Case 1: The Individual and Aggregate Effects of Unemployment on Happiness: Evidence from International Cross-Section Data Base

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Abstract

The present paper analyze the different dimensions of the relation between unemployment and subjective well-being. First of all, we observe a robust negative effect of individual unemployment status on happiness. Besides, we point out that a change on individual employment status affects also individuals who belong to the same reference group in a way depending on the level of aggregation. Furthermore, we identify a some degree of heterogeneity in the effect of aggregate unemployment rates, mainly depending on whether individuals themselves are employed or unemployed. We then focus on the impact of the unemployment rate of different socio-economic groups on individual happiness, and not only their own group. We follow Van Praag (2011) who observes that individuals do not only care about their own reference group, but all of them, although with different individual distributions. Using a random coefficients approach, we observe that while the effect of the unemployment rate of the lower-working class is negative and homogeneous across individuals, the effect of the unemployment rate on the upper class is positive and highly heterogeneous. Our results also exploit external data from the European Social Survey (ESS), and use a combination of the Continuum Approach and the Reference Distribution Method to provide verbal responses with a more natural cardinal interpretation.

1 Introduction

In this paper we study the effects of unemployment on happiness at individual and aggregate level. First we motivate our interest on happiness economics, then we briefly discuss the related literature, which is followed by presenting our research questions and summarizing our results.

1.1 Why Study Happiness?

Adam Smith, Ludovico Muratori and other prominent XVIII century economists stated, implicit or explicitly, that the ultimate goal of Political Economy was to improve the happiness level of a society. Besides, the work of well-known economists and psychologists of the XIX and early XX centuries assumed that such subjective utility/satisfaction level could be measurable and one can do interpersonal comparisons.[1] However, the revolution of ordinal utility, based on the belief that individual minds are inscrutable, proposed that it was sufficient to treat utility function as way of ranking agent preferences to explain perfectly the choices a rational individual could take (Hicks and Allen (1934), Pareto (1906)). So, in the quest of an economic science closer to the paradigm of physics, economists decided to dismiss the measurability (and cardinality) of subjective utility function, as a consequence, there was no room for happiness in Economics.

Nevertheless, since the late XX century, there has been a revolution in behavioral sciences which has advocated to focus more on subjective measures of individual satisfaction rather than objective ones, because the latter could be a very inaccurate measure about the individual well-being. This research field has led some economists to challenge the conventional economic results. For instance, textbooks microeconomics teach that there exists a mapping of income and market prices to utility levels (indirect utility function) that reflects the optimal choices of a rational individual. However, Easterlin (1974) finds that the relation between income and a measure of subjective well-being (henceforth SWB) depends on the level of comparison: within a country, the relationship is positive until some limit; across countries or time, the relationship is less clear. Easterlin's explanation was that what matters for individuals is not the absolute income, but the relative one. Additionally, Van Praag (2011) argues that SWB depends on individual characteristics (such as age, income, marital status, etc.) and *reference group* characteristics.

From a more theoretical approach, Ng (1997) advocates in favor of the cardinality of the utility function, something that was axiomatically assumed by early XX century economists, arguing there is a compelling interpretation for such a property: individuals are concerned, ultimately, about their net happiness (enjoyment minus suffering, including the sensuous as well as the spiritual). Hence, if an individual wants money, it is not for their own sake, but for obtaining more pleasure (satisfaction). Thus, the study of happiness permits to broaden the analysis and take into account subjective measures of individual well-being, measured through life-satisfaction questions of the type "How satisfied are you with your financial situation, job, health, etc.?", and, also, allows to investigate what the effects of demographic, financial and economic, and institutional factors on SWB measures are, often challenging the conventional perspective.

Far from being a philosophical issue, the assumptions we make on the properties of SWB measures (ordinality, cardinality) have direct consequences on the methods we can use to analyze them. Ferrer-i Carbonell and Frijters (2004) somewhat minimize this discussion by showing that results are similar regardless of the assumption we made on ordinality-cardinality (and therefore the methods we use to analyze them).

1.2 Research Question

It is inside this framework that our paper investigates on the following two questions: (i) what are the effects of individual employment status and the effects of aggregate unemployment rates at different levels on individual SWB?, and (ii) how does aggregate happiness (or

[1] In fact, Edgeworth (1879) is an essay about the hedonical calculus

aggregate SWB) changes when individual unemployment changes?

1.3 Literature Review

Let us start with a macroeconomics textbook theoretical result: rational individuals choose optimally how much of their total available time to spend on labor market. Then this would imply that given that unemployment is voluntary, individual happiness cannot be affected by occupational status.

Clark and Oswald (1994) analyze whether the government should seek to reduce the attractiveness of being unemployed or to look for alternatives to tackle unemployment. Obviously, the decision depends on whether being unemployed is a voluntary (an optimal decision) or not. They use a measure for mental well-being scores from a form of psychiatric evaluation (known as General Health Questionnaire, which is argued to be a reliable indicator of psychological distress or dis-utility (Argyle, 2013)). Using a panel survey of British households in the 1990s and applying ordered probit models, they find evidence against the textbook result. Besides, compared to other major events, being unemployed is worse, in terms of happiness or loss of utility, than divorce. Additionally, their results suggest that areas with high unemployment levels are correlated with relatively low dis-utility from joblessness.

Additionally, in a well known paper Tella et al. (2003) show that the microeconomic patterns of the determinants of SWB are robust across countries. Particularly robust is the relation of occupational status (1 for being unemployed, 0 otherwise) which is negative for US and Europe. Regarding the effect of GDP on happiness, they find a clear positive effect in short run, but a null effect in the long run, which is evidence in favor of the hypothesis of attenuation effect. In the same vein, Helliwell (2003) explores the effect of individual-level and national-level variables on subjective well-being. His main finding is that social capital has a positive and significant effects on happiness, the intuition is that networks and shared norms or values facilitate cooperation within and among groups.

Maybe even more important for our analysis, they suggest that macroeconomic variables have a robust effect on individual well-being even after controlling for individuals characteristics. In particular, Tella et al. (2003) find that the effects of unemployment rate or inflation are robustly negative on happiness. Moreover, the costs of recessions go beyond the falls in GDP and rise in unemployment, as it creates psychic losses on people who lose their job. This is one the key findings from our point of view: unemployment can affect individuals even once we control for the employment situation of the individual. That is, individuals care not only about their unemployment situation but also about the unemployment rate of family, neighbors, region or some other reference group to which individuals compare to asses their own levels of well-being. Recently, Van Praag (2011) (also see references therein) suggested that the reference group phenomenon should be taken into consideration while establishing the determinants of well-being, which has also been supported by Clark et al. (2008) as an explanation of the Easterlin Paradox. That is, the evaluation of individuals about their own situation is done by comparing themselves with others. For example, the fact that individual satisfaction with his own financial situation depends on that of others is now a standard result.

Unemployment rates (regional, family, etc.) are known to affect individuals through several channels. For example feelings of guilt could make employed workers sadder as the unemployment rate goes up, while it could make other employees happier as they have less pressure to lose their jobs (Clark et al., 2010). In this sense, it has been argued that perceptions about labor market risk could be even more important that the individual own personal situation (Eisenberg and Lazarsfeld, 1938).

(Clark et al., 2010) is the closest work to our main research interest. They try to quantify the effects that aggregate unemployment has on subjective well-being, in addition to the direct impact of the personal employment situation of individuals. They not only confirmed the extent of the results found by Tella et al. (2003), recognizing that higher unemployment rates in a country (or region) has a pervasive effect on individual happiness. They observe that the more unemployed people there are in some region the greyer the future prospects an individual has. Furthermore, they are able to show that the effects of aggregate unemployment measure is highly heterogeneous, which could be explained by the "social norm" hypothesis: as more people become unemployed, one's own unemployment is closer to the social norm. Clark et al. (2010) further observe that the heterogeneity of this results is not between unemployed and employed, but rather between high and low levels of job security (as Knabe and Rätzel (2011) suggest). Although this is clear for men, while it is more ambiguous for women.

1.4 Overview of the paper and main results

The main messages in the literature: (i) not only individual characteristics plays a role on individual happiness determination, but also aggregate-level variables are relevant. Probably, as Van Praag (2011) suggests, the individual are comparing all the time with some relevant reference group. (ii) The effects of both individual and aggregate variables on happiness heterogeneity will be present all the time in our happiness regressions, that is why our methodology should control for such heterogeneity (using fixed effects or a random coefficient approach); (iii) when one adds aggregate level variables, simultaneity issues arise with individual explanatory variables. Thus, we need to consider just truly exogenous personal characteristics; (iv) for controlling possible simultaneity of aggregate level variables and happiness, specially when one uses macroeconomic aggregates, it is recommendable to use lags of aggregate level variables. Finally, it is difficult to interpret results as causal effects, because in general one does not have appropriate instrumental variables.

In our study we assess the first two issues in detail, while presenting some possible extensions to address the last points. First of all, we show evidence that people do make consistent ordinal comparisons by presenting results that only one latent class exists. Furthermore, in the present work we will make some efforts to transform our data so that assuming cardinality will appear to be more sensible, regardless that responses are given in verbal form and not in the usual numerical scale. For that, we will use a combination the Continuum Approach (Kalmijn, 2010; Kalmijn et al., 2011) and the Reference Distribution Method (de Jonge et al., 2014), by exploiting data of 8-th round of the European Social Survey (ESS) conducted in 2016 for 18 European countries. This will allow as to use linear regressions which make the computation of the multiplier more intuitive.

Then, using this transformation of the data, we build a model of SWB based on individual variables in order to check for the robustness of our results and compare them with previous findings in the literature. We later extend this model to include aggregate variables, where the focus will be put on the aggregate unemployment rates at different levels of aggregation. Using these results the multiplier between the detrimental effect of individual employment situation and the total effect of that personĂŹs unemployment on the well-being on several groups is computed. The result, computed just for linear model regression, shows that the multiplier (absolute value) of country level unemployment rate and the individual unemployment is around 10. But, if we follow Glaeser et al. (2003) methodology, the multiplier (absolute value) is around 2.

Furthermore, we extend this model by allowing heterogeneous effects depending on reference groups by working class. However we do not find a some degree of heterogeneity between employed and unemployed population.

Finally, we focus on the effects of the unemployment rate of different socio-economic group (classes) on individual well-being. Differently from the previous model, we do not only include the unemployment rate from our own reference group, but, inspired by Van Praag (2011) we make an argument in favor of ”random” references group. That is, we suggest that it is not true that an individual looks only at his main reference group (which we consider it is their own socio-economic group or class), but that they care about all socio-economics groups but with individual weights. To address the relation of each group on individual well-being we run a random coefficient model. There, we can observe that while the relation of the lower-working class unemployment rate affects individual SWB negatively and homogeneously across the whole population, there is a high degree of heterogeneity in the effects of the unemployment rate of the upper class. On the other hand, the unemployment rate of the middle class shows a positive relation with individuals happiness, and it is strongly homogeneous.

We consider these results very illustrative. First, it can be pointing out the low awareness of the middle class individuals as a common group: not even individuals inside their group care too much about the fate of their workers. On the other hand, unemployment of the working class seems to affect equally individuals of all classes. Both the self-awareness of the working class as a unified group and the empathy they produce in other sectors of the society could be behind this result. Finally, the unemployment rate of the upper class shows a high degree of heterogeneity: while a increase on the unemployment rate of this group has a positive effect on some individuals, it is negative for other. This shows that egalitarians views of a large part of the society collide with the negative perceptions about labor market risk that individuals of the upper class could have derived from a higher unemployment rate across individuals of their group.

The paper is structured as follows: part 2 gives a description of our data base and the main variables we employ on the different regressions. Part 3 explains with some detail our empirical methodology. In part 4, we present our main results. Finally, part 5 concludes and discusses our findings.

2 Data

In order to analyze the relation between SWB, employment status, and its consequences on our peers, we used the 1999–2001 wave of the European Values Studies (EVS). Although our data set included information of three other waves, we drop it due to availability and consistency of key variables such as income (measured in levels, which in turn allows us to build inequality measures), which is found in the last two waves, and socio-economic status, which is found in the first three waves. Furthermore, as we do not intend to use pseudo-panel techniques, there is no significant loss resulting from this decision. The European Values Study is a large-scale, cross-national, and longitudinal survey research program on basic human values initiated by the European Value Systems Study Group (EVSSG) in 1971. Although not all European countries were represented from the beginning, the analyzed wave of the EVS covers more than 20 European countries. Individuals who do not respond to some of the questions included on our analysis are dropped from our sample. In total, there are 13.855 individuals in our smallest sample.

2.1 Subjective Well-Being

The database considers different aspects of happiness, such as mental health, job satisfaction or financial satisfaction. Nevertheless, in this work we choose to use an overall measure of SWB, measured by the question “Taking all things together, would you say you are...”. Respondents could answer “Very Happy”, “Quite Happy”, “Not Very Happy”, “Not at all Happy”.

We are aware that there has been a lot of controversy about such vague questions, and many academics have presented doubts about its use in any meaningful empirical research. However, observed patterns in the answers are very robust and quite similar across countries (Blanchflower and Oswald, 2004; Ferrer-i Carbonell and Frijters, 2004). Besides, these measures have been widely used by psychologists, who understand the quality of the data better than anyone; in fact, well-being data has consistently passed what is called validations exercises by psychologists. That is, happiness responses are correlated with physical reactions that can be thought of as describing true, internal happiness (Ekman et al., 1990; Pavot et al., 1991; Shedler et al., 1993). These reasons make us confident about their use in our study (see Alesina et al., 2004, for a discussion on these issues). Later we argue for the growing consensus that this measure has a cardinal interpretation (Easterlin, 2006).

We are also aware that this kind of question could induce some measurement errors; however, as happiness level is our dependent variable, we expect that the potential measurement errors only affect the precision of our estimates, but not their consistency.

2.2 Employment

As it was stated in the introduction, occupational status and employment-related variables will be the main explanatory variables in our model. Veenhoven (2015) identifies work decisions as milestones in determining happiness. In this sense, the prime decision is to work or not to work. Most empirical works have established that individual unemployment reduces happiness levels (Clark and Oswald, 1994; Winkelmann and Winkelmann, 1998). The individual will be considered unemployed if she declares being in that situation to the question "Are you yourself employed now or not?".

Further, we will explore several dimensions of individual employment that have been shown to affect the levels of well-being in order to shed some light on the mechanisms governing the relationship between happiness and employment. Additionally, Veenhoven (2015) emphasized that job conditions play an important role in happiness determination. In particular, he suggests that self-employed workers tend to show lower levels of happiness, although the evidence is not conclusive (Andersson, 2008). Furthermore, there is also compelling evidence that retirement, in particular early retirement, substantially affects well-being levels (Börsch-Supan and Jürges, 2006), which we also control for.

As we mentioned before, unemployment can affect individuals through at least two channels: (i) unemployed people are less happy due to losing their jobs and the awareness of the reduction in their income, but also (ii) a psychological effect takes place in many situations. However, there should be a negative effect derived from the rising in unemployment rate of a city or region: the fear to go into unemployment if you are employed, or also the negative expectations that an unemployed person could form about his professional career. Although, we recognize this effect could be heterogeneous. These aggregate measures of unemployment will be computed from the same data source. We aggregate at three different levels: country (`unempC`, region (measure by NUTS 3-digit code, collected by variable `X048C`) (`unempR`), and socio-economics group in each country (unempB (coded by the variable `x046`. [2]. We are interested in the codification of socio-economic group as it is very likely that individuals compare themselves with other people inside their reference group. Hence, we expect to find stronger ties between aggregated variables at this level.

2.3 Other determinants of happiness

Additionally, in the following we describe and justify the inclusion of several covariates which could confound the relationship between happiness and employment. See (Helliwell, 2003) for a thorough discussion on the expected effect of determinants of well-being usually found in previous empirical works. In a recent analysis of the determinants of happiness, Veenhoven (2015) suggested that almost 30% of the happiness levels can be explained by genetics (Bartels and Boomsma, 2009), and that luck could explain around 15% of happiness (Headey and Wearing, 1992). Unfortunately, with the data at hand we cannot control for most of such factors. However, Veenhoven (2015) also highlights that socio-economic position, social ties, and life-choices can have a relevant role explaining our levels of happiness. There is also extensive evidence that the effect of many of these variables is quite stable across samples and time (Blanchflower and Oswald, 2004; Ferrer-i Carbonell and Frijters, 2004).

First of all, ever since the appearance of Easterlin's seminal paper (Easterlin, 1974), much of the discussion about happiness has revolved around the effects of income on individual well-being. Cross section studies have usually find positive effects of income, both in developed (Shields and Price, 2005) and developing countries Graham and Pettinato (2004) Clark et al.

[2] Answers are coded as: 1. Upper, upper-middle class, 2. Middle, non-manual workers, 3. Manual workers - skilled, semi-skilled, 4. Manual workers - unskilled, unemployed

(see 2008, for a review of the relation between income and happiness). Thus, we are going to control for individual income.

Veenhoven (2015) includes family decisions as a crucial component of happiness. His work highlights that, although there is much promotion about the joys of singlehood, psychological research findings show that being married has positive effects on happiness. For this reason, we include `married`, indicating with a 1 if the individual is married. We will also include gender as a control variable (0 for male and 1 otherwise), because men and women could be affected in different forms. Although the literature has not found conclusive evidence about the existence of differences in this dimension (see Diener et al., 1999, for an extensive discussion). Veenhoven (2015) also comments that adults who have spent more years in school tend to be happier, but highlights that some studies have shown that people who reach the highest levels of education are not always the happiest ones, pointing out that the highest levels of happiness are obtained at median levels of education. Then, we will control for education by including the number of years of completed education (`educ`) (Helliwell, 2003), and it is computed using the declared age when individual finished their formal education minus 6 (resulting negative numbers are replaced by a zero). Then we drop individuals above the 99th percentile. Regarding age, there exists well documented evidence of a U-shaped relationship between age and happiness (Blanchflower and Oswald, 2004; Frijters and Beatton, 2012), which justifies the inclusion of a quadratic term of age.

The relative income of individuals with respect to a *reference group* is also included as a determinant of well-being in the spirit of Clark et al. (2008). Thus, the relative income will measure y_i/y^*, where y_i is the income of individual i and y^* is the aggregate income of the reference group defined by region `relincR`, country `relincC`, and socio-economic status in the country of the respondent `relincB`. Besides, Alesina et al. (2004) make a strong case for the inclusion of inequality measures as a source of individual well-being, which we do by including aggregate Gini indicators (`GiniR`, `GiniC`, `GiniB`).

Finally, aggregate macroeconomic data, namely, per-capita GDP or inflation, were obtained from the IMF World Economic Outlook Data Base. In the case of per-capita GDP, it is measured at PPP dollars, which allows for comparison between countries.

2.4 Descriptive statistics

The marginal distribution of happiness categories (see Table A1 in the Appendix) is the following: 2.6% of the respondents report to be “Not at all happy”; 15.0%, “Not very unhappy”; 56.8%, “Quite happy”; 22.8%, “Very happy”.

In Figure 2.1 one can observe how the distribution of happiness categories changes across income level. The “Not at all happy” category along with that of “Not very happy” are strongly concentrated at low income levels, while the other two categories corresponding to a higher happiness level exhibit higher variance and, in particular, fat right tails. Thus, one can suspect a significant degree of heterogeneity in income across happiness levels.

Figure 2.2 shows the distribution of happiness by occupational status. It is straightforward to notice that both distributions are similar, but there are more unemployed people that report to be unhappy (“Not at all happy” or “Not very happy”) than employed people.

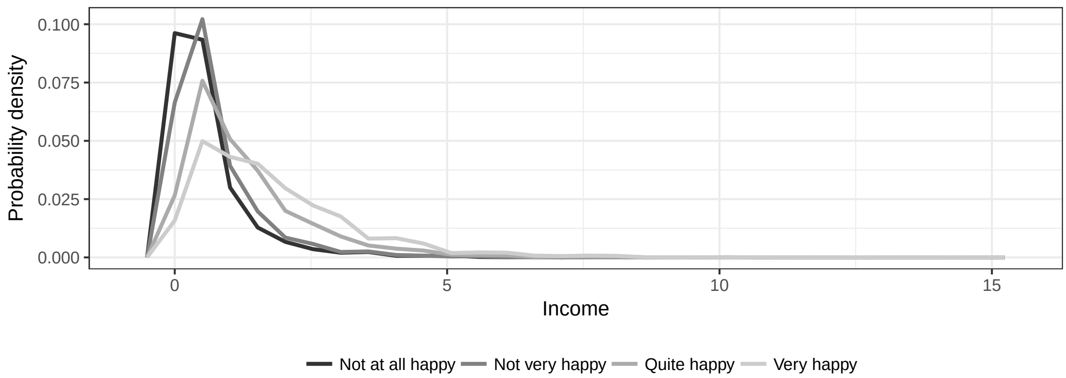

Figure 2.1: Happiness distribution by income.

The opposite relationship can be observed for "Quite happy" and "Very happy" categories. This suggests a negative correlation between unemployment and happiness.

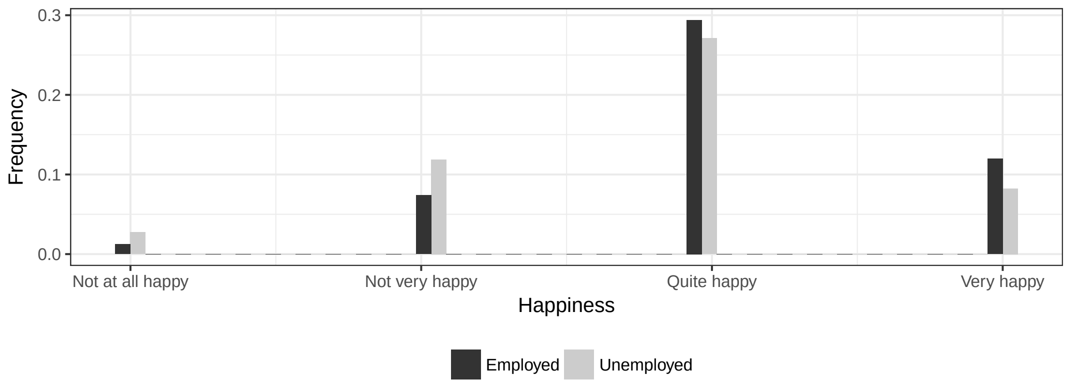

Figure 2.2: Happiness distribution by occupational status.

Figure 2.3 shows the relation between average happiness levels and unemployment rates for across regions. Notice that the graph already pictures the transformed SWB measures (it will be explained how to obtain these values in detail in the next section). Every observation is depicted as a transparent point so that a black dot corresponds to a high number of overlapping points. Hence, given a particularly high concentration of observations at the lower right corner one suspects a certain degree of negative correlation between average happiness and unemployment rate across regions.

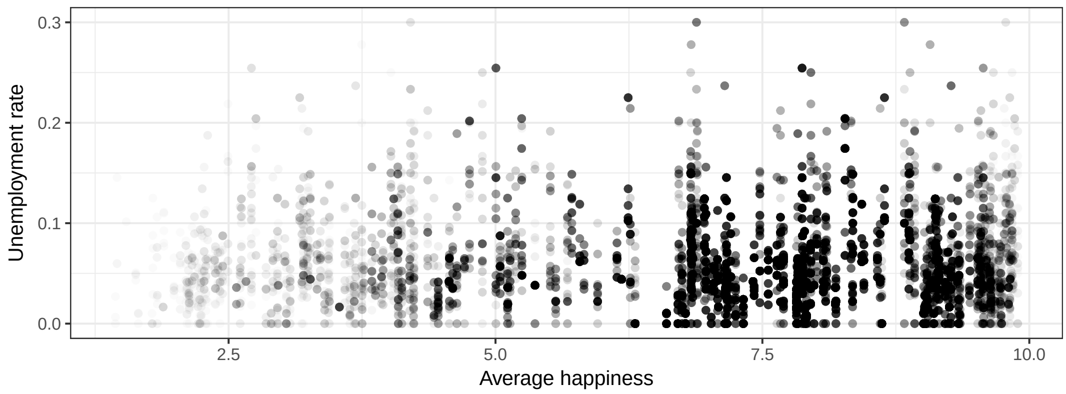

Figure 2.3: Happiness distribution and aggregate unemployment rate.

3 Methodology

The most widespread econometric techniques in the literature of happiness of economics are the ordinary least squares estimator, the ordered probit model, and the probit-adapted OLS estimator. However, the adequacy of their usage heavily relies on such assumptions as their cardinality or ordinality. In addition to that, each of those standard models presents us with some limitations.

In this paper we are provided with an individual happiness measure taking values in a verbal scale. For this reason, our approach consists of, firstly, evaluating the adequacy of the cardinality assumption and its consequences and, secondly, of applying some flexible econometric techniques to relax several of the restrictive assumptions behind the models.

In this section we describe in detail all the techniques applied in the rest of the paper. Namely, we start with the continuum approach taking advantage of an external source of happiness data to estimate a distribution of the underlying continuous happiness random variable, which is then combined with the reference distribution method so assign numerical values to each element of a verbal scale. Next, we consider the ordinary least squares estimator, ordered probit and logit models, and a generalized probit-adapted OLS estimator as practically convenient approaches, yet featuring some limitations. As an additional tool, we will use Heckman and Singer's approach to infer the degree of heterogeneity in the latent variable thresholds across individuals. As it is a special case of the latent class model, we describe it as well. Lastly, we consider the semi-nonparametric extended ordered probit estimator allowing to obtain arbitrarily accuracy approximation of the underlying errors distributions, instead of restricting attention to the standard normal distribution. We conclude with a list of econometric issues and limitations.

3.1 Continuum Approach

Possible values of the individual happiness level vary significantly across surveys: from verbal categories "Not too happy", "Pretty happy", and "Very happy" to the set of integers $\{ 0, 1, \ldots, 10 \}$. This limited uniformity across results slows down the accumulation of knowledge and hinders their interpretation. The simplest possible method to standardize the results is the Linear Stretch method (Hull, 1922), where numerical response options are rescaled to a common range (e.g., the interval $[0,10]$). Then mean, standard deviation, and any other statistics are computed using the transformed numbers. Given verbal categories of individual happiness, one alternative is to ask a set of judges to assign a numerical value to each of the categories; then the average evaluation of each category provides a secondary set of possible answers amenable to numerical computations (e.g., Lim, 2008). Similarly, judges may be asked to assess the transition points from one happiness category to another (Veenhoven, 2009). In such a case, the mid-interval value between two transition points of a verbal response is assigned as the numerical value of the corresponding response.

In our paper we employ a more sophisticated approach based on probability distributions discussed in (DeJonge et al., 2015). Namely, the continuum approach (Kalmijn, 2010; Kalmijn et al., 2011) assumes that there exists a latent continuous random variable H^* underlying the survey happiness random variable H, and the distribution of H^* is estimated using the survey responses. In particular, Kalmijn suggests to consider $H^* \sim \mathrm{Beta}(\alpha,\beta)$—a beta distribution over the interval $[0,10]$ with the corresponding density function

$$f(h;\alpha,\beta) := \frac{h^{\alpha-1}(10-h)^{\beta-1}}{10\cdot \mathrm{B}(\alpha,\beta)},$$

where $\mathrm{B}(\cdot,\cdot)$ denotes the beta function, α and β are the shape parameters, and let $F(\cdot\,;\alpha,\beta)$ denote the corresponding cumulative distribution function.

Now let a vector $\mathbf{h} = (h_1,\ldots,h_n)'$ of observed individual happiness levels, taking values in $\{\,0,1,\ldots,10\,\}$, be given. Then, depending on the interpretation, one may want to maximize one of the following three likelihood functions:

$$\begin{aligned}
\mathcal{L}_1(\alpha,\beta;\mathbf{h}) &= \prod_{i=1}^{n}\Big\{F(h_i;\alpha,\beta) - F(h_i-1;\alpha,\beta)\Big\},\\
\mathcal{L}_2(\alpha,\beta;\mathbf{h}) &= \prod_{i=1}^{n}\Big\{F(h_i+1;\alpha,\beta) - F(h_i;\alpha,\beta)\Big\},\\
\mathcal{L}_3(\alpha,\beta;\mathbf{h}) &= \prod_{i=1}^{n}\Big\{F(\min\{h_i-1/2,10\};\alpha,\beta) - F(\max\{h_i-1/2,0\};\alpha,\beta)\Big\}.
\end{aligned}$$

In particular, one would use $\mathcal{L}_1$ if the respondent chooses $0,1,\ldots,10$ when the unobserved latent happiness h_i^* belongs to $\{0\},(0,1],\ldots,(9,10]$, respectively, so that h_i corresponds to a certain transition point. Similarly, $\mathcal{L}_2$ would be maximized if the corresponding intervals are $[0,1),[1,2),\ldots,\{10\}$, and h_i is a certain transition point as well. Lastly, $\mathcal{L}_3$ is appropriate when the respective intervals are $[0,1/2),[1/2,3/2),\ldots,[9+1/2,10]$ so that now h_i are, except for 0 and 10, the mid-interval values between two transition points.

However, since the beta distribution is continuous, sets $\{0\}$ and $\{10\}$ have zero probability mass, contrary to what is observed in our sample. Thus, it must be that only the third interpretation is statistically valid and $\mathcal{L}_3$ should be used. Given the parameter estimates $\hat{\alpha}_n$ and $\hat{\beta}_n$, one is able to estimate the (latent) mean happiness and other parameters of interest. The procedure is implemented using the **R** package and the function `mle` from its library **stats4**.

It is also noteworthy that the beta distribution could be replaced with any other, perhaps rescaled and shifted, probability distribution of bounded support (e.g., any distribution doubly truncated at 0 and 10). Nevertheless, we expect the beta distribution to be flexible enough to accommodate the shape of the distribution of interest.

3.2 Reference Distribution Method

In the case when the set of possible responses to the subjective well-being question contains totally ordered verbal values, one may combine the continuum approach with the reference distribution method (de Jonge et al., 2014). In particular, suppose that $\mathbf{h} = (h_1, \ldots, h_n)'$ is a vector of verbal responses and that $(\hat{\alpha}, \hat{\beta})$ is a pair of estimates of a beta distribution on the interval $[0, 10]$ obtained using some external dataset with the possible response values being $\{ 0, 1, \ldots, 10 \}$. Further, let $\hat{F}_n$ denote the empirical cumulative distribution function of a random variable H. That is,

$$\hat{F}_n(h) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}_{\{ H_i \leq h \}},$$

where $\mathbb{1}_{\mathbf{A}}(\cdot)$ denotes the indicator function of a set $\mathbf{A}$, the usage of $\leq$ is well-defined as the verbal values are totally ordered, and H_i, $i = 1, \ldots, n$, are i.i.d. copies of H.

The task then is, for every unique value h that the elements of $\mathbf{h}$ take to assign a numerical value from the interval $[0, 10]$, say $\tilde{h}$. A natural choice is

$$\tilde{h}_i := F^{-1}_{\hat{\alpha},\hat{\beta}}(\hat{F}_n(h_i)).$$

That is, $\tilde{h}$ is the $\hat{F}_n(h)$-th quantile of the Beta$(\hat{\alpha}, \hat{\beta})$ distribution. Figure 3.1 provides an example. The black curve corresponds to the cumulative distribution function of the estimated (using simulated data) beta distribution. The simulated vector $\mathbf{h}$ takes five distinct verbal values depicted on the left of the graph, where the height of the corresponding grey square shows the frequency of this value in the sample. Then the corresponding distinct numerical values $(5.6, 6.5, 7.5, 8.8)$ are obtained using the displayed grey dotted lines.

Figure 3.1: An illustration of the continuum approach and the reference distribution method. The dashed lines lead to the transition points, while the dotted lines lead to the estimated numerical values corresponding to the original verbal values.

Those values then are interpreted as transition points. That is, the intervals corresponding to responses “Not happy”, “Slightly happy”, “Fairly happy”, “Quite happy”, and “Very happy” are $[0, 5.6)$, $[5.6, 6.5)$, $[6.5, 7.5)$, $[7.5, 8.7)$, and $[8.8, 10]$ (up to zero measure changes), respectively.

Following Veenhoven (2009) we then would set $\hat{h}^*$ as the mid-interval values between two transition points. However, such an approach is reasonable only given a constant slope between every two transition points. In particular, setting $\hat{h}^*_{\text{Not happy}} = 2.8$ would lead to biased estimates in further analysis because, according to the estimated distribution, almost all the individuals choosing “Not happy” should have $h_i^* \geq 3$.

Thus, instead of considering the mid-intervals in the x-axis, we consider the category-specific probability mass centers or, in other words, the mid-intervals in the y-axis:

$$\hat{h}_i^* := F^{-1}_{\hat{\alpha},\hat{\beta}}\Big(\hat{F}_n(h_i - 1) + \hat{\mathbb{P}}_n(h_i)/2\Big),$$

where $\mathbb{P}_n$ is the empirical probability measure defined as

$$\hat{\mathbb{P}}_n(h) = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{\{\, H_i = h \,\}}.$$

The paths to the resulting values

$$\hat{h}^*_{\text{Not happy}} = 5, \quad \hat{h}^*_{\text{Slightly happy}} = 6.1, \quad \hat{h}^*_{\text{Fairly happy}} = 7,$$
$$\hat{h}^*_{\text{Quite happy}} = 8.1, \quad \hat{h}^*_{\text{Very happy}} = 9.1.$$

are depicted in Figure 3.1 with as black dashed lines.

3.3 Ordinary Least Squares

As a benchmark we first consider ordinary least squares estimation. While it is a commonly used approach in the literature of economics of happiness (e.g., Clark and Senik, 2010; Di Tella et al., 2010; Frijters and Beatton, 2012; Nikolova, 2016), mostly due to computational ease and intuitive interpretation, it is typically as cardinal only when the scale of happiness values is numerical; e.g., the set $\{\, 0, 1, \ldots, 10 \,\}$. There are, however, some exceptions where applying ordinary least squares to a dependent variable of a verbal scaled mapped into, e.g., a set $\{\, 1, 2, 3 \,\}$ is argued to yield robust enough results (e.g., Di Tella et al., 2001).

The main issue with the latter approach is that, while the verbal response options are ordered, there are no obvious numerical values—happiness gains—that could be assigned to the jumps between subsequent verbal responses. Thus, for this reason one must be particularly cautious when interpreting the OLS results and it is necessary to consider models that are more statistically consistent with the data generating process.

3.4 Ordered Probit and Logit Models

If one is not willing to consider a certain well-being measure to be cardinal, then linearity-based estimators, such as the OLS estimator, are not suitable. In any case, there is a consensus that responses to subjective well-being questions are interpersonal ordinal comparable. Several arguments have justified this view. For one, individuals seem to be able to recognize and predict satisfaction levels of others. Also, individuals who share the language have a common understanding on the wording of the questions, and can translate internal feelings into a numerical scale in a similar way (Van Praag, 1991); see (Ferrer-i Carbonell and Frijters, 2004) for a more detailed discussion on this issue. Hence, in such instances, latent regression models are suitable.

Let us start with a general framework for ordered response models. As with many limited dependent variable models, consider the underlying random utility or latent regression model given by

$$Y_i^* = \mathbf{X}_i'\boldsymbol{\beta} + \varepsilon_i \quad \text{for} \quad i = 1, \dots, n,$$

where $\mathbf{X}_i$ is a random vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of unknown parameters, and ε_i is an error term with a fully specified cumulative distribution function F. If Y_i^* were observable, $\boldsymbol{\beta}$ could be consistently estimated by ordinary least squares without requiring to assume the distribution of ε_i. Instead, in practice one observes a discretized counterpart of the continuous latent measure Y_i^* censored in the following way:

$$Y_i = \begin{cases} 0 & \text{if } \mu_0 < Y_i^* \leq \mu_1, \\ 1 & \text{if } \mu_1 < Y_i^* \leq \mu_2, \\ \cdots & \\ J & \text{if } \mu_J < Y_i^* \leq \mu_{J+1}, \end{cases}$$

where, among other normalizations necessary to identify the model parameters, we assume that the thresholds—additional parameters—satisfy $-\infty = \mu_0 < \mu_1 < \cdots < \mu_J < \mu_{J+1} = +\infty$. Consequently, the probability of observing an alternative j is

$$\mathbb{P}(Y_i = j \mid \mathbf{X}_i) = F(\mu_{j+1} - \mathbf{X}_i'\boldsymbol{\beta} \mid \mathbf{X}_i) - F(\mu_j - \mathbf{X}_i'\boldsymbol{\beta} \mid \mathbf{X}_i) > 0 \quad \text{for} \quad j = 0, 1, \dots, J.$$

Hence, the model parameter estimation is based on maximizing the log likelihood function

$$\mathcal{L}\left(\boldsymbol{\beta}, \{\mu_j\}_{j=1}^J \mid \mathbf{X}_1, \dots, \mathbf{X}_n\right) = \sum_{i=1}^n \ln\left[F(\mu_{j_i+1} - \mathbf{X}_i'\boldsymbol{\beta}) - F(\mu_{j_i} - \mathbf{X}_i'\boldsymbol{\beta})\right] \tag{3.1}$$

with respect to the sequence of thresholds $\{\mu_j\}_{j=1}^J$ and the parameter vector $\boldsymbol{\beta}$, where j_i denotes the alternative chosen by the j-th respondent.

By far the most commonly used models of this type in happiness economics literature as well as more generally have been the ordered probit and ordered logit models. In particular, in this paper we consider the ordered probit model introduced by Aitchison and Silvey (1957) that imposes the normalization restrictions of unit variance, zero intercept, and assumes that $F = \Phi$, where Φ denotes the cumulative distribution function of a standard normal random variable.

The ordered probit model is a standard approach in the literature of happiness economics (see, e.g., Alesina et al., 2004; Di Tella and MacCulloch, 2008; Van Praag and Baarsma, 2005;

Van Praag et al., 2003). Just as ordinary least squares, it is attractive for its computational speed. On top of that, it is statistically consistent with the data generating process described above and is amenable to using happiness measures in a verbal scale. Also, while it is fast, it fails to handle large numbers of covariates and, ence, is less reliable, particularly in comparison to the models described below. For instance, optimization routines may fail due to its nonlinear likelihood function, it assumes homogeneous individual effects on happiness, fixed thresholds μ_j across individuals, and that the errors follow a normal distribution. As the adequacy of those assumptions is far from obvious, we consider relaxing them by utilizing a number of alternative models.

For the implementation we use the `polr` function from the **MASS** library in **R** package.

3.5 Generalized Probit-Adapted OLS

An attractive alternative to the ordered probit model described before has been proposed by Van Praag and Ferrer-i Carbonell (2004). It tries to combine the advantages of ordinary least squares squares estimation with those of the ordered probit model, while still yielding results similar to using the latter approach. In particular, it cardinalizes the ordinal dependent variable in order to apply the OLS estimator, in this way making computations much faster and stable relative to the ordered probit model, especially with more complicated models. This approach has also been widely applied in the happiness economics literature (see, e.g., Clark et al., 2010; Geishecker, 2012; Luechinger, 2009; Luechinger et al., 2010; Stevenson and Wolfers, 2008).

To explain the motivation behind the model, consider again the latent regression

$$Y_i^* = \mathbf{X}_i'\boldsymbol{\beta} + \varepsilon_i \quad \text{for} \quad i = 1, \dots, n$$

along with the same censoring mechanism for Y_i as before. Let also P_j be the sample frequency of category j given by

$$P_j := \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{\{Y_i=j\}} \quad \text{for} \quad j = 0, 1, \dots, J.$$

which can be estimated given a sample $\{y_i, \mathbf{x}_i\}_{i=1}^n$. Recalling that

$$\mathbb{P}(Y_i = j \mid \mathbf{X}_i) = \mathbb{P}(\mu_j \le Y_i^* < \mu_{j+1} \mid \mathbf{X}_i) = \mathbb{P}(Y_i^* < \mu_{j+1} \mid \mathbf{X}_i) - \mathbb{P}(Y_i^* \le \mu_j \mid \mathbf{X}_i)$$

and maintaining the assumption that ε_i follows the standard normal distribution suggests a system of equations

$$\begin{cases} \hat{P}_0 & = \Phi(\hat{\mu}_1), \\ \hat{P}_1 & = \Phi(\hat{\mu}_2) - \Phi(\hat{\mu}_1), \\ \dots \\ \hat{P}_J & = 1 - \Phi(\hat{\mu}_J), \end{cases}$$

which, when solved, yields that

$$\hat{\mu}_j = \Phi^{-1}\left(\sum_{i=1}^{j} \hat{P}_{i-1}\right) \qquad \text{for} \qquad j = 1, \ldots, J,$$

where Φ^{-1} stands for the quantile function of the standard normal distribution. On the other hand, if the sequence of the true thresholds were known, the best guess $\tilde{y}$ of any such unobserved latent value y_i^* that $y_i = j$ would be

$$\tilde{y} = \mathbb{E}[Y_i^* \mid \mu_j \leq Y_i^* < \mu_{j+1}] = \frac{\phi(\mu_j) - \phi(\mu_{j+1})}{\Phi(\mu_{j+1}) - \Phi(\mu_j)}, \tag{3.2}$$

where $\phi(\cdot)$ denotes the probability density function of the standard normal distribution. Consequently, for every $i = 1, \ldots, n$ such that $y_i = j$ we estimate

$$\hat{y}_i^* = \frac{\phi(\hat{\mu}_j) - \phi(\hat{\mu}_{j+1})}{\hat{P}_j}. \tag{3.3}$$

The Probit-Adapted OLS method then consists of regressing $\hat{y}_i^*$ on the explanatory variables $\mathbf{x}_i$. Notice, however, that $\{\hat{y}_i^*\}_{i=1}^n$ take only $J+1$ distinct values and do not depend on the explanatory variables. The true latent value Y_i^* can be written as the sum of its conditional mean and a rounding error induced by the fact that we only observe the interval in which the true Y_i^* is situated.

Nevertheless, the Probit-Adapted OLS (POLS) remains to have the rest of the shortcoming discussed before, such as homogeneity. For instance, Boes and Winkelmann (2006); Greene and Hensher (2010b); Ierza (1985); Pudney and Shields (2000) provide evidence of potential individual heterogeneity in the thresholds.

Lastly, notice that it is straightforward to generalize this model to distributions other than the standard normal one. In particular, if we replace Φ with any other cumulative distribution function, all the equations above remain to hold with the exception of (3.2) and (3.3). However, as $\hat{y}_i^*$ attain only a few values, we may employ a Monte Carlo method to estimate them. In particular, if $\varepsilon_i \sim F$, then for every $i = 1, \ldots, n$ such that $y_i = j$ we estimate

$$\hat{y}_i^* = \frac{1}{R}\sum_{r=1}^{R} z_r \cdot \mathbb{1}_{\{\hat{\mu}_j \leq z_r < \hat{\mu}_{j+1}\}},$$

where $\{z_r\}_{r=1}^R$ are R independent draws from F.

3.6 Latent Class Model and Heckman and Singer's Interpretation

3.6.1 Latent Class Model

The conventional ordered probit model is potentially limited in that it fixes the threshold values across individuals. This can lead to inconsistent estimates of the effects of variables. A considerable number of studies have been devoted to relax this limitation (see Greene and Hensher, 2010a); the main direction is to add individual heterogeneity in that the threshold values would vary across individuals. The latent class model is a particularly popular approach to achieve that.

The latent class model, also known as the finite mixture model, accommodates the heterogeneity by assuming that there are C classes with class-specific threshold and parameter values. Formally, the class membership follows a discrete distribution:

$$\mathbb{P}(\text{Individual } i \text{ is a member of class } c) = \pi_c.$$

The typical consistency restrictions are $\pi_c > 0$ for each $c = 1, \ldots, C$ and $\sum_{c=1}^{C} \pi_c = 1$. Augmenting the ordered probit model with this class membership distribution gives

$$\mathbb{P}(Y_i = j \mid \mathbf{X}_i) = \sum_{c=1}^{C} \pi_c \cdot \Big[\Phi(\mu_{j+1,c} - \mathbf{X}_i^{'}\boldsymbol{\beta}_c \mid \mathbf{X}_i) - \Phi(\mu_{j,c} - \mathbf{X}_i^{'}\boldsymbol{\beta}_c \mid \mathbf{X}_i)\Big].$$

The way to interpret this model as a heterogeneous one is to notice that

$$\mu_{j,c} - \mathbf{X}_i^{'}\boldsymbol{\beta}_c = \mu_j + \nu_c - \mathbf{X}_i^{'}\boldsymbol{\beta},$$

where $\nu_c = \mathbf{X}_i^{'}\boldsymbol{\gamma}_c$ and $\boldsymbol{\beta}_c = \boldsymbol{\gamma}_c - \boldsymbol{\beta}$ so that the unobserved heterogeneity ν_c is correlated with explanatory variables $\mathbf{X}_i$.

One drawback of this model is that one needs to estimate the thresholds and coefficients of the explanatory variables for each class. While the usual estimation method is the Expectation-Maximization algorithm, it may be computationally expensive if the number of explanatory variables is large.

3.6.2 Heckman and Singer's Interpretation

If one is willing to assume that the unobserved heterogeneity term ν is independent of other explanatory variables, we may greatly reduce the computational complexity. This is because the only heterogeneity source then would be the thresholds for each individual i in that

$$\mu_{j,i} = \mu_j + \nu_i,$$

where ν_i is a random variable with a probability density function $g(\cdot)$ and independent of other explanatory variables.

Incorporate this setting into our standard ordered probit model, the conditional probability of category j for individual i becomes

$$\mathbb{P}(Y_i = j \mid \mathbf{X}_i, \nu_i) = \Phi(\mu_{j+1} + \nu_i - \mathbf{X}_i'\boldsymbol{\beta} \mid \mathbf{X}_i) - \Phi(\mu_j + \nu_i - \mathbf{X}_i'\boldsymbol{\beta} \mid \mathbf{X}_i)$$

so that the marginal probability then is

$$\mathbb{P}(Y_i = j \mid \mathbf{X}_i) = \int \Big[\Phi(\mu_{j+1} + \nu_i - \mathbf{X}_i'\boldsymbol{\beta} \mid \mathbf{X}_i) - \Phi(\mu_j + \nu_i - \mathbf{X}_i'\boldsymbol{\beta} \mid \mathbf{X}_i)\Big] g(\nu_i)\, \mathrm{d}\nu_i.$$

In general, the closed-form of such probability is difficult to get. Heckman and Singer (1984) advocate to use a discrete distribution to approximate the true underlying heterogeneity distribution. The procedure is as follow. Let Q be the (unknown) number of support points of this discrete distribution, and let ν_q with π_q, $q = 1, \dots, Q$, be the associated location scalars and probabilities. For an ordered probit model, the associated probability of category j then is

$$\mathbb{P}(Y_i = j \mid \mathbf{X}_i) = \sum_{q=1}^{Q} \pi_c \cdot \left[\Phi(\mu_{j+1} + \nu_q - \mathbf{X}_i^{'}\boldsymbol{\beta} \mid \mathbf{X}_i) - \Phi(\mu_j + \nu_q - \mathbf{X}_i^{'}\boldsymbol{\beta} \mid \mathbf{X}_i)\right]$$

and, hence, the log-likelihood function can be written as

$$\mathcal{L}\left(\boldsymbol{\beta}, \{\nu_q, \pi_q\}_{q=1}^{Q}, \{\mu_j\}_{j=1}^{J}\right) = \sum_{n=1}^{N} \ln\left(\sum_{q=1}^{Q} \pi_q \cdot \left[\Phi(\mu_{j_i+1,q} - \mathbf{X}_n^{'}\boldsymbol{\beta} \mid \mathbf{X}_i) - \Phi(\mu_{j_i,q} - \mathbf{X}_n^{'}\boldsymbol{\beta} \mid \mathbf{X}_i)\right]\right),$$

where j_i is the response category of respondent i, and $\mu_{j_i,q} = \mu_{j_i} + \nu_q$. The estimation procedure is then to maximize the likelihood function with respect to $\boldsymbol{\beta}$ and thresholds $\mu_{j_i,q}$ as well as the heterogeneity parameters ν_q and their corresponding probabilities π_q. It is convenient to assume the probabilities having multinomial logit form,

$$\pi_q = \frac{\exp(\tilde{\pi}_q)}{\sum_{q=1}^{Q} \exp(\tilde{\pi}_q)},$$

as in this way one does not need to perform the constrained optimization.

There is no firm law of pinning down the number Q. In practice, we begin with $Q = 2$ and keep adding new support points until there is no gain in the likelihood function value. If the Q is known for some reason, the model reduces to the standard latent class model with independent assumption. Thus one may view the latent class model as a discrete approximation to the continuous distribution. This is the Heckman and Singer's interpretation.

Heckman and Singer (1984) have proven that such estimator is consistent, but its asymptotic behaviour is unknown. Gaure et al. (2007) provide Monte Carlo evidence indicating the parameter estimates obtained by this approach are consistent and approximately normally distributed and, hence, can be used for standard inference purposes.

We manually write the likelihood function code in C++ and wrap it into **R** using **Rcpp** package.

3.7 Semi-nonparametric Extended Ordered Probit (SNEOP)

Stewart (2004, 2005) proposes an estimator using the "semi-nonparametric" series estimators of an unknown density, proposed by Gallant and Nychka (1987), which approximates the density using a Hermite form. The approximation can be written as the product of a squared polynomial and a normal distribution density, yielding a polynomial expansion with Gaussian leading term. In this manner, one accounts for the individual heterogeneity in the sense that the distribution of errors is no longer restricted to be standard normal one. To ensure that the density approximation is valid, it is specified as

$$f_K(\varepsilon) = \frac{1}{\theta}\left(\sum_{k=0}^{K} \gamma_k \varepsilon^k\right)^2 \phi(\varepsilon) \quad \text{with} \quad \theta = \int_{-\infty}^{\infty}\left(\sum_{k=0}^{K} \gamma_k \varepsilon^k\right)^2 \phi(\varepsilon)\,\mathrm{d}\varepsilon.$$

This general density specification is invariant to multiplication of the vector $\boldsymbol{\gamma} = (\gamma_0, \ldots, \gamma_K)'$ by a scalar, and a normalization is required, with $\gamma_0 = 1$ being a convenient option. Consequently, the cumulative distribution function of interest then is

$$F_K(u) = \frac{\int_{-\infty}^{u} \left(\sum_{k=0}^{K} \gamma_k \varepsilon^k\right)^2 \phi(\varepsilon)\,\mathrm{d}\varepsilon}{\int_{-\infty}^{\infty} \left(\sum_{k=0}^{K} \gamma_k \varepsilon^k\right)^2 \phi(\varepsilon)\,\mathrm{d}\varepsilon}. \tag{3.4}$$

In this manner, we define a family of "semi-nonparametric" (SNP) distributions for increasing values of K.

The series provides a valid approximation as K increases for a wide range of densities satisfying certain smoothness and tail regularity conditions (see Gallant and Nychka, 1987). Other than particularly oscillatory density functions, any form of skewness, kurtosis, etc. is permitted. Under those and other mild regularity conditions, as K increases with the sample size, the model parameters can be consistently estimated by maximizing the pseudo-likelihood function (3.1) with F given by the F_K in (3.4). To assure semi-parametric identification, a location normalization is achieved by setting the first threshold to its ordered probit estimate.

Interestingly, Stewart (2004) argues that the model reduces to the ordered probit model for $K = 0, 1, 2$ so that the model with $K = 3$, therefore, is the first model in the series generalizing the ordered probit model. The inference is conducted conditional on K, where the final value of K is chosen by tests between them.

The model is estimated using the `sneop` command in **STATA** in conjunction with the `stata` function from the **Rstata** library of **R**.

3.8 Technical econometric issues and limitations

All the econometric tools we have mentioned are imperfect. The weakness of one is the strengths of another. For example, the simple OLS heavily relies on the assumption of cardinality, which is not welcomed universally. Ordered probit reduces this assumption to ordinality, but suffers of computational issues due to its non-linear likelihood function. In particular, optimization routines may fail because of the complex shape of likelihood function (could be multimodal or have kinks). In fact, in our study, when we try to include country/region fixed effect to the ordered probit model, the function `polr` from package **MASS** fails to deliver the results.

The POLS is an attractive alternative. Yet, like OLS and ordered probit, it lacks the ability to include heterogeneity, which may be a concern as individual heterogeneity could play a crucial role. The latent class model is designed to handle the heterogeneity issue, but it requires to pick an arbitrary number of classes before everything. The conventional number is $C = 2$, but there is no reason for it except its convenience. In addition, latent class model is highly nonlinear, making numerical optimization difficult.

The Heckman and Singer's interpretation aims to tackle the issue of artificial number of classes. By expanding the mass points (classes) gradually until no gain of likelihood value is obtained, one may have confidence that the current number of classes fits the data well.

However, the estimator's asymptotic behaviour is not clear in theory, although there is some Monte Carlo evidence that suggest that the estimators are approximately normal distributed. In addition, there is no solid criteria about the definition of "no gain in the value of likelihood function".

The semi-nonparametric extended ordered probit (SNEOP) is particularly attractive as it uses Hermite polynomials to approximate the true data generation process. The estimators obtained from this method are consistent and one does not need to worry about the heterogeneity issue. This is the main advantage of the SNEOP method, but, at the same time, it is also his weakness, as one can not study the sources of heterogeneity. In addition, due to its non-parametric nature, it is relatively time consuming.

Another general issue is that the errors might be spatially correlated and should be clustered. However, as we will demonstrate later, our empirical results are in line with existing literature, therefore we may expect that these issues will not create too much harm to our conclusions.

4 Results

In the following sub-sections we discuss our main results across the different methodologies we implement. We first transform the data and present some evidence which provides support for assuming ordinality and cardinality of our SWM. Then we regress the transformed SWM on several individual specific variables to check the robustness of our baseline specification. Then we explore the magnitude of the multiplier effect and possible heterogeneity. Finally, we present a random coefficients model to inspect the degree of heterogeneity in terms of the effect of several socio-economic reference groups.

4.1 Heckman and Singer's Approach

As a starting point to explore the degree of heterogeneity in terms of thresholds, we employ the Heckman and Singer's approach described before. Estimating the model with the number of classes equal to $Q = 1$ and $Q = 2$ and comparing the corresponding likelihood function values we conclude that $Q = 1$ cannot be rejected, the log likelihood value for one class is -8037 and is -8036.99 for two classes. It implies that there is no need to consider heterogeneity in individual thresholds and one may restrict attention to the ordered probit model. On the other hand, it supports our next step of mapping the verbal response scale of happiness into a numerical one. In particular, the fact that thresholds are homogeneous means that there exists a unique numerical scale conformable with our data.

4.2 Continuum Approach and the Reference Distribution Method

Given that the underlying latent variable thresholds appear to be homogeneous, we employ the continuum approach in conjunction with the reference distribution method. In particular, we first use an external dataset of the 8th round of the European Social Survey (ESS) conducted in 2016 for 18 European countries. In this way, we estimate shape parameters of a beta distribution on the interval $[0, 10]$ using pooled data from all the eighteen countries.

Next, for each wave and each country separately we use the reference distribution method to assign numerical values for every verbal response. For instance, Figure B.1 and Figure B.2 demonstrate how we obtain those values in the case of the 4th wave in Denmark and Portugal, respectively. More generally, Figure 4.1 shows values assigned across countries and across waves. Note that, while Heckman and Singer's approach allowed us to use a single class, with the aim of improving model accuracy we do not use the same mapping of verbal scale into a numerical one across countries and waves.

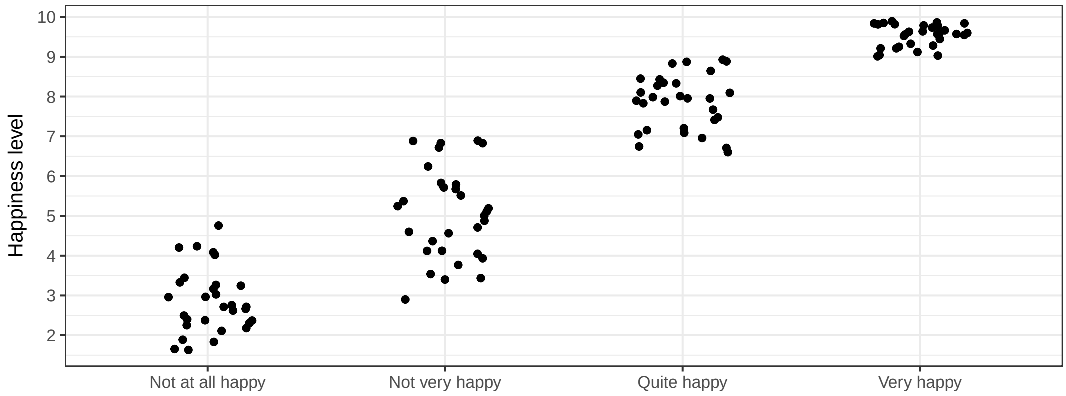

Figure 4.1: Numerical values assigned to happiness levels across countries.

4.3 Individual level models

The following results are the product of the estimation of models with individual data using the third wave (1999–2001) of the EVS survey. As we mentioned before, the decision to include only one wave is due to limitation on the variable availability. In particular, a continuous measure of income, which allows to build inequality measures at different levels of aggregation is only available in the 1999–2001 and 2008–2010 wave. On the other hand, socio-economic status of the respondents is reported for waves 1981–1984, 1990–1993 and 1999–2001. Unfortunately, we cannot include a measure of self assessed health for this wave.

Table 1 presents the results obtained using OLS, Ordered Probit and POLS. We include the OLS results not only for its simplicity, but also because the transformation of SWB measures described in the previous section provides an strong case to assume cardinality. Nevertheless, we do not observe large deviations on the quantitative and qualitative results of the OLS model with respect to Ordered Probit and POLS. Robustness across methodological approaches, which draw on different assumptions about ordinality and cardinality is a well known result by now (Ferrer-i Carbonell and Frijters, 2004).

In addition, notice that although it would be desirable, the Ordered Probit model does not include country fixed effects. This is entirely due to computational problems while optimizing the likelihood function, which has been noted to be a problem by Van Praag and Ferrer-i Carbonell (2004). We address this limitation by estimation the POLS, which can be readily estimated with fixed effects. It is also important to notice that several parameters changes their significance as we introduce fixed effects by country, thus its importance should not be underestimated.

Table 1: Individual level estimation results

	OLS	Ordered Probit	POLS
`Constant`	2.47*** (0.04)	—	0.65*** (0.05)
`age`	-0.03*** (0.00)	-0.04*** (0.00)	-0.03*** (0.00)
`age2`	0.02*** (0.00)	0.04*** (0.00)	0.03*** (0.00)
`sex`	0.03*** (0.01)	0.04*** (0.01)	0.03*** (0.01)
`educ`	0.00*** (0.00)	0.00 (0.00)	0.01*** (0.00)
`married`	0.26*** (0.01)	0.33*** (0.02)	0.31*** (0.01)
`unemp`	-0.24*** (0.02)	-0.36*** (0.03)	-0.28*** (0.02)
`selfemp`	-0.03 (0.02)	-0.09*** (0.03)	-0.04 (0.02)
`retired`	-0.03** (0.02)	-0.07** (0.03)	-0.03 (0.02)
`income`	0.20*** (0.02)	0.81*** (0.02)	0.24*** (0.02)
`income2`	-2.73*** (0.28)	-10.86*** (0.39)	-3.10*** (0.34)
`threshold 1`	—	-1.99*** (0.06)	—
`threshold 2`	—	-0.86*** (0.02)	—
`threshold 3`	—	0.89*** (0.02)	—
Country FE	Yes	No	Yes

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

Results in Table 1 resemble most the the previous results found by the literature on the individual determinants on happiness. First, using OLS results for the estimation, observe that being unemployed lowers subjective well being by 0.24 points in a $[0, 10]$ scale (remember we have transformed data into that scale). This estimation is somewhat lower than previously found clark1994unhappiness, helliwell2003s, but confirms the sign of the effect. Result of self employment are not significant once we include fixed effects which may be reflecting the heterogeneity of the quality of the self-employed jobs across countries. Slightly surprising is the result of retirement on SWB. Although the effect is not significant under POLS, OLS provides evidence of a negative effect on happiness, which contradicts some of the previous results (Tella et al., 2003).

The effect of age is standard, confirming the U-shape relationship between happiness and age (Blanchflower and Oswald, 2004). The effect of individual income also is the expected: we observe a positive relation between income and SWB, which is decreasing in the level of income (Graham and Pettinato, 2004; **?**). Being married shows a positive effects on happiness, while education has a very small influence.

Lastly, Table A3 and Table A5 show the results from estimating the SNEOP model. In particular, the first table contains all the generalizations of the ordered probit model up to order $K = 7$, and each time we failed to accept the hypothesis that there is no improvement upon the $K - 1$ order. In fact, one should continue with $K = 8$ until the hypothesis is accepted. Those results among with the central moments of the estimated errors distribution are provided in the second table.

4.4 Aggregate level models

Table 2 expands our set of covariates and includes, apart from the individual explanatory variables , aggregated ones, such as the unemployment rate, inequality (measured by the Gini coefficient) or relative income at different levels (region (R), country (C) and bin (B), which refers to reference group in your own country) and the per-capita GDP of the previous year (as Tella et al. (2003) suggest in order to avoid simultaneity). Table 2 shows the estimation for the new variables, the full specification is found in Table A4

For the unemployment rates, the relation of the country level is positive (higher unemployment, higher SWB) while the reltaion with socio-economic group unemployment rate is negative. On the other hand, regional unemployment does not seem to have a significant effect. First of all we need to be careful about the interpretation of these estimates as the variables unemployment varies between (0,1). Then, from SNEOP we can see that in general individuals are affected negatively by increments in the unemployment rates of their closer socio-economic group, but this effects are partial out by the positive relation between national unemployment rate and SWB.

Furthermore, the relation of relative income, at different level of aggregation, is not significant in almost any case, but in the SNEOP regression. Although this was unexpected, it could be due to the large number of different reference groups and measures we have included. On the other hand, the relation of SWB with inequality is negative among regional and country levels of aggregation. Nevertheless it has a weak and positive relation with the socio-economic reference group. This relations are in line with Ferrer-i Carbonell and Ramos (2014) and the references there in, that suggests that on average people dislike inequality.

Finally, as Tella et al. (2003) find, GDP perc-capita and individual happiness is positive have a positive relation (at least in the short-run, which is the case of our sample).

From the previous discussion we can observe that although that the effects of employments status has very different effects depending on the level of aggregation we consider. While its seems to affect negatively to are consider our peers, once this effect is canceled out individuals values the new opportunities generated by larger unemployment.

We also follow Clark et al. (2010) strategy and look for the existence of different effects of regional and country level unemployment rates upon employed and unemployed individuals. That is we aim to investigate the difference between coefficients of two intersection variables: one's own employed status with aggregated unemployement rates and one's own unemployed status with aggregated unemployment rates. Table 3 presents the results, the full results can be found in A6.

If we consider the interaction between these aggregate unemployment rates with the occupations status (a way to deal with possible heterogeneous effects) we find that employed individuals increase their SWB as the unemployment rates of the country increases, while

Table 2: Estimation of SWB using individual and aggregate level data

	OLS	POLS	SNEOP
`unemp`	-0.20*** (0.03)	-0.22*** (0.03)	-0.26*** (0.05)
`unempR`	-0.09 (0.22)	-0.10 (0.24)	-0.07 (0.24)
`unempC`	2.00*** (0.42)	2.03*** (0.45)	1.54*** (0.44)
`unempB`	-0.76*** (0.16)	-0.90*** (0.17)	-1.15*** (0.27)
`relincR`	-0.01 (0.04)	-0.04 (0.04)	-0.11 (0.08)
`relincC`	0.01 (0.04)	0.04 (0.04)	0.24*** (0.07)
`relincB`	-0.05* (0.03)	-0.05* (0.03)	0.01 (0.05)
`GiniR`	-0.52* (0.29)	-0.52* (0.31)	0.92*** (0.34)
`GiniC`	-1.13*** (0.29)	-1.68*** (0.31)	-2.89*** (0.65)
`GiniB`	0.31 (0.25)	0.50* (0.27)	0.88*** (0.32)
`GDPpc`	0.02*** (0.00)	0.02*** (0.00)	0.05*** (0.01)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

Table 3: Estimation on SWB including interactions between unemployment rates and employment status

	OLS	POLS
`unempR:emp`	-0.06 (0.24)	-0.06 (0.26)
`unempC:emp`	2.02*** (0.43)	2.06*** (0.46)
`unemp:unempR`	-0.14 (0.58)	-0.22 (0.63)
`unemp:unempC`	1.48 (1.22)	1.24 (1.31)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

the direct effect of regional unemployment rate is homogeneous across both populations, and this results are robust across both methodologies.

4.4.1 Multipliers Computation

The essential of this project is to find out to which degree the average impact of unemployment on well-being is higher than merely the contribution of those who are unemployed themselves, thus a good measure would be the ratio of these two effects. For example in table 2, the multiplier (absolute value) of country level unemployment rate and the individual unemployment is around 10 for OLS model.

Glaeser et al. (2003) propose, the “social” multiplier could be defined as the ratio between the effect of individual and the aggregated ones. The practical procedure is first run OLS just with individual covariates, find the predicted values of happiness. Then calculated group's aggregated happiness level as dependent variable and run the second OLS on the predicted values. The multiplier is defined as the ration between aggregated effect and individual effects. Using this method, we define the group aggregate happiness as the average of country's happiness level and obtain the multiplier (absoulute value) is around 2.

4.5 Random Parameters Model

Finally, we focus on the effects of the unemployment rate of different socio-economic group (classes) on individual SWB. In contrast to the previous model, we not only include the unemployment rate from our own reference group, but, inspired by Van Praag (2011), we suggest that it is not true that an individual looks only at his main reference group (which we consider it is their own socio-economic group), instead they care about all socio-economics groups but weighted differently by each individual. Then, to identify the individual effect of each group on individual SWB we run a random parameters model.

We consider 4 class groups: (i) upper-middle class (labeled as Upper), (ii) non-manual workers (labeled as Middle), (iii) Manual workers-skilled, semi-skilled; and (iv) Manual workers-unskilled, unemployed. On the one hand, we observe that the effect of the unemployment rate of the lower-working class affects individual SWB negatively and quite homogeneously among individuals (observe in Table 4 we do not reject that the standard deviation of the lower classes is equal to 0, both for skill and unskilled workers). Table 4 shows only the the coefficients that were randomized, to see the full specification check the appendix.

Table 4)

Table 4

	Random parameters model
`mean.unempUpper`	4.68*** (1.12)
`mean.unempMiddle`	4.78*** (1.01)
`mean.unempMsk`	-2.49*** (0.70)
`mean.unempMunsk`	-0.10 (0.19)
`sd.unempUpper`	10.93*** (0.68)
`sd.unempMiddle`	0.18 (3.46)
`sd.unempMsk`	0.22 (2.37)
`sd.unempMunsk`	0.07 (0.48)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

On the other hand, there is a high degree of heterogeneity in the effects of the unemployment rate of the upper-working class. In fact, Table 4 shows that we strongly reject that the standard deviation of the coefficient associated with the unemployment rate of the upper class is equal to 0. It can be seen from Figure 4.2 that while a large group of people is more happy from a higher unemployment rate, a group of people suffer negative effects from it. Finally the effect of the unemployment rate of the middle class is positive and homogeneous, which is unexpected, but it could point the low degree of awareness that the middle class has of themselves as a group.

We consider these results very illustrative. On the other hand, unemployment of the

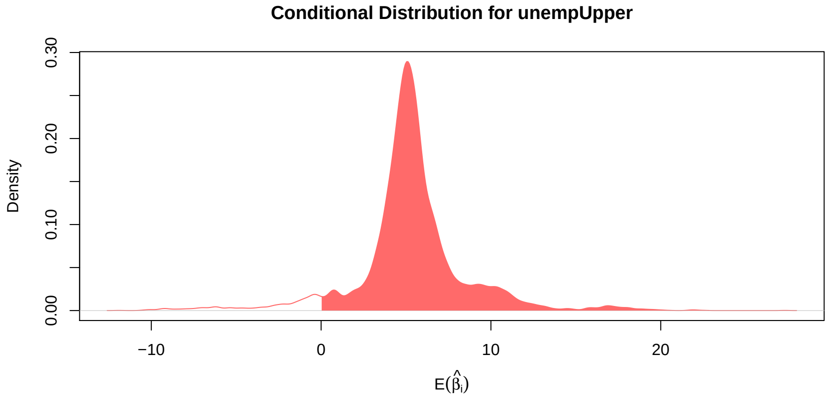

Figure 4.2: Distribution of the Partial Effect of Unemployment rate of the Upper working class

working class seems to affect equally individuals of all classes. Both the self-awareness of the working class as a unified group and the empathy they produce in other sectors of the society could be behind this result. On the other hand, the unemployment rate of the upper class shows a high degree of heterogeneity: while an increase on the unemployment rate of this group has a positive effect on some individuals, it is negative for other. Unfortunately, we cannot associate exactly who individuals belong to each area of the distribution, it is believed that individuals for whose the impact is negative belongs to the same socio-economic class, that is richer ones.

This shows that egalitarians views of a large part of the society collide with the negative perceptions about labor market risk that individuals of the upper class could have derived from a higher unemployment rate across individuals of their same group.

4.6 Discussion

4.6.1 Causality

One of the most important in economics is the ability to find a causal relationship. In our case, we should be interesting on finding happiness as a function of exogenous variables. In this sense, should we interpret our results as causal effects? Unfortunately, the answer is negative. Our results just reflects partial correlations between the dependent and explanatory variables.

But why cannot we interpret these partial correlations as causal effects? One of the main issues is simultaneity (or reverse causality). Our regression equation includes as explanatory variables individual income and aggregate income. So, if interpret the coefficients as a causal relationship, we could conclude that higher income level causes higher happiness levels. However, one could find that people that are happier are, as consequence of this, more productive which implies higher income (at individual and aggregate level). Hence, since we do not have at hand external information (an instrumental variable that controls for changes income that are uncorrelated directly with happiness), it is impossible to identify the estimated parameters as causal effects.

Other reason is the unobserved individual heterogeneity. Ferrer-i Carbonell and Frijters

(2004) argue that the practical effects of ordinal or cardinal measures of happiness on the results of happiness determinants is unimportant. What really matters is the time-invariant unobserved components. For example, They show that the positive influence of income on happiness measures is reduced by about two thirds when one control for these fixed-effects unobserved heterogeneity.

How to find a causal relationship? In the absence of suitable instrumental variables for endogenous explanatory variables, we cannot aim for identification of causal relation of income and other variables that implies a decision process (for example, marriage). Another possibility is to use simultaneous equations and imposes some identification restrictions (usually exclusion restrictions), which poses the attention on how meaningful are such restrictions. Tella et al. (2003) proposed just to include truly exogenous explanatory variables in our regression model (such as, age, gender) or lagged levels (when aggregate data is included). However, according to this approach, we cannot estimate the effect of income or unemployment on happiness.

Nonetheless, even though we have a structural model or instrumental variable, using cross-section information it is just not possible to deal with individual unobserved heterogeneity. The way we can control for this issue is to use longitudinal information (panel data base). Unfortunately, we do not have this information available. One further alternative would have been to construct a pseudo-panel. However,

Therefore, given these limitations we have choose to be cautious about the causal interpretations in our work. We have chosen to focus our work on the high degree of heterogeneity that exist in the relationship between employment and happiness.

4.7 Policy Implications

As one can observe form the different models, the negative influence of being unemployed on individual SWB is robust. Then, as Clark and Oswald (1994) analyzed, government should take into consideration, when labor policies are thought, the effects on individual SWB. Here, we provide further evidence of how much policy makers should care about unemployment. From the previous evidence and our results, starts to be clear that individual unemployment not only affect that person, but also impact on several peers who care about the general situations of their environment. In particular, policy-maker should be aware that effects differnt between different groups, and consider them individually while designing policy. For instance, it is not cear how looking for a more flexible labor market (in the sense, that employers could fire workers freely or at a low cost) could benefit workers in terms of their SWB.

Besides, from the fact the unemployment rate of unskilled workers impacts negatively in everybody, and given that unskilled work is very procyclical (see Mukoyama and Şahin (2006)), economic policy should be oriented to attenuate their vulnerability, through, for saying, training programs. This is particular important at current time, where many young people in some developed and developing countries are unemployed and are low-skilled.

4.8 Extensions and further research.

(a) **Alternatives with our data**. In this paper we use as dependent variable the overall measure of happiness. However, as Van Praag and Ferrer-i Carbonell (2004) (chapter 4) suggest: individual overall life satisfaction is a multidimensional result. That is, depends on different domain satisfaction, such as: job satisfaction, health satisfaction, financial situation satisfaction, and others. Then, the effect of any explanatory variable (in our case, unemployment) on overall SWB can be seen as a composition of the effect of such explanatory variable on the different domain satisfaction.

Thus, a direct extension of our work is using the different domain satisfaction questions we have in our data base and quantify the effect of unemployment on each of them. After that, we can estimate an econometric model relating the overall life satisfaction with its components. The advantage of this extension is that we can explain which dimensions of happiness are in favor of the effect on aggregate SWB, and through which dimensions the effect is attenuated.

Another extension of our work could be regarding to the computation of multipliers. Our simple definition is the comparison of the aggregated direct effect on unemployment and the individual effect. However, this simple approach is accurate on the linear case, and because of our models are highly non-linear (ordered probit or POLS), then the ratio of aggregate direct effect over individual ones does not need to be a good approximation of the multiplier effect.

What we can do? We believe that, for some non-complicated regressions, a simulation-based approach can be used. We can compute an original situation and compute the aggregate happiness level, then change the occupation status for some individual i and, using the fitted values for reduced forms, compute the new aggregate happiness level and take the difference and compare this with the difference on individual happiness individual i. The comparison of these two magnitudes could be a less inexact measure of the multiplier effect.

Finally, we are aware that the random coefficient model is not what Van Praag (2011) had in mind when he wrote his paper. Instead, he emphasizes that our reference group is probability distribution. In that sense our random coefficient model just draws on this idea, but in a future extension we would like to actually implement more closely the ideas of the cited paper.

(b) **Possible with different data.** As we mentioned before, Ferrer-i Carbonell and Frijters (2004) highlight the importance of time-invariant unobserved heterogeneity. Then, with a panel data base we can control for this unobserved heterogeneity, reducing the omitting variable biased. Additionally, a panel data information could allow us to test some hypothesis regarding the effects of aggregate variables in the long run. For example, with a sufficient large temporal dimension (more than 4 periods) "habituation" hypothesis could be tested. We should control for the lagged effects of aggregate unemployment (for instance, as Tella et al. (2003) do for GDP, it can be introduced up to 3 lags of unemployment rate). Then, the summation of the partial effects of each lag could be interpreted as the "long-run" effect of aggregate unemployment. If the "habituation" hypothesis were true, this cumulative effect should be near to zero.

(c) There are a number of alternative semiparametric and nonparametric estimator applicable in our case but not explored in this paper. Chen and Khan (2003), for instance, propose a semiparametric estimators for the heteroskedastic ordered probit model. It is a two step estimator combining kernel estimation with maximizing a likelihood function. As expected, it has been shown to outperform the maximum likelihood estimators assuming homoskedastic errors. Further, Lewbel (2000) considers an ordered choice model allowing for heteroskedasticity of unknown form. The estimation procedure is noninterative and simply using ordinary least squares suffices with one complication that a continuous conditional density has to be estimated. Similarly, Bellemare et al. (2002) consider an ordered choice model based on a partially linear semiparametric ordered probit model. Estimation involves iterating back and forth between maximum likelihood estimates of two sets of parameters. See (Greene and Hensher, 2010a) for a more extensive review.

5 Conclusion

The ultimate goal of this paper was to quantify the effects of individual unemployment not only on themselves but also on the aggregate SWB (happiness). Textbook result points out that unemployment is an optimal decision that a rational agent takes given the market conditions (prices) and its preferences. This would imply that unemployment may not have impact on life perception, once we control for income and other personal characteristics. However, using a broader framework, that uses individual subjective levels of life satisfaction as a dependent variable, psychologists and economists have found that the conventional result would be wrong (see Clark and Oswald (1994), Helliwell (2003) and Eisenberg and Lazarsfeld (1938) and references therein). This research points out that being unemployed poses some psychic negative effects on individuals (for instance, the awareness that their market value depreciates when one is unemployed for a long period). Additionally, Clark et al. (2010) and other works find that there exists an effect derived from aggregate unemployment, the intuition behind this result is that individuals usually compares themselves with other people who belongs to the same reference group. In this sense, previous works have found negative effects of aggregate level of unemployment, that affects not only unemployed people, but also employed ones.

We provide further evidence to support that individual unemployment do not only affect the individual whose employment status have changed but also several groups of people, who look at their environment to assess their own levels of happiness.

Further, in line with Clark et al. (2010) work, we found that the effect of aggregate unemployment if heterogeneous on individual happiness. In fact, it is highly dependent on the reference group.

References

John Aitchison and Samuel D Silvey. The generalization of probit analysis to the case of multiple responses. *Biometrika*, 44(1/2):131–140, 1957.

Alberto Alesina, Rafael Di Tella, and Robert MacCulloch. Inequality and happiness: are europeans and americans different? *Journal of Public Economics*, 88(9-10):2009–2042, 2004.

Pernilla Andersson. Happiness and health: Well-being among the self-employed. *The Journal of Socio-Economics*, 37(1):213–236, 2008.

Michael Argyle. *The psychology of happiness*. Routledge, 2013.

Meike Bartels and Dorret I Boomsma. Born to be happy? the etiology of subjective well-being. *Behavior genetics*, 39(6):605, 2009.

Charles Bellemare, Bertrand Melenberg, and Arthur Van Soest. Semi-parametric models for satisfaction with income. *Portuguese Economic Journal*, 1(2):181–203, 2002.

David G Blanchflower and Andrew J Oswald. Well-being over time in britain and the usa. *Journal of public economics*, 88(7-8):1359–1386, 2004.

Stefan Boes and Rainer Winkelmann. Ordered response models. *Allgemeines Statistisches Archiv*, 90(1):167–181, 2006.

Axel Börsch-Supan and Hendrik Jürges. Early retirement, social security and well-being in germany. Technical report, National Bureau of Economic Research, 2006.

Songnian Chen and Shakeeb Khan. Rates of convergence for estimating regression coefficients in heteroskedastic discrete response models. *Journal of Econometrics*, 117(2):245–278, 2003.

Andrew Clark, Andreas Knabe, and Steffen Rätzel. Boon or bane? others' unemployment, well-being and job insecurity. *Labour Economics*, 17(1):52–61, 2010.

Andrew E Clark and Andrew J Oswald. Unhappiness and unemployment. *The Economic Journal*, 104(424):648–659, 1994.

Andrew E Clark and Claudia Senik. Who compares to whom? the anatomy of income comparisons in europe. *The Economic Journal*, 120(544):573–594, 2010.

Andrew E Clark, Paul Frijters, and Michael A Shields. Relative income, happiness, and utility: An explanation for the easterlin paradox and other puzzles. *Journal of Economic literature*, 46(1):95–144, 2008.

Tineke de Jonge, Ruut Veenhoven, and Lidia Arends. Homogenizing responses to different survey questions on the same topic: Proposal of a scale homogenization method using a reference distribution. *Social Indicators Research*, 117(1):275–300, 2014.

Tineke DeJonge, Wim Kalmijn, Ruut Veenhoven, and Lidia Arends. Stability of boundaries between response options of response scales: does âĂŸvery happyâĂŹremain equally happy over the years? *Social Indicators Research*, 123(1):241–266, 2015.

Rafael Di Tella and Robert MacCulloch. Gross national happiness as an answer to the easterlin paradox? *Journal of Development Economics*, 86(1):22–42, 2008.

Rafael Di Tella, Robert J MacCulloch, and Andrew J Oswald. Preferences over inflation and unemployment: Evidence from surveys of happiness. *American economic review*, 91(1): 335–341, 2001.

Rafael Di Tella, John Haisken-De New, and Robert MacCulloch. Happiness adaptation to income and to status in an individual panel. *Journal of Economic Behavior & Organization*, 76(3):834–852, 2010.

Ed Diener, Eunkook M Suh, Richard E Lucas, and Heidi L Smith. Subjective well-being: Three decades of progress. *Psychological bulletin*, 125(2):276, 1999.

Richard A Easterlin. Does economic growth improve the human lot? some empirical evidence. In *Nations and households in economic growth*, pages 89–125. Elsevier, 1974.

Richard A Easterlin. Life cycle happiness and its sources: Intersections of psychology, economics, and demography. *Journal of Economic Psychology*, 27(4):463–482, 2006.

Francis Ysidro Edgeworth. The hedonical calculus. *Mind*, 4(15):394–408, 1879.

Philip Eisenberg and Paul F Lazarsfeld. The psychological effects of unemployment. *Psychological bulletin*, 35(6):358, 1938.

Paul Ekman, Richard J Davidson, and Wallace V Friesen. The duchenne smile: Emotional expression and brain physiology: Ii. *Journal of personality and social psychology*, 58(2): 342, 1990.

Ada Ferrer-i Carbonell and Paul Frijters. How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, 114(497):641–659, 2004.

Ada Ferrer-i Carbonell and Xavier Ramos. Inequality and happiness. *Journal of Economic Surveys*, 28(5):1016–1027, 2014.

Paul Frijters and Tony Beatton. The mystery of the u-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization*, 82(2-3):525–542, 2012.

A Ronald Gallant and Douglas W Nychka. Semi-nonparametric maximum likelihood estimation. *Econometrica: Journal of the Econometric Society*, pages 363–390, 1987.

Simen Gaure, Knut Røed, and Tao Zhang. Time and causality: A monte carlo assessment of the timing-of-events approach. *Journal of Econometrics*, 141(2):1159–1195, 2007.

Ingo Geishecker. Simultaneity bias in the analysis of perceived job insecurity and subjective well-being. *Economics Letters*, 116(3):319–321, 2012.

Edward L Glaeser, Bruce I Sacerdote, and Jose A Scheinkman. The social multiplier. *Journal of the European Economic Association*, 1(2-3):345–353, 2003.

Carol L Graham and Stefano Pettinato. *Happiness and hardship: Opportunity and insecurity in new market economies*. Brookings Institution Press, 2004.

William H Greene and David A Hensher. *Modeling ordered choices: A primer*. Cambridge University Press, 2010a.

William H Greene and David A Hensher. Ordered choices and heterogeneity in attribute processing. *Journal of Transport Economics and Policy (JTEP)*, 44(3):331–364, 2010b.

Bruce Headey and Alexander James Wearing. *Understanding happiness: A theory of subjective well-being*. Longman Cheshire, 1992.

James Heckman and Burton Singer. A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society*, pages 271–320, 1984.

John F Helliwell. How's life? combining individual and national variables to explain subjective well-being. *Economic modelling*, 20(2):331–360, 2003.

John R Hicks and Roy GD Allen. A reconsideration of the theory of value. part i. *Economica*, 1(1):52–76, 1934.

Clark L Hull. The conversion of test scores into series which shall have any assigned mean and degree of dispersion. *Journal of Applied Psychology*, 6(4):298–300, 1922.

Joseph V Ierza. Ordinal probit: a generalization. *Communications in Statistics-Theory and Methods*, 14(1):1–11, 1985.

Wim Kalmijn. *Quantification of Happiness Inequality*. PhD thesis, E, December 2010.

WM Kalmijn, LR Arends, and Ruut Veenhoven. Happiness scale interval study. methodological considerations. *Social Indicators Research*, 102(3):497–515, 2011.

Andreas Knabe and Steffen Rätzel. Scarring or scaring? the psychological impact of past unemployment and future unemployment risk. *Economica*, 78(310):283–293, 2011.

Arthur Lewbel. Semiparametric qualitative response model estimation with unknown heteroscedasticity or instrumental variables. *Journal of Econometrics*, 97(1):145–177, 2000.

Hock-Eam Lim. The use of different happiness rating scales: Bias and comparison problem? *Social Indicators Research*, 87(2):259–267, 2008.

Simon Luechinger. Valuing air quality using the life satisfaction approach. *The Economic Journal*, 119(536):482–515, 2009.

Simon Luechinger, Stephan Meier, and Alois Stutzer. Why does unemployment hurt the employed? evidence from the life satisfaction gap between the public and the private sector. *Journal of Human Resources*, 45(4):998–1045, 2010.

Toshihiko Mukoyama and Ayşegül Şahin. Costs of business cycles for unskilled workers. *Journal of Monetary Economics*, 53(8):2179–2193, 2006.

Yew-Kwang Ng. A case for happiness, cardinalism, and interpersonal comparability. *The Economic Journal*, 107(445):1848–1858, 1997.

Milena Nikolova. Minding the happiness gap: Political institutions and perceived quality of life in transition. *European Journal of Political Economy*, 45:129–148, 2016.

Vilfredo Pareto. *Manuale di economia politica*, volume 13. Societa Editrice, 1906.

William Pavot, ED Diener, C Randall Colvin, and Ed Sandvik. Further validation of the satisfaction with life scale: Evidence for the cross-method convergence of well-being measures. *Journal of personality assessment*, 57(1):149–161, 1991.

Stephen Pudney and Michael Shields. Gender, race, pay and promotion in the british nursing profession: estimation of a generalized ordered probit model. *Journal of Applied Econometrics*, pages 367–399, 2000.

Jonathan Shedler, Martin Mayman, and Melvin Manis. The illusion of mental health. *American Psychologist*, 48(11):1117, 1993.

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

B. Stevenson and J. Wolfers. Economic growth and subjective well-being: Reassessing the easterlin paradox. *Brookings Papers on Economic Activity*, pages 1–87, 2008.

Mark B Stewart. Semi-nonparametric estimation of extended ordered probit models. *Stata Journal*, 4(1):27–39, 2004.

Mark B Stewart. A comparison of semiparametric estimators for the ordered response model. *Computational statistics & data analysis*, 49(2):555–573, 2005.

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

Bernard Van Praag. Well-being inequality and reference groups: an agenda for new research. *The Journal of Economic Inequality*, 9(1):111–127, 2011.

Bernard Van Praag and Barbara E Baarsma. Using happiness surveys to value intangibles: The case of airport noise. *The Economic Journal*, 115(500):224–246, 2005.

Bernard MS Van Praag. Ordinal and cardinal utility: an integration of the two dimensions of the welfare concept. *Journal of econometrics*, 50(1-2):69–89, 1991.

Bernard MS Van Praag and Ada Ferrer-i Carbonell. *Happiness quantified: A satisfaction calculus approach*. Oxford University Press, 2004.

Bernard MS Van Praag, Paul Frijters, and Ada Ferrer-i Carbonell. The anatomy of subjective well-being. *Journal of Economic Behavior & Organization*, 51(1):29–49, 2003.

Ruut Veenhoven. The international scale interval study: Improving the comparability of responses to survey questions about happiness. In *Quality of life and the millennium challenge*, pages 45–58. Springer, 2009.

Ruut Veenhoven. Informed pursuit of happiness: What we should know, do know and can get to know. *Journal of Happiness Studies*, 16(4):1035–1071, 2015.

Liliana Winkelmann and Rainer Winkelmann. Why are the unemployed so unhappy? evidence from panel data. *Economica*, 65(257):1–15, 1998.

Appendix

A Tables

Table A1: Summary statistics.

Individual variables							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
`age`	15.00	30.00	43.00	44.99	59.00	108.00	0.4%
`educ`	0.00	9.00	12.00	12.28	15.00	31.00	4.9%
`happyCard`	1.35	6.95	7.83	7.60	8.83	9.94	2.7%

	Possible values				NA's
`happy`	0 (2.6%)	1 (15.0%)	2 (56.8%)	3 (22.8%)	2.7%
`married`	0 (39.4%)		1 (60.0%)		0.6%
`sex`	0 (45.9%)		1 (54.1%)		0.1%

Survey variables					
	Possible values				NA's
`wave`	1 (11.7%)	2 (23.2%)	3 (24.9%)	4 (40.2%)	0.0%

	Most common values						NA's
`country`	Germany (5.4%)	Spain (4.6%)	Belgium (4.5%)	Italy (4.2%)	Czech Republic (3.5%)	France (3.2%)	0.0%

Social classes			
	Possible values		NA's
`clMiddle`	0 (25.9%)	1 (12.0%)	62.1%
`clMsk`	0 (24.5%)	1 (13.4%)	62.1%
`clMunsk`	0 (30.7%)	1 (7.3%)	62.1%
`clUpper`	0 (32.7%)	1 (5.3%)	62.1%

Unemployment variables							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
`unempB`	0.00	0.03	0.05	0.07	0.09	0.45	0.2%
`unempC`	0.00	0.04	0.06	0.07	0.09	0.35	0.2%
`unempMiddle`	0.00	0.02	0.03	0.03	0.04	0.08	61.4%
`unempMsk`	0.00	0.02	0.04	0.05	0.06	0.15	61.4%
`unempMunsk`	0.01	0.08	0.13	0.15	0.17	0.45	61.4%
`unempR`	0.00	0.04	0.09	0.07	0.10	1.00	0.0%
`unempUpper`	0.00	0.01	0.02	0.02	0.02	0.11	61.4%

	Possible values		NA's
`retired`	0 (79.0%)	1 (20.0%)	1.0%
`selfemp`	0 (93.4%)	1 (5.6%)	1.0%
`unemp`	0 (91.7%)	1 (7.3%)	1.0%

Note:

Table A2: Summary statistics.

Income variables							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
income	0.00	0.45	0.93	1.31	1.77	14.73	50.6%
relincB	0.00	0.52	0.84	1.00	1.28	22.47	50.6%
relincC	0.00	0.51	0.82	1.00	1.29	22.47	50.6%
relincR	0.00	0.41	0.76	1.00	1.31	12.78	50.6%

Inequality							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
GiniB	0.16	0.30	0.35	0.35	0.42	0.57	40.2%
GiniC	0.22	0.31	0.35	0.36	0.42	0.57	40.2%
GiniR	0.11	0.34	0.49	0.43	0.49	0.49	40.1%

Note:

Table A3: SNEOP estimation results

	$K = 3$	$K = 4$	$K = 5$	$K = 6$	$K = 7$
age2	0.03***	0.04***	0.05***	0.04***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
age	-0.03***	-0.05***	-0.06***	-0.04***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sex	0.04***	0.05**	0.05**	0.05**	0.05**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
educ	0.01***	0.01***	0.01***	0.01***	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
married	0.32***	0.42***	0.45***	0.39***	0.42***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
unemp	-0.36***	-0.48***	-0.51***	-0.45***	-0.48***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
selfemp	-0.10***	-0.12**	-0.11*	-0.10*	-0.09
	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
retired	-0.06**	-0.07*	-0.08**	-0.06*	-0.09**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
income	0.81***	1.16***	1.22***	1.13***	1.25***
	(0.02)	(0.10)	(0.06)	(0.08)	(0.08)
income2	-11.04***	-15.62***	-16.41***	-15.16***	-16.53***
	(0.46)	(1.48)	(0.95)	(1.16)	(1.22)
1|2	-1.99	-1.99	-1.99	-1.99	-1.99
	(5.00)	(5.00)	(5.00)	(5.00)	(5.00)
2|3	-0.95***	-0.51***	-0.41***	-0.56***	-0.30**
	(0.02)	(0.10)	(0.05)	(0.08)	(0.14)
3|4	0.80***	1.85***	2.09***	1.70***	2.18***
	(0.03)	(0.26)	(0.13)	(0.20)	(0.23)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

B Figures

Table A4: Estimation of SWB using individual and aggregate level data

	OLS	POLS	SNEOP
Constant	2.32*** (0.10)	1.74*** (0.11)	—
age	-0.03*** (0.00)	-0.03*** (0.00)	-0.04*** (0.01)
sex	0.07*** (0.01)	0.08*** (0.02)	0.05*** (0.02)
educ	-0.00 (0.00)	0.00 (0.00)	0.01*** (0.00)
married	0.21*** (0.02)	0.21*** (0.02)	0.34*** (0.04)
unemp	-0.20*** (0.03)	-0.22*** (0.03)	-0.26*** (0.05)
selfemp	-0.08** (0.03)	-0.10*** (0.03)	-0.05 (0.03)
retired	-0.01 (0.03)	-0.02 (0.03)	-0.04 (0.03)
unempR	-0.09 (0.22)	-0.10 (0.24)	-0.07 (0.24)
unempC	2.00*** (0.42)	2.03*** (0.45)	1.54*** (0.44)
unempB	-0.76*** (0.16)	-0.90*** (0.17)	-1.15*** (0.27)
income	0.25*** (0.04)	0.28*** (0.04)	0.14*** (0.05)
relincR	-0.01 (0.04)	-0.04 (0.04)	-0.11 (0.08)
relincC	0.01 (0.04)	-0.04 (0.04)	0.24*** (0.07)
relincB	-0.05* (0.03)	-0.05* (0.03)	0.01 (0.05)
GiniR	-0.52* (0.29)	-0.52* (0.31)	0.92*** (0.34)
GiniC	-1.13*** (0.29)	-1.68*** (0.31)	-2.89*** (0.65)
GiniB	0.31 (0.25)	0.50* (0.27)	0.88*** (0.32)
GDPpc	0.02*** (0.00)	0.02*** (0.00)	0.05*** (0.01)
age2	0.02*** (0.00)	0.02*** (0.00)	0.03*** (0.01)
income2	-3.09*** (0.53)	-3.74*** (0.57)	-2.24*** (0.67)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

Figure B.1: A graphical visualization of the application of the continuum approach and the reference distribution method in the case of Denmark.

Table A5: SNEOP order selection results

	$K=3$	$K=4$	$K=5$	$K=6$	$K=7$
$\hat{\gamma}_1$	-0.21*** (0.06)	0.01 (0.03)	0.20*** (0.04)	-0.10*** (0.03)	0.52*** (0.13)
$\hat{\gamma}_2$	0.03* (0.01)	-0.03** (0.01)	-0.05*** (0.01)	-0.19*** (0.03)	-0.18*** (0.05)
$\hat{\gamma}_3$	0.02*** (0.01)	0.03*** (0.01)	-0.03* (0.01)	0.10*** (0.02)	-0.35*** (0.11)
$\hat{\gamma}_4$	—	0.03*** (0.01)	0.04*** (0.00)	0.10*** (0.01)	0.10*** (0.02)
$\hat{\gamma}_5$	—	—	0.01*** (0.00)	-0.01*** (0.00)	0.08*** (0.02)
$\hat{\gamma}_6$	—	—	—	-0.01*** (0.00)	-0.01*** (0.00)
$\hat{\gamma}_7$	—	—	—	—	-0.00*** (0.00)
Log likelihood	-23963	-23901	-23892	-23886	-23874
Test against OP	32.80*** (0.00)	157.21*** (0.00)	175.28*** (0.00)	186.78*** (0.00)	211.94*** (0.00)
Test against $K-1$	32.80*** (0.00)	62.20*** (0.00)	9.03*** (0.00)	5.75*** (0.02)	12.58*** (0.00)
Variance	1.05	1.91	2.09	2.01	2.38
Skewness	0.32	0.12	0.12	0.38	0.32
Kurtosis	3.29	3.23	3.10	4.49	4.04

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

Figure B.2: A graphical visualization of the application of the continuum approach and the reference distribution method in the case of Portugal.

Table A6: Estimation on SWB including interactions between unemployment rates and employment status

	OLS	POLS
`Constant`	2.32*** (0.10)	1.74*** (0.11)
`age`	-0.03*** (0.00)	-0.03*** (0.00)
`sex`	0.07*** (0.01)	0.08*** (0.02)
`educ`	-0.00 (0.00)	-0.00 (0.00)
`married`	0.21*** (0.02)	0.21*** (0.02)
`unemp`	-0.14* (0.08)	-0.14 (0.09)
`selfemp`	-0.08*** (0.03)	-0.10*** (0.03)
`retired`	-0.01 (0.03)	-0.02 (0.03)
`unempB`	-0.77*** (0.16)	-0.92*** (0.17)
`income`	0.25*** (0.04)	-0.28*** (0.04)
`relincR`	-0.02 (0.04)	0.04 (0.04)
`relincC`	0.01 (0.04)	-0.04 (0.04)
`relincB`	-0.05* (0.03)	-0.05* (0.03)
`GiniR`	-0.51* (0.29)	-0.52* (0.31)
`GiniC`	-1.13*** (0.29)	-1.68*** (0.31)
`GiniB`	0.32 (0.25)	0.51* (0.27)
`GDPpc`	0.02*** (0.00)	0.02*** (0.00)
`age2`	0.02*** (0.00)	0.02*** (0.00)
`income2`	-3.08*** (0.54)	-3.72*** (0.57)
`unempR:emp`	-0.06 (0.24)	-0.06 (0.26)
`unempC:emp`	2.02*** (0.43)	2.06*** (0.46)
`unemp:unempR`	-0.14 (0.58)	-0.22 (0.63)
`unemp:unempC`	1.48 (1.22)	1.24 (1.31)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.

Table A7

	Random parameters model
kappa.1	1.11*** (0.03)
kappa.2	3.05*** (0.04)
constant	3.51*** (0.17)
age	-0.05*** (0.00)
sex	0.08*** (0.02)
educ	-0.01* (0.00)
married	0.40*** (0.03)
unemp	-0.37*** (0.05)
selfemp	-0.13** (0.06)
retired	0.09** (0.04)
unempB	-1.24*** (0.23)
income	0.73*** (0.05)
relincR	-0.04 (0.07)
relincC	-0.09 (0.08)
relincB	-0.18*** (0.05)
GiniR	0.86 (0.62)
GiniC	-4.84*** (0.68)
GiniB	1.30*** (0.45)
age2	0.04*** (0.00)
income2	-9.00*** (0.80)
mean.unempUpper	4.68*** (1.12)
mean.unempMiddle	4.78*** (1.01)
mean.unempMsk	-2.49*** (0.70)
mean.unempMunsk	-0.10 (0.19)
sd.unempUpper	10.93*** (0.68)
sd.unempMiddle	0.18 (3.46)
sd.unempMsk	0.22 (2.37)
sd.unempMunsk	0.07 (0.48)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively.