16)	0.0203	(0.87)
d_maternityleave	0.2216***	(7.41)	0.0411	(1.06)
d_familycare	-0.0415*	(-2.42)	-0.0785***	(-4.10)
d_other	-0.0127	(-0.34)	0.0012	(0.03)
Health				
health==poor	0.2865***	(9.28)	0.4129***	(12.66)
health==fair	0.5124***	(16.09)	0.7852***	(22.94)
health==good	0.6907***	(21.45)	0.9862***	(28.26)
health==excellent	0.7902***	(24.07)	1.1125***	(31.34)
docvisits: 1-2	0.0059	(0.95)	-0.0113	(-1.80)
docvisits: 3-5	-0.0060	(-0.72)	-0.0595***	(-6.69)
docvisits: 6+	-0.0312**	(-2.86)	-0.1381***	(-11.91)
accidents: 1	-0.0230**	(-2.65)	-0.0231*	(-2.43)
accidents: 2	-0.0481	(-1.78)	-0.0583	(-1.85)
accidents: 3+	-0.0226	(-0.41)	-0.0915	(-1.46)
log(hosp. days+1)	0.0027	(0.80)	-0.0151***	(-4.21)
d_longtermsick	-0.2816***	(-10.46)	-0.3476***	(-11.37)
Income				
log(income)	0.0113**	(2.97)	0.0013	(0.30)
Social				
d_nevermarried	-0.0456**	(-2.70)	0.0547**	(2.80)
d_separated	-0.1365***	(-4.66)	-0.1956***	(-5.51)
d_widowed	-0.2229***	(-5.83)	-0.2162***	(-6.57)
d_divorced	-0.0296	(-1.22)	0.0446	(1.69)
Education (CASMIN)				
1b elementary	0.0042	(0.04)	0.0563	(0.50)
1c basic vocational	-0.0598	(-1.00)	-0.0048	(-0.06)
2b middle general	0.1370*	(2.17)	0.0598	(0.80)
2a middle vocational	0.1558	(1.51)	0.1410	(1.12)
2c high general	0.1480*	(2.32)	0.0772	(1.04)
2c hi vocational	0.0841	(1.18)	0.0950	(1.14)
3a low tertiary	0.1536*	(2.25)	0.1044	(1.36)
3b high tertiary	0.0941	(1.37)	0.0832	(1.06)
Other				
children: 1	-0.0049	(-0.45)	0.0009	(0.07)
children: 2	-0.0189	(-1.36)	0.0017	(0.11)
children: 3+	-0.0063	(-0.29)	0.0287	(1.21)
age	-0.2563	(-1.33)	-0.3250	(-1.65)
age^2	-0.0119	(-1.10)	0.0206	(1.95)
Constant	-0.6330***	(-6.34)	-0.9182***	(-8.05)
Observations	116865		116865	
R^2	0.041		0.067	
F	37.2443		49.9423	
df_r	23058.0000		23058.0000	

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

Source: Authors' calculations.
Notes: Robust standard errors clustered on the individual. We report standard regression coefficients for non-dummy variables. Dependent variables are standardized and differ between the two model columns, with life satisfaction as dependent variable in column (1), and the GHQ-12 mental well-being variable in column (2). Year and region dummies are used in the regressions but not reported here.

Table 3 QFE Regressions with Standardized Coefficients all Bootstrapped Standard Errors (100 replications).

Quantile fixed effects regressions

	(1) life satisfaction		(2) mental well-being	
q10				
d_unemployed	-0.414***	(-17.34)	-0.467***	(-15.56)
log(income)	0.0310***	(7.36)	0.00375	(0.68)
age	-0.239***	(-29.61)	-0.243***	(-27.18)
d_longtermsick	-0.348***	(-13.62)	-0.360***	(-13.78)
d_widowed	-0.344***	(-17.83)	-0.332***	(-20.07)
q20				
d_unemployed	-0.333***	(-16.46)	-0.374***	(-16.14)
log(income)	0.0196***	(5.87)	0.00267	(0.71)
age	-0.243***	(-47.84)	-0.278***	(-49.27)
d_longtermsick	-0.326***	(-18.24)	-0.364***	(-19.53)
d_widowed	-0.288***	(-22.53)	-0.272***	(-24.93)
q30				
d_unemployed	-0.287***	(-18.36)	-0.339***	(-19.97)
log(income)	0.0165***	(6.18)	0.000141	(0.05)
age	-0.249***	(-62.58)	-0.303***	(-68.38)
d_longtermsick	-0.324***	(-20.51)	-0.354***	(-23.13)
d_widowed	-0.267***	(-22.09)	-0.239***	(-26.51)
q40				
d_unemployed	-0.250***	(-21.03)	-0.305***	(-39.30)
log(income)	0.0112***	(7.90)	-0.000582	(-0.54)
age	-0.259***	(-86.04)	-0.324***	(-98.79)
d_longtermsick	-0.329***	(-23.20)	-0.359***	(-26.86)
d_widowed	-0.235***	(-33.32)	-0.222***	(-31.68)
q50				
d_unemployed	-0.256***	(-66.61)	-0.325***	(-45.77)
log(income)	0.0119***	(20.68)	0.00290***	(3.91)
age	-0.250***	(-140.80)	-0.321***	(-158.46)
d_longtermsick	-0.290***	(-58.42)	-0.351***	(-32.08)
d_widowed	-0.226***	(-52.78)	-0.211***	(-38.35)
q60				
d_unemployed	-0.227***	(-14.78)	-0.305***	(-20.72)
log(income)	0.0120***	(7.09)	0.00499***	(3.78)
age	-0.248***	(-74.52)	-0.335***	(-101.68)
d_longtermsick	-0.295***	(-20.26)	-0.345***	(-25.09)
d_widowed	-0.208***	(-21.83)	-0.191***	(-26.85)
q70				
d_unemployed	-0.202***	(-14.01)	-0.277***	(-18.74)
log(income)	0.00891***	(3.79)	0.00475*	(2.19)
age	-0.264***	(-67.41)	-0.355***	(-99.45)
d_longtermsick	-0.268***	(-20.58)	-0.344***	(-25.44)
d_widowed	-0.170***	(-17.16)	-0.155***	(-19.20)
q80				
d_unemployed	-0.173***	(-12.41)	-0.250***	(-15.18)
log(income)	0.000723	(0.25)	0.00216	(0.83)
age	-0.271***	(-64.64)	-0.379***	(-83.99)
d_longtermsick	-0.241***	(-13.24)	-0.336***	(-22.85)
d_widowed	-0.137***	(-11.35)	-0.136***	(-13.83)
q90				
d_unemployed	-0.0975***	(-5.13)	-0.229***	(-11.86)
log(income)	-0.00967**	(-2.90)	-0.00240	(-0.62)
age	-0.279***	(-49.18)	-0.409***	(-57.12)
d_longtermsick	-0.181***	(-7.80)	-0.320***	(-15.34)
d_widowed	-0.112***	(-5.84)	-0.108***	(-7.73)
Observations	116865		116865	
0.10 Pseudo R2	.2097		.2308	
0.20 Pseudo R2	.2067		.2533	
0.30 Pseudo R2	.2057		.2699	
0.40 Pseudo R2	.209		.2829	
0.50 Pseudo R2	.206		.2862	
0.60 Pseudo R2	.1865		.2769	
0.70 Pseudo R2	.1626		.2615	
0.80 Pseudo R2	.1396		.2383	
0.90 Pseudo R2	.1154		.2062	

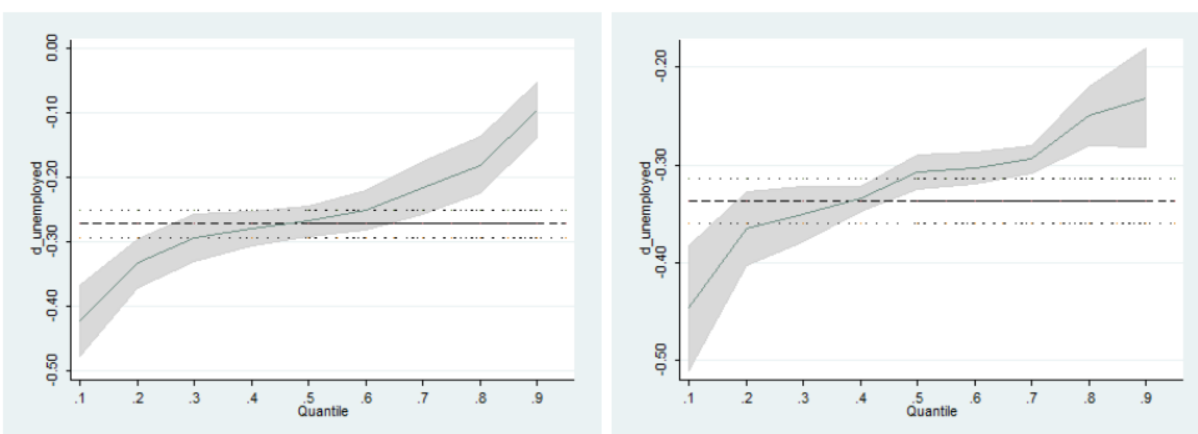
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors' calculations.
Notes: Dependent variables are standardized and differ between the two model columns, with life satisfaction as dependent variable in column (1) and the GHQ-12 mental well-being variable in column (2). The analysis uses the same variables as the baseline regression, but we only report a few coefficients over the deciles to conserve space. Year and region dummies are used in the regressions but not reported here.

3.4. Quantile Analysis

The results for the quantile regression analysis are depicted in Table 3. We can see similar trends over the deciles for both measures. Coefficients for the unemployment dummy are highly significant over all deciles. As opposed to the average case, we see a monotonic decrease in the impact of unemployment over the deciles. For the unhappiest 10% in our sample, becoming unemployed has nearly double the impact than in the average case (-.41), whereas the happiest individuals (90% decile) suffer only about one third as strongly from unemployment than the average person (-.10). Note that the median effect (50% decile) is nearly identical to the average results in Table 2. A similar picture emerges for mental wellbeing. Here, too, we find a monotonic decrease in the impact of unemployment over the deciles of the mental well-being distribution (but with a smaller range; see also Figure 1). Being mentally less well-off leads to nearly twice the decrease in mental well-being after becoming unemployed than on average (-.47). In contrast to the life satisfaction case, however, higher mental well-being does not cut the impact of unemployment to one third, but only in half (-.23). Overall, it becomes evident that a focus on average effects can obscure considerable heterogeneity across the subjective well-being distribution. Moreover, the choice of wellbeing variable turns out to be crucial when it comes to judging the effect size of life events on well-being. While effects measured on our subjective well-being construct are less severe, this is not the case for mental well-being.

Figure 1 Coefficients (Becoming Unemployed) for Life Satisfaction (left) and Mental Well-being (right) Over the Quantiles



Source: Authors' calculations.

A limitation of this analysis lies in the way longer-term unemployment is handled in the UK: some of the longer-term unemployed might actually have been officially relegated into labor force categories of "long-term sick" in order to favorably alter unemployment rates in the UK. This might limit our study to estimating the effect of lighter/shorter cases of unemployment which, given findings from the literature, might underestimate the true effect of unemployment if the "worst" cases of unemployment are not captured with this classification. To allow the comparison of effect sizes here, we have also added the corresponding category of "being long-term" sick in the presentation of our results. It exhibits a similar monotonic decline over the well-being distribution, with larger effect sizes than becoming unemployed. Unfortunately, however, this class of individuals plausibly will also contain individuals that are of ill health, thus confounding sickness and unemployment.

In sum, for individuals scoring high in their respective well-being scores, well-being can be conjectured to act as a shield when they become unemployed. We hypothesize that for a small subset of happy individuals, unemployment seems to provide an opportunity to improve in certain life domains, for example by having more time to spend on personal relations, avoiding stress, and generally "putting one's house in order." While this seems certainly to be a speculative explanation, such an interpretation is consistent with findings from Knabe et al. (2010), who show that unemployed can more extensively enjoy leisure activities and do have more time at their hands to pursue them. Our results here add that individuals that are mentally well-off seem to cope with unemployment in a much more positive and resilient way than individuals already scoring low on mental well-being. Our results are consistent with findings from the literature on "resilience" that argues that positive emotions can build resilience in individuals and help them deal better with adverse life events (Cohn et al., 2009; Skodol, 2010; Tugade and Fredrickson, 2004).

3.5. Quantile Effects for Different Domain Satisfactions

In order to further explore this heterogeneity in the relationship between unemployment and well-being, we conduct four further robustness exercises. First, we have disaggregated our results by gender, noting that unemployment has been shown in the literature to affect males more strongly than females (e.g., Clark et al., 2008a). Differences in gender over the quantiles are, however, rather small (e.g., -.430 for males vs. -.418 for females in the lowest decile and

-.123 for males vs. -.076 for females in the highest decile) with a tendency of males suffering more strongly than females.[8]

Second, we have restricted our analysis to the working age populace of individuals being between 16 and 65 years of age (reducing our sample to 96,836 observations; regression tables not reported to conserve space), but again, results do not substantially differ from the main analysis. Coefficients over the quantiles are slightly higher for this restricted subset (at the median -.263 vs. -.256 in the full sample), underscoring the importance of being in employment for individuals in working age. Dropping elderly individuals, who mostly are retired and thus do not experience decreased well-being from not having a job would be expected to lead to this increase in effect sizes of the sample (e.g., Bonsang and Klein, 2011).

Third, we shed light on why different individuals are impacted differently by unemployment by looking into how unemployment impacts different life domains and individuals' satisfaction with life domains. This helps us in exploring whether there are some characteristics of the high well-being individuals with respect to different life domains that could explain the reduced impact of becoming unemployed on life satisfaction. Our analysis of the heterogeneous impact of unemployment on different life domains reinforces the importance of going beyond the average case in assessing the impact of life events on satisfaction variables (see Table 4 and Figure 2 in the Appendix). We begin by focusing on these domains, where losing one's job can be conjectured to have the worst impact, namely satisfaction with one's income as well as more directly satisfaction with one's job. Satisfaction with income is strongly impacted by unemployment, the more dissatisfied one is in this domain. The relationship is strongly significant over all quantiles and even for the highest decile the effect is still strongly negative (column 2). Here we confirm results by Powdthavee (2012) and show that the average picture gives a useful summary of the unemployment-satisfaction relationship. A similar picture emerges for satisfaction with one's job (column 5), however, here, the decrease is much more pronounced from the lowest to the highest deciles. These individuals who are least satisfied with their job experience the highest well-being loss, whereas individuals in the highest deciles are comparatively less affected. In interpreting this result, it is important to keep in mind that a large number of individuals without a job have not responded by giving their (dis)satisfaction with unemployment but rather checked "inapplicable." Our results reflect the minority of individuals who actually have expressed their satisfaction with the job domain on a seven-point Likert scale. Moreover, as was shown in Powdthavee (2012), becoming unemployed has lead- or anticipation effects the year before becoming unemployed. We can thus hypothesize that here we are picking up endogeneity in the sense that individuals in the lowest decile of job satisfaction already anticipate their job loss and thus are extremely dissatisfied with their job situation.

Table 4 QFE Regressions with Standardized Coefficients and Bootstrapped Standard Errors (100 Replications)

Quantile fixed effects regressions over different life domains

	(1) health	(2) income	(3) house	(4) spouse	(5) job	(6) social	(7) leisure: amount	(8) leisure: use
q10								
d_unemployed	-0.0689**	-0.586***	-0.108***	-0.0486	-1.028***	-0.223***	0.234***	-0.110***
	(-3.06)	(-24.11)	(-3.32)	(-1.12)	(-11.81)	(-8.55)	(10.43)	(-4.88)
log(income)	0.00751*	0.160***	0.0544***	0.0395***	0.00580	0.0192***	-0.0170***	0.00846
	(2.15)	(32.59)	(9.83)	(5.61)	(0.75)	(4.62)	(-4.59)	(1.84)
age	-0.0306***	0.480***	0.302***	-0.228***	0.192***	-0.279***	-0.687***	-0.211***
	(-3.91)	(65.26)	(33.75)	(-16.89)	(14.71)	(-38.30)	(-103.74)	(-26.21)
q20								
d_unemployed	-0.0456**	-0.544***	-0.0766***	-0.0141	-0.809***	-0.191***	0.297***	-0.0623**
	(-3.14)	(-32.30)	(-4.70)	(-0.40)	(-9.93)	(-11.14)	(16.08)	(-3.18)
log(income)	0.00215	0.141***	0.0410***	0.0128***	0.000531	0.0130***	-0.0125***	0.00337
	(0.89)	(38.28)	(10.42)	(3.47)	(0.12)	(4.34)	(-4.20)	(0.91)
age	-0.0310***	0.480***	0.234***	-0.255***	0.130***	-0.287***	-0.687***	-0.214***
	(-5.50)	(88.29)	(41.69)	(-32.59)	(16.33)	(-55.45)	(-134.71)	(-38.64)
q30								
d_unemployed	-0.0284*	-0.519***	-0.0537*	-0.00129	-0.697***	-0.168***	0.315***	-0.0394*
	(-2.32)	(-31.87)	(-2.57)	(-0.20)	(-10.27)	(-9.74)	(19.03)	(-2.16)
log(income)	-0.000711	0.122***	0.0278***	0.0104***	-0.00790*	0.00789**	-0.0149***	-0.00314
	(-0.32)	(40.02)	(9.78)	(12.98)	(-1.99)	(2.58)	(-5.73)	(-0.93)
age	-0.0320***	0.474***	0.201***	-0.267***	0.102***	-0.295***	-0.691***	-0.221***
	(-7.45)	(110.11)	(40.63)	(-119.67)	(15.46)	(-61.80)	(-151.46)	(-40.57)
q40								
d_unemployed	-0.0339***	-0.499***	-0.0239**	-0.0146***	-0.632***	-0.140***	0.340***	-0.0120
	(-3.64)	(-31.24)	(-3.00)	(-5.11)	(-32.00)	(-11.30)	(24.88)	(-1.09)
log(income)	-0.00238	0.104***	0.0225***	0.0124***	-0.0113***	0.00139	-0.0151***	-0.00482***
	(-1.89)	(48.53)	(28.90)	(29.77)	(-7.75)	(0.99)	(-9.58)	(-3.62)
age	-0.0354***	0.462***	0.167***	-0.273***	0.0712***	-0.310***	-0.708***	-0.232***
	(-11.36)	(125.98)	(56.99)	(-262.74)	(20.89)	(-85.02)	(-199.19)	(-64.31)
q50								
d_unemployed	-0.0427***	-0.488***	-0.0405***	-0.0183***	-0.655***	-0.148***	0.331***	-0.0287***
	(-14.40)	(-156.04)	(-9.90)	(-6.32)	(-135.80)	(-72.51)	(159.05)	(-15.62)
log(income)	0.000116	0.0982***	0.0225***	0.0132***	-0.00840***	0.00333***	-0.0136***	-0.00212***
	(0.23)	(194.90)	(37.39)	(30.18)	(-12.44)	(8.39)	(-32.13)	(-4.62)
age	-0.0246***	0.461***	0.169***	-0.279***	0.0695***	-0.305***	-0.705***	-0.230***
	(-12.92)	(240.25)	(93.94)	(-268.87)	(32.42)	(-170.18)	(-449.52)	(-120.29)
q60								
d_unemployed	-0.0489***	-0.492***	-0.0514***	-0.0206**	-0.676***	-0.158***	0.325***	-0.0404**
	(-4.59)	(-27.88)	(-3.45)	(-3.24)	(-11.57)	(-11.29)	(22.85)	(-2.91)
log(income)	0.00336*	0.0954***	0.0211***	0.0138***	-0.00554*	0.00485*	-0.00961***	0.00101
	(2.35)	(37.22)	(9.64)	(15.88)	(-2.19)	(2.39)	(-4.92)	(0.60)
age	-0.0172***	0.464***	0.145***	-0.288***	0.0479***	-0.307***	-0.702***	-0.233***
	(-4.81)	(106.70)	(33.09)	(-121.15)	(9.70)	(-66.37)	(-188.24)	(-55.50)
q70								
d_unemployed	-0.0247*	-0.469***	-0.0266*	0.0162	-0.547***	-0.134***	0.358***	-0.0181
	(-1.98)	(-29.89)	(-2.06)	(0.78)	(-9.76)	(-7.12)	(20.99)	(-1.43)
log(income)	0.00232	0.0792***	0.0152***	0.0131***	-0.0114***	0.00250	-0.0113***	-0.00113
	(1.25)	(30.81)	(6.67)	(6.09)	(-3.64)	(0.94)	(-4.09)	(-0.40)
age	-0.0210***	0.451***	0.115***	-0.316***	0.0201***	-0.321***	-0.715***	-0.248***
	(-6.46)	(101.76)	(29.71)	(-68.76)	(3.58)	(-67.66)	(-172.41)	(-53.67)
q80								
d_unemployed	0.00586	-0.426***	0.00316	0.0351	-0.510***	-0.112***	0.395***	0.0114
	(0.42)	(-20.51)	(0.19)	(1.43)	(-10.38)	(-6.68)	(19.95)	(0.68)
log(income)	-0.00177	0.0647***	0.0112***	0.00888**	-0.0150***	-0.00636*	-0.0165***	-0.00732*
	(-0.76)	(20.80)	(3.99)	(3.05)	(-3.61)	(-2.27)	(-5.66)	(-2.36)
age	-0.0227***	0.446***	0.0869***	-0.334***	-0.00542	-0.328***	-0.737***	-0.264***
	(-5.19)	(83.88)	(20.09)	(-59.96)	(-0.81)	(-63.11)	(-148.93)	(-49.90)
q90								
d_unemployed	0.0145	-0.377***	0.0242	0.0776**	-0.357***	-0.0747***	0.462***	0.0643**
	(1.10)	(-17.21)	(1.03)	(2.98)	(-5.26)	(-3.77)	(19.23)	(2.99)
log(income)	-0.0122***	0.0465***	-0.00476	-0.00953	-0.0311***	-0.0183***	-0.0181***	-0.00986**
	(-3.84)	(12.97)	(-1.50)	(-1.74)	(-5.13)	(-4.67)	(-5.23)	(-3.07)
age	-0.0315***	0.429***	0.0377***	-0.355***	-0.0391***	-0.344***	-0.767***	-0.280***
	(-6.57)	(69.78)	(5.56)	(-47.35)	(-4.89)	(-48.15)	(-107.51)	(-41.21)
Observations	116865	116865	116865	83584	74163	116865	116865	116865
0.10 Pseudo R2	.3195	.1982	.0919	.1893	.3135	.1793	.2733	.1207
0.20 Pseudo R2	.3289	.2235	.0932	.2455	.3221	.1851	.3024	.123
0.30 Pseudo R2	.3206	.2434	.0988	.2803	.303	.1941	.3303	.1301
0.40 Pseudo R2	.3067	.2609	.1094	.3051	.285	.2057	.3559	.1414
0.50 Pseudo R2	.2866	.2724	.1089	.3063	.2624	.2114	.3733	.1482
0.60 Pseudo R2	.2551	.2698	.0896	.2852	.2306	.2018	.3755	.1382
0.70 Pseudo R2	.2198	.2644	.0714	.2502	.203	.1893	.3719	.1272
0.80 Pseudo R2	.1812	.2571	.057	.2128	.177	.1737	.3626	.1158
0.90 Pseudo R2	.1347	.2504	.0467	.1801	.148	.1524	.3415	.1062

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

Source: Authors' calculations.
Notes: Dependent variables are standardized and represent satisfaction with different life domains (from (1) satisfaction with health to (8) satisfaction with use of leisure time). The analysis uses the same variables as the baseline regression, but we only report a few coefficients over the deciles to conserve space. Year and region dummies are used in the regressions but not reported here.

With regards to health (column 1) and housing (column 3) satisfaction, we also find heterogeneity, and the coefficient reverses its sign when going from unhappy to happy individuals. Individuals not satisfied in these domains (lower deciles) report decreasing satisfaction in these domains, while those comparatively satisfied report higher satisfaction (although this is not statistically significant).

In the social domain, satisfaction with one's social life (column 6) and with one's spouse (column 4) exhibit striking patterns: becoming unemployed negatively impacts one's satisfaction with social life, but the effect is not nearly as strong as dissatisfaction with job or income. For those who are relatively satisfied with their social life, unemployment only weakly negatively influences this. This suggests that an active social life outside work can contribute much to countering negative effects of unemployment. The fact that we find significantly negative effects in this domain further underscores the social aspects of work. In this case, our finding goes beyond the analysis of Powdthavee (2012) and can show that the average case might be misleading. Dissatisfaction with social life is heterogeneous over the quantiles and the average effect is driven by those individuals who are already very dissatisfied with their social lives, whereas satisfied individuals are only weakly impacted in this domain. In addition to the above, being in a supportive marriage even more strongly supports our hypothesis that a supporting social environment of loved ones can counteract negative effects of unemployment: those individuals that score high in spousal satisfaction report increased domain satisfaction when becoming unemployed (those who are dissatisfied report a negative impact, which is, however, not statistically significant).

The last two domain satisfactions pertain to the amount and usage of leisure time. Regarding satisfaction with the amount of leisure time, we find a positive relationship that increases over the quantiles (and doubles in effect size from the most dissatisfied to the most satisfied individuals). Such a relationship can thus be expected to be present in average effects, too (Powdthavee, 2012). The more one is already satisfied with one's amount of leisure time, the better received is the additional leisure time one gets from unemployment. The picture is different, however, when it comes to how one can use the leisure time available. Individuals who are dissatisfied with their use of leisure time are negatively impacted after unemployment, while those who are amongst the most satisfied get a positive boost from unemployment. While becoming unemployed might negatively impact some life domains, at least for those who enjoy their leisure time, we can conclude that the latter will "have a good time" even after becoming unemployed (Knabe et al., 2010). In this case, we also see again the necessity of looking into different quantiles, as the positive and negative effects at the extremes of the distribution seem to cancel themselves out in an analysis focused on averages, leading in sum to a non-significant result (Powdthavee, 2012).

In conclusion, we find a very heterogeneous impact of unemployment not only on life satisfaction proper, but also on domain satisfactions and again within the domain satisfaction distributions. If one subscribes to a model where overall life satisfaction is a measure of well-being that is an aggregate of separate domain satisfactions (compare van Praag et al., 2003; Powdthavee, 2012), our findings strongly underscore the necessity of decomposing life satisfaction scores into their domain satisfaction building blocks in order to account for the heterogeneity of the effect of unemployment on life satisfaction. This will likely generalize to other important determinants of subjective well-being as well, and shows the need for modes of analysis that allow for substantial heterogeneity in the relationship between subjective well-being and its determinants. Such heterogeneity could also explain diverging sets of findings within the literature: there might exist heterogeneity in the importance of different life domains for subjective well-being across countries and cultures, an area of research that deserves more attention.

Fourth, we further explore our hypothesis that heterogeneity in the unemployment-happiness nexus might stem from the fact that some resilient individuals will experience unemployment less as a devastating event and more as an opportunity for growth and the pursuit of other interests outside the job domain. In order to examine the evidence for this hypothesis and unpack the heterogeneity aspect further, we conducted a quantile analysis for the above-mentioned life domains for the subgroup of individuals that exhibit very high levels of mental well-being. Focusing on the group of individuals in the highest decile of mental well-being allows us to capture the effects of unemployment on people who are mentally stable and can be conjectured to be resilient and have the necessary psychological coping resources (Cohn et al., 2009; Skodol, 2010; Tugade and Fredrickson, 2004). Results are generally in favor of this hypothesis in this strongly reduced subsample (only 19,624 observations at most in the domains; the results table is presented in the Appendix, see Table 6): satisfaction with job and income are strongly negatively impacted also for high mental well-being individuals, but this does not translate into an overall loss of life satisfaction. If we subscribe to a model of life satisfaction, where domain satisfactions make up the overall life satisfaction score (e.g., van Praag et al., 2003), such a result will plausibly be caused by the strongly positive effect of unemployment for our subgroup in the domains of satisfaction with amount and use of leisure time. As opposed to the full sample, individuals in the highest mental well-being decile are strongly satisfied with amount of leisure time (the effect is very uniform over the quantiles, from .474 at the lowest decile to .415 at the highest decile) as well as their use of leisure time, which is also rather uniform over the quantiles of their domain satisfaction (from .096, n.s. at the lowest decile to .202 at the highest decile). Highly mentally stable individuals are thus able to cope with unemployment by focusing their life on the positive aspects of unemployment (leisure time) and they derive a much higher amount of satisfaction from this and especially from their use of this leisure time (as compared to the full sample). Our findings here complement and extend the hypothesis by Knabe et al. (2010) that there might be positive impacts of unemployment for subgroups of people who find a meaningful way to spend their newfound free time.

4 CONCLUSION

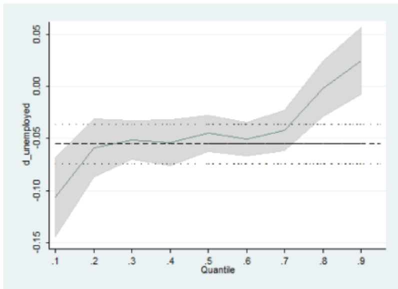
Losing one's job can be a traumatic experience for an individual. Not only does that individual lose a good portion of work income (even if unemployment benefits are paid, these are likely to not fully compensate the income loss), but joblessness also decreases subjective well-being. Happiness research has shown that this negative effect on subjective well-being is robust over time and around the world, and goes beyond the negative effect one would expect as a result of the associated income loss. This psychic cost of losing one's job is conjectured to be the result of a number of factors, ranging from loss of meaning and the need to redefine one's self-identity, to the social stigma of being unemployed while others are in employment (e.g., Layard et al., 2012).

In the present paper, we have unpacked the unemployment-unhappiness relationship further using panel quantile regressions (Canay, 2011) to get a wider and more detailed perspective on the unemployment-unhappiness relationship. For the average case we have found that unemployment has a stronger effect on mental well-being than on life satisfaction. Extending our analysis to the full subjective well-being distribution, we have found considerable heterogeneity over the different quantiles (and dependent variables). We have found that the strongest effect of becoming unemployed is on the lower deciles of the well-being distribution. We have found considerable heterogeneity in the effect along the distribution, with strong negative coefficients for individuals with below median well-being. Individuals in the highest deciles, on the other hand, showed a weaker association between unemployment and well-being, a likely cause being that well-being acts as a shield for adverse life events such as becoming unemployed. This suggests that some resilient individuals respond to entry into unemployment by avoiding stress, rebuilding relationships, and restructuring their lifestyles and attitudes in a positive way. We have explored this conjecture more fully by focusing on the effects of unemployment on different domain satisfactions as well as for subgroups of highly mentally stable individuals. In both cases, we find considerable heterogeneity of the effect of unemployment on well-being. This will likely generalize to other important determinants of subjective well-being as well, and underscores the need for modes of analysis that allow for substantial heterogeneity in the relationship between subjective well-being and its determinants.

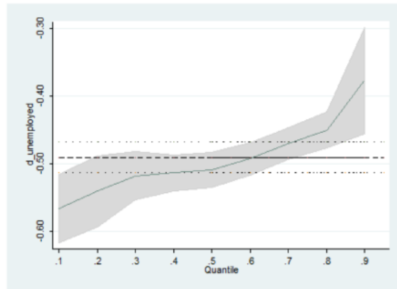
We can conclude that looking at the full well-being distribution instead of focusing on average effects help us to better understand when and to what extent unemployment is detrimental to subjective well-being, an area that deserves far more future research attention. Our results should serve as a note of caution when using subjective well-being for public policy: one-size-fits-all policy measures that do not account for heterogeneity in people's responses to unemployment are likely misplaced. If one were to effectively use public policy to mitigate the well-being loss of the unemployed, more research would be needed into what psychological resources help individuals to deal with job loss more efficiently, for example.

Appendix

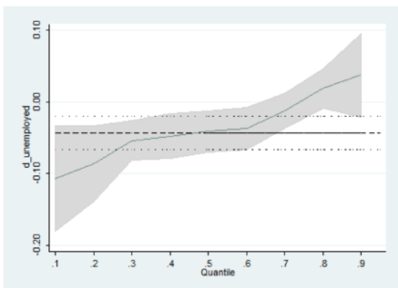
Figure 2 Coefficients (Becoming Unemployed) for Different Domain Satisfactions over the Quantiles



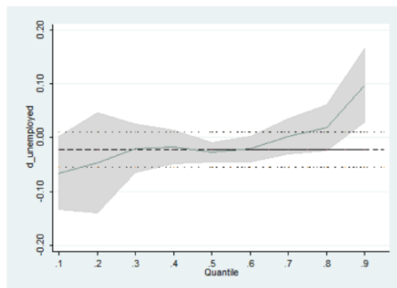
Satisfaction: health



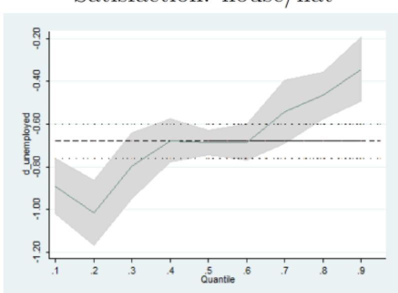
Satisfaction: income



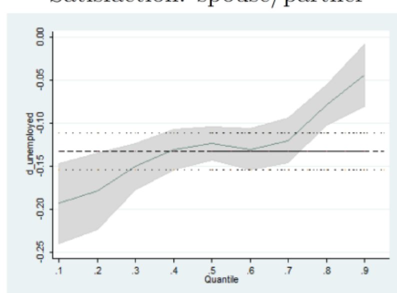
Satisfaction: house/flat



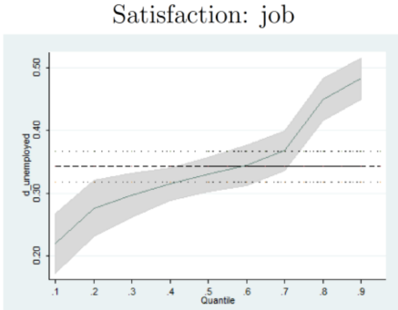
Satisfaction: spouse/partner



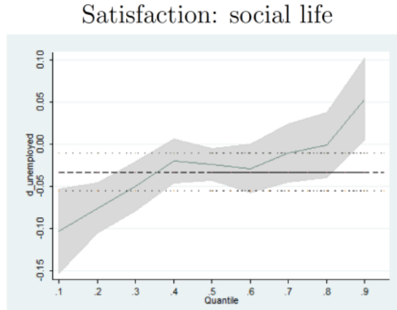
Satisfaction: job



Satisfaction: social life



Satisfaction: amount of leisure time



Satisfaction: use of leisure time

Source: Authors' calculations.

Table 5 Correlations in Main Variables

Correlations

	life satisfaction	mental well-being	subj. health	log(income)	d_unemployed	d_employed	education	age	gender
life satisfaction	1.0000								
mental well-being	0.5590***	1.0000							
	(0.0000)								
subj. health	-0.3373***	-0.3826***	1.0000						
	(0.0000)	(0.0000)							
log(income)	0.0771***	0.0780***	-0.1345***	1.0000					
	(0.0000)	(0.0000)	(0.0000)						
d_unemployed	-0.0896***	-0.0581***	0.0265***	-0.1153***	1.0000				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
d_employed	0.0114***	0.0924***	-0.2187***	0.2942***	-0.1906***	1.0000			
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
education	0.0001	0.0668***	-0.1978***	0.3040***	-0.0549***	0.2679***	1.0000		
	(0.9859)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
age	0.0793***	-0.0385***	0.1861***	-0.0233***	-0.1096***	-0.3669***	-0.2546***	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
gender	-0.0064*	-0.1308***	0.0611***	-0.0607***	-0.0463***	-0.0686***	-0.0559***	0.0234***	1.0000
	(0.0295)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Observations	116865								

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

Source: Authors' calculations.

Table 6 Quantile FE Regressions for High Mental Well-being Subgroup

Quantile fixed effects regressions for high mental well-being subgroup

	(1) life satisf.	(2) health	(3) income	(4) house	(5) spouse	(6) job	(7) social	(8) leisure: amnt	(9) leisure: use
q10									
d_unemployed	-0.0422	0.0479	-0.617***	-0.0610	0.0862	-1.131***	0.00412	0.474***	0.0956
	(-0.82)	(1.27)	(-7.72)	(-0.82)	(1.20)	(-3.82)	(0.07)	(9.63)	(1.61)
log(income)	0.00184	0.000689	0.169***	0.0518***	0.00489	0.0265	0.00574	-0.00236	0.00409
	(0.27)	(0.07)	(20.23)	(4.19)	(0.38)	(1.83)	(0.60)	(-0.24)	(0.44)
age	0.0839***	0.0439**	0.0885***	0.237***	-0.240***	0.438***	-0.146***	-0.649***	0.229***
	(5.85)	(3.15)	(5.83)	(13.02)	(-9.73)	(19.62)	(-9.81)	(-40.65)	(15.00)
q20									
d_unemployed	-0.0455	0.0309	-0.503***	-0.0696	0.00799	-0.660**	0.00713	0.460***	0.170***
	(-1.10)	(0.89)	(-8.26)	(-1.06)	(0.25)	(-2.64)	(0.17)	(12.07)	(4.09)
log(income)	0.00981	-0.00758	0.134***	0.0318***	0.000492	0.00869	-0.00673	-0.0121*	-0.00741
	(1.55)	(-1.82)	(16.41)	(4.11)	(0.16)	(0.96)	(-0.86)	(-2.04)	(-1.18)
age	0.0722***	0.0398***	0.0750***	0.185***	-0.264***	0.382***	-0.144***	-0.641***	0.214***
	(6.59)	(4.67)	(6.45)	(14.55)	(-52.10)	(22.47)	(-12.46)	(-48.26)	(17.19)
q30									
d_unemployed	-0.00839	0.0413	-0.473***	-0.0374	0.0135	-0.659***	0.00356	0.419***	0.151***
	(-0.46)	(1.85)	(-11.32)	(-0.80)	(1.29)	(-9.75)	(0.15)	(16.73)	(5.54)
log(income)	-0.00778***	-0.00818*	0.106***	0.0174***	0.00298**	0.00292	-0.0123**	-0.0172***	-0.00560
	(-3.77)	(-2.18)	(16.58)	(4.30)	(3.18)	(0.54)	(-3.07)	(-3.53)	(-1.37)
age	0.0837***	0.0343***	0.0764***	0.154***	-0.266***	0.367***	-0.157***	-0.652***	0.201***
	(19.20)	(4.87)	(8.17)	(17.55)	(-146.62)	(46.82)	(-20.14)	(-65.84)	(26.48)
q40									
d_unemployed	0.00600	0.0354**	-0.431***	-0.0308*	0.0220**	-0.630***	0.00105	0.395***	0.148***
	(0.49)	(3.08)	(-18.97)	(-2.17)	(3.16)	(-7.65)	(0.08)	(33.76)	(8.27)
log(income)	-0.00665***	-0.00557**	0.0927***	0.0162***	0.00400***	0.00692	-0.0110***	-0.0155***	-0.00559**
	(-3.47)	(-3.09)	(36.47)	(8.73)	(6.25)	(1.82)	(-5.14)	(-7.10)	(-2.73)
age	0.0848***	0.0395***	0.0670***	0.141***	-0.269***	0.362***	-0.154***	-0.658***	0.199***
	(21.05)	(8.48)	(11.45)	(29.89)	(-152.42)	(50.60)	(-30.61)	(-136.02)	(45.95)
q50									
d_unemployed	-0.0223	0.0304	-0.353***	-0.0380	0.0238**	-0.557	-0.00275	0.358***	0.147***
	(-1.29)	(1.66)	(-6.79)	(-1.77)	(2.81)	(-1.14)	(-0.10)	(17.73)	(6.25)
log(income)	-0.0114**	-0.000142	0.0864***	0.0139***	0.00416***	0.00385	-0.0111**	-0.0129***	-0.00334
	(-3.23)	(-0.05)	(20.90)	(4.76)	(4.66)	(0.56)	(-3.14)	(-4.13)	(-0.99)
age	0.0776***	0.0448***	0.0659***	0.130***	-0.273***	0.343***	-0.160***	-0.658***	0.202***
	(13.17)	(7.28)	(8.75)	(21.05)	(-110.49)	(3.37)	(-26.00)	(-94.05)	(31.18)
q60									
d_unemployed	0.00278	0.0496	-0.362***	-0.0468	0.0144	-0.523***	0.0122	0.353***	0.154***
	(0.08)	(1.78)	(-10.20)	(-1.42)	(1.13)	(-6.21)	(0.39)	(8.65)	(5.23)
log(income)	-0.0128**	0.00213	0.0633***	0.00676	0.00646**	-0.00270	-0.0162**	-0.0115*	-0.00392
	(-2.58)	(0.63)	(11.01)	(1.72)	(3.07)	(-0.34)	(-3.01)	(-2.43)	(-0.73)
age	0.0540***	0.0426***	0.0495***	0.0970***	-0.283***	0.318***	-0.173***	-0.666***	0.175***
	(6.01)	(5.94)	(5.02)	(12.17)	(-55.46)	(24.37)	(-20.24)	(-72.70)	(22.21)
q70									
d_unemployed	0.0118	0.0390	-0.367***	-0.0387	-0.00138	-0.559***	0.0216	0.404***	0.121***
	(0.35)	(1.54)	(-10.10)	(-0.94)	(-0.04)	(-4.32)	(0.71)	(9.12)	(3.51)
log(income)	-0.0255***	-0.00193	0.0493***	0.00714	0.00463	-0.00477	-0.0226***	-0.0119*	-0.00873
	(-4.97)	(-0.45)	(8.62)	(1.35)	(1.30)	(-0.50)	(-4.43)	(-2.10)	(-1.46)
age	0.0464***	0.0433***	0.0385***	0.0585***	-0.312***	0.293***	-0.179***	-0.687***	0.151***
	(5.25)	(5.68)	(3.51)	(6.10)	(-33.08)	(21.87)	(-19.99)	(-80.40)	(14.23)
q80									
d_unemployed	0.0605	0.0469	-0.350***	-0.0295	0.00586	-0.333	0.0458	0.422***	0.149**
	(1.57)	(1.50)	(-7.49)	(-0.84)	(0.14)	(-1.88)	(1.14)	(11.55)	(3.21)
log(income)	-0.0287***	-0.000884	0.0311***	-0.00536	0.00551	-0.0140	-0.0263***	-0.0191**	-0.0170**
	(-4.75)	(-0.15)	(5.62)	(-0.87)	(0.97)	(-1.50)	(-4.05)	(-2.85)	(-2.61)
age	0.0376**	0.0442***	0.0358**	0.0382***	-0.327***	0.283***	-0.191***	-0.710***	0.130***
	(3.23)	(4.46)	(2.75)	(3.99)	(-24.71)	(19.11)	(-17.27)	(-63.07)	(10.82)
q90									
d_unemployed	0.0539	0.0507	-0.340***	-0.0210	0.0221	-0.294	-0.00411	0.415***	0.202**
	(1.13)	(1.15)	(-6.82)	(-0.33)	(0.26)	(-1.69)	(-0.07)	(7.46)	(3.12)
log(income)	-0.0372***	-0.0169*	0.00761	-0.0258*	-0.0169	-0.0218	-0.0447***	-0.0252**	-0.0235***
	(-5.16)	(-2.48)	(0.97)	(-2.34)	(-1.50)	(-1.48)	(-4.86)	(-2.60)	(-3.48)
age	0.0329*	0.0427***	0.0213	0.00854	-0.348***	0.241***	-0.204***	-0.722***	0.118***
	(2.33)	(4.26)	(1.33)	(0.54)	(-21.48)	(11.60)	(-13.18)	(-39.07)	(8.20)
Observations	19624	19624	19624	19624	13801	13148	19624	19624	19624
0.10 Pseudo R2	.1152	.2378	.1444	.1493	.2007	.1906	.1636	.3334	.1269
0.20 Pseudo R2	.121	.2251	.1474	.1735	.3003	.2128	.1805	.3808	.145
0.30 Pseudo R2	.1399	.2178	.1563	.2058	.37	.2291	.2042	.415	.1654
0.40 Pseudo R2	.1405	.2072	.1629	.2337	.3952	.2323	.2183	.4363	.1735
0.50 Pseudo R2	.1234	.1854	.153	.2423	.3909	.2209	.2123	.4395	.162
0.60 Pseudo R2	.1044	.1606	.138	.2432	.3646	.2065	.1996	.4337	.1433
0.70 Pseudo R2	.0896	.1372	.1239	.2458	.3294	.1899	.1882	.4232	.1251
0.80 Pseudo R2	.0798	.1157	.1099	.2513	.2891	.1718	.1763	.4053	.1053
0.90 Pseudo R2	.0729	.0923	.0943	.2444	.2455	.1483	.1595	.3728	.0852

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

Source: Authors' calculations.
Notes: Impact on domain satisfactions for individuals with high mental well-being (score of mental well-being of 30+ on 36-point-scale; this represents the mentally most stable decile of the sample). QFE regressions with standardized coefficients and bootstrapped standard errors (100 replications). Dependent variables are standardized and represent life satisfaction and satisfaction with different life domains (from (1) overall life satisfaction to (8) satisfaction with use of leisure time). The analysis uses the same variables as the baseline regression, but we only report a few coefficients over the deciles to conserve space. Year and region dummies are used in the regressions but not reported here.

References

BHPS (2009). British Household Panel Survey. http://www.iser.essex.ac.uk/ulsc/bhps/.

Binder, M. and Coad, A. (2011). From Average Joe's Happiness to Miserable Jane and Cheerful John: Using Quantile Regressions to Analyze the Full Subjective Well-being Distribution. *Journal of Economic Behavior & Organization*, 79(3):275–290.

Binder, M. and Freytag, A. (2012). Volunteering, Subjective Well-being and Public Policy. *Journal of Economic Psychology*, 34(1):97–119.

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

Bonsang, E. and Klein, T. J. (2011). Retirement and Subjective Well-being. Mimeo.

Boyce, C. J., Wood, A. M., and Brown, G. D. (2010). The Dark Side of Conscientiousness: Conscientious People Experience Greater Drops in Life Satisfaction Following Unemployment. *Journal of Research in Personality*, 44(4):535–539.

Cade, B. S. and Noon, B. R. (2003). A Gentle Introduction to Quantile Regression for Ecologists. *Frontiers in Ecology and the Environment*, 1(8):412–420.

Canay, I. A. (2011). A Simple Approach to Quantile Regression for Panel Data. The *Econometrics Journal*, 14:368–386.

Clark, A. E. (2003). Unemployment as a Social Norm: Psychological Evidence from Panel Data. *Journal of Labor Economics*, 21(2):323–351.

Clark, A. E., Diener, E., Georgellis, Y., and Lucas, R. E. (2008a). Lags and Leads in Life Satisfaction: A Test of the Baseline Hypothesis. *The Economic Journal*, 118:F222–F243.

Clark, A. E., Frijters, P., and Shields, M. A. (2008b). Relative Income, Happiness, and Utility: An explanation for the Easterlin Paradox and Other Puzzles. *Journal of Economic Literature*, 46(1):95–144.

Clark, A. E. and Georgellis, Y. (2012). Back to Baseline in Britain: Adaptation in the British Household Panel Survey. *Economica.*

Clark, A. E., Georgellis, Y., and Sanfey, P. (2001). Scarring: The Psychological Impact of Past Unemployment. *Economica*, 68(270):221–241.

Clark, A. E. and Oswald, A. J. (1994). Unhappiness and Unemployment. *The Economic Journal*, 104(424):648659.

Coghill, R. C., McHaffie, J. G., and Yen, Y.-F. (2003). Neural Correlates of Interindividual Differences in the Subjective Experience of Pain. Proceedings of the National Academy of Sciences, 100(14):85388542

Cohn, M. A., Fredrickson, B. L., Brown, S. L., Mikels, J. A., and Conway, A. M. (2009). Happiness Unpacked: Positive Emotions Increase Life Satisfaction by Building Resilience. *Emotion*, 9(3):361–368.

Darity, William, J. and Goldsmith, A. H. (1996). Social Psychology, Unemployment and Macroeconomics. *The Journal of Economic Perspectives*, 10(1):121–140.

Di Tella, R., MacCulloch, R. J., and Oswald, A. J. (2001). Preferences Over Inflation and Unemployment: Evidence from Surveys of Happiness. *The American Economic Review*, 91(1):335–341.

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

Diener, E. and Seligman, M. E. P. (2004). Beyond Money - Toward an Economy of Well-being. *Psychological Science in the Public Interest*, 5(1):1–31.

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

Dolan, P., Peasgood, T., and White, M. (2008). Do We Really Know What Makes Us Happy? A Review of the Economic Literature on the Factors Associated with Subjective Well-being. *Journal of Economic Psychology*, 29:94–122.

Easterlin, R. A. (2002). Happiness in Economics. Edward Elgar, Cheltenham/UK.

Ezzy, D. (1993). Unemployment and Mental Health: A Critical Review. *Social Science & Medicine*, 37(1):41–52.

Fernandez-Dols, J.-M. and Ruiz-Belda, M.-A. (1995). Are Smiles a sign of Happiness?: Gold Medal Winners at the Olympic Games. *Journal of Personality and Social Psychology*, 69(6):1113–1119.

Ferrer-i-Carbonell, A. and Frijters, P. (2004). How Important is Methodology for the Estimates of the Determinants of Happiness? *The Economic Journal*, 114:641–659.

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

Frey, B. S. and Stutzer, A. (2002a). Happiness and Economics. Princeton University Press, Princeton/New Jersey.

_____ (2002b). What Can Economists Learn from Happiness Research? *Journal of Economic Literature*, 40(2):402–435.

Gardner, J. and Oswald, A. J. (2007). Money and Mental Wellbeing: A Longitudinal Study of Medium-sized Lottery Wins. *Journal of Health Economics*, 26:49–60.

Goldberg, D. P., Gater, R., Sartorius, N., Ustun, T. B., Piccinelli, M., Gureje, O., and Rutter, C. (1997). The Validity of Two Versions of the GHQ in the WHO Study of Mental Illness in General Health Care. *Psychological Medicine*, 27(01):191–197.

Graham, C. (2009). Happiness Around the World. Oxford University Press, Oxford/New York.

Helliwell, J. F. (2003). How's life? Combining Individual and National Variables to Explain Subjective Well-being. *Economic Modelling*, 20:331–360.

_____(2006). Well-being, Social Capital and Public Policy: What's New? *Economic Journal*, 116:C34–C45.

Helliwell, J. F. and Wang, S. (2012). The State of World Happiness. In Helliwell, J., Layard, R., and Sachs, J., editors, World Happiness Report, chapter 2. The Earth Institute.

Jahoda, M. (1981). Work, Employment, and Unemployment: Values, Theories, and Approaches in Social Research. *American Psychologist*, 36(2):184–191.

_____(1988). Economic Recession and Mental Health: Some Conceptual Issues. Journal of *Social Issues*, 44(4):13–23.

Kahneman, D. and Deaton, A. (2010). High Income Improves Evaluation of Life but Not Emotional Well-being. Proceedings of the National Academy of Sciences, 107(38):16489– 16493.

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

Kahneman, D., Fredrickson, B. L., Schreiber, C. A., and Redelmeier, D. A. (1993). When More Pain is Preferred to Less: Adding a Better End. *Psychological Science*, 4(6):401–405.

Kassenboehmer, S. C. and Haisken-De New, J. (2009). You're Fired! The Causal Negative Effect of Entry Unemployment on Life Satisfaction. *The Economic Journal*, 119:448–462.

Knabe, A. and Raetzel, S. (2011). Scarring or Scaring? The Psychological Impact of Past Unemployment and Future Unemployment Risk. *Economica*, 78:283–293.

Knabe, A., Rätzel, S., Schöb, R., and Weimann, J. (2010). Dissatisfied with Life but Having a Good Day: Time-use and Well-being of the Unemployed. *The Economic Journal*, 120(547):867–889.

Koenker, R. (2004). Quantile Regression for Longitudinal Data. *Journal of Multivariate Analysis*, 91:74–89.

Koenker, R., and Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1):33–50.

Krueger, A. B. and Mueller, A. I. (2012). Time Use, Emotional Well-being, and Unemployment: Evidence from Longitudinal Data. American Economic Review: Papers and Proceedings, 102(3):594599.

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

Layard, R., Clark, A. E., and Senik, C. (2012). The Causes of Happiness and Misery. In Helliwell, J., Layard, R., and Sachs, J., editors, World Happiness Report, chapter 3, pages 58–90. The Earth Institute.

Layard, R., Mayraz, G., and Nickell, S. (2010). Does Relative Income Matter? Are the Critics Right? In Diener, E., Helliwell, J. F., and Kahneman, D., editors, International Differences in Well-Being. Oxford University Press, New York.

Levy, H. and Jenkins, S. P. (2008). Documentation for Derived Current and Annual Net Household Income Variables, BHPS waves 1-16. Mimeo.

Lucas, R. E., Clark, A. E., Georgellis, Y., and Diener, E. (2004). Unemployment Alters the Set Point for Life Satisfaction. *Psychological Science*, 15(1):8–13.

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

Powdthavee, N. (2012). Jobless, Friendless and Broke: What happens to different areas of life before and after unemployment*? Economica*, 79(315):557–575.

Ryff, C. D. and Keyes, C. L. M. (1995). The Structure of Psychological Well-being Revisited. *Journal of Personality and Social Psychology*, 69(4):719–727.

Sandvik, E., Diener, E., and Seidlitz, L. (1993). Subjective Well-being: The Convergence and Stability of Self-report and Non-self-report Measures. *Journal of Personality*, 61(3):317–342.

Shiv, B. and Huber, J. (2000). The Impact of Anticipating Satisfaction on Consumer Choice. *Journal of Consumer Research*, 27(2):202–216.

Shizgal, P. (1999). On the Neural Computation of Utility: Implications from Studies of Brain Stimulation Reward. In Kahneman et al. (1999), pages 500–524.

Skodol, A. E. (2010). The Resilient Personality. In Reich, J. W., Zautra, A. J., and Hall, J. S., editors, Handbook of Adult Resilience, chapter 6, pages 112–125. Guilford Press, New York.

Taylor, M. F. E. (2009). British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices. Edited with John Brice, Nick Buck and Elaine Prentice-Lane. Colchester: University of Essex.

Tugade, M. M. and Fredrickson, B. L. (2004). Resilient Individuals Use Positive Emotions to Bounce Back from Negative Emotional Experiences. *Journal of Personality and Social Psychology*, 86(2):320–333.

van Praag, B., Frijters, P., and i Carbonell, A. F. (2003). The Anatomy of Subjective Well-being. *Journal of Economic Behavior & Organization*, 51(1):2949.

Winkelmann, L. and Winkelmann, R. (1998). Why are the Unemployed So Unhappy? Evidence from Panel Data. *Economica*, 65(257):1–15.

Notes

[1] For more extensive surveys over recent advances in subjective well-being research, see Layard et al. (2012); Frey and Stutzer (2002b); Dolan et al. (2008); Clark et al. (2008b). In the literature, subjective well-being is often used as an umbrella term for a number of well-being measures that can range from broad mental well-being measures, to affect-centered happiness measures (happiness here used in a narrower sense) to cognitively-centered life satisfaction measures (Ryff and Keyes, 1995; Easterlin, 2002; Frey and Stutzer, 2002a; Diener and Seligman, 2004). While these tend to correlate well with each other, they do not correlate perfectly since they measure distinct things. These measures also correlate differently with important life domains influencing well-being, such as income: affect measures tend to correlate less strongly with income (but more so with social factors) than life satisfaction measures (Kahneman and Deaton, 2010; Helliwell and Wang, 2012; Layard et al., 2012). Overall, affect measures also seem to depend less strongly on “major life circumstances” (Helliwell and Wang, 2012, p. 15) than life satisfaction measures. In general, the validity of subjective well-being measures has been established within the psychological and economic literature (Diener et al., 1999; Helliwell and Wang, 2012; Layard et al., 2010), and subjective well-being measures correlate in the expected directions with a number of objective factors such as emotional expressions like smiling (Fernandez-Dols and Ruiz-Belda, 1995), brain activity (Shizgal, 1999; Coghill et al., 2003) and biomarkers such as hypertension (Blanchflower and Oswald, 2008). Individuals’ happiness ratings also correlate well with overt behavior in the expected direction, for example with individuals discontinuing unsatisfactory behaviors (Kahneman et al., 1993; Shiv and Huber, 2000) or unhappy individuals exhibiting much higher suicide rates (Helliwell, 2006). Individuals are also able to (ordinally) compare and assess other individuals’ happiness, for example when individuals’ self-reports are correlated with reports of friends and family (Sandvik et al., 1993; Diener and Lucas, 1999). Regarding these measures’ reliability, the consensus is that they quite reliably measure the intended individual well-being. 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), somewhat lower than some other economic variables’ reliability.

[2] The negative relationship tends also to be stronger for males than females (e.g., Winkelmann and Winkelmann, 1998; Clark, 2003; Lucas et al., 2004).

[3] Another intertemporal aspect of the unemployment-happiness-nexus is “scarring”, i.e. the negative effect past unemployment has on present subjective well-being (Clark et al., 2001). It

is, however, not fully clear whether past unemployment impacts on subjective well-being by leaving scars on one's psyche or whether the negative effect is more likely to be a "scaring" effect of creating negative expectations of future unemployment, as Knabe and Raetzel (2011) argue.

[4] But unemployment does not only cause loss of income and subjective well-being: it has a bearing on psychological health more general (Ezzy, 1993) and has also been shown to increase mortality, suicide risk, marriage and social problems, drug abuse such as alcoholism and higher incidence of criminal behavior (see Winkelmann and Winkelmann, 1998, and the sources cited therein).

[5] Quantile regressions are designed for dependent variables that are continuous. Our raw dependent variable is categorical, which can nevertheless be considered as approximately continuous if there are a large number of categories (as is the case for our mental well-being analysis). Furthermore, quantile regression is performed with reference to conditional quantiles of the dependent variable (that is, conditional on the regressors; or in other words, quantiles of the residual), and the residual will be even better approximated by a continuous distribution than the raw dependent variable. In any case, we investigate the robustness of our results by using a range of alternative dependent variables, and obtain a coherent and theoretically meaningful set of results.

[6] Note that domain satisfaction with regard to spouse and job are not elicited from all individuals that do not have a spouse and/or job because, here, respondents could also check "not applicable". We are forced to restrict our analysis of these domains later on to the subset of individuals who have actually not chosen the non-applicable-category, which results in a sample of 74, 163 in the case of job and 83, 584 observations in the case of spousal satisfaction.

[7] As in the case of mental well-being, we have reversed the numerical order of the Likert scale to consistently use higher values for higher 'achievement' in these domains. Note that in the 1999 wave, a different coding of this indicator has been used. Since comparability between the different scalings is nontrivial, we have chosen to discard the observations of this wave to have a more consistent panel at our disposal.

[8] To conserve space, we do not report this disaggregated exercise. Detailed results are available from the authors on request.