Case 2: About the Transmission Channels of Unemployment Rate on Individual Happiness

Team 3

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Abstract

In the present discussion we are not only interested on the effects of employment on several dimension of our SWB, but also we pretend to elucidate the mechanisms that underline this relation. 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 some degree of heterogeneity in the effect of aggregate unemployment rates, mainly depending on whether individuals themselves are employed or unemployed. We use a linear simultaneous equation model to obtain the effects of unemployment mediated by several variables: crime, trust on our peers and social interactions. We further explore if this effects can also be obtained indirectly from the mediated effect of employment on different life domains satisfaction. We obtain further evidence of how unemployment affects well-being by estimating 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 how the effects of individual unemployment on others are mediated, that is we explores the mechanisms for which individual unemployment affects others subjective well-being. 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, mainly, on the following question: (i) what are the mechanism trough which individual unemployment affects others' subjective well-being (henceforth SWB)? (ii) does unemployment affect all life domains equally? A

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

derived research question is that whether our estimates are sensitive to the definition of unemployment?

1.3 Literature Review

How is general subjective well-being (henceforth SWB) determined? Van Praag et al. (2003a) suggest that SWB is a composition of different dimensions of individual's life (something they call two-layers model). Thus, the way that one factor (say, age) affects general SWB will not be the same to the effects of such factor on the different dimensions of individual's life.

As general result, Van Praag and Ferrer-i Carbonell (2004) (chapter 3) finds that the partial effects of different individual characteristics affects in different ways or in different magnitudes to different domain satisfactions. They suggest, also, that this partial effects are heterogeneous along some dimension (workers and non-workers or regions). Cummins (1996) tries to study some attempts to group 173 different domains names derived from the literature under seven headings as used by the Comprehensive Quality of Life Scale (ComQol). He finds that 68% could be classified in this way. Besides, a hierarchy of domain satisfaction was found which was dominated by the domain of intimacy. The other ComQol domains were quite tightly clustered within a range of 1.08 standard deviations. According to him, from this analysis emerges the result that the domains of life satisfaction are not equally perceived, thus, should not be equally affected by one common factor (age, gender, etc).

In this sense, when researchers want to find out the effects of some variable (age, gender, occupational status, social capital, etc) on life satisfaction, they choose which domain to use (overall life satisfaction or an specific domain). For instance, egarding life and job-satisfaction, 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.

Respect to health satisfaction, Gordo (2006) analyzes the effects of short and long term unemployment on health satisfaction using the German Socio-Economic Panel (GSOEP) which, allows her to deal with the endogeneity problem. The three different models she estimates show that short-term unemployment has only a significant and negative effect for men, while for women, short-term unemployment does not have a significant effect on health satisfaction. On the other hand, being unemployed for a long period has a significant and negative effect for both men and women.

Other aspect of life that has an impact on overall life satisfaction is housing satisfaction, because housing is the largest consumption and investment item of their lifetime. Vera-Toscano and Ateca-Amestoy (2008) find that housing satisfaction is affected by an array of individual, housing and neighbourhood attributes and social interactions. According to them, individuals evaluate their housing situation taking into account not only whether they are owners or renters, but simultaneously assessing othersâĂŹ ownership status. In this sense, individualsâĂŹ housing satisfaction is negatively affected by the fact of being a renter surrounded by owners, while owners do not feel more satisfied with their housing if being surrounded by renters.

However, no much research has focused on quantifying the different channels through which domain satisfaction leads to a general satisfaction result. Van Praag et al. (2003a) suggest the following transmission channels:

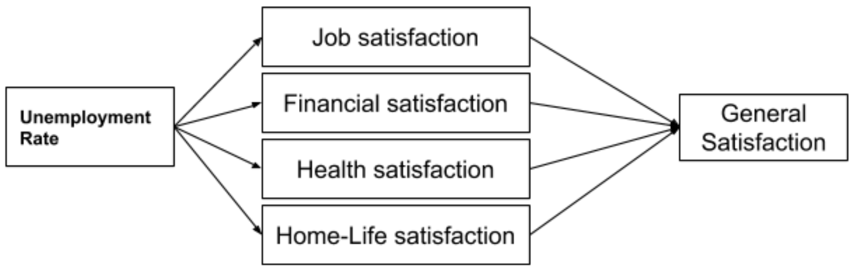

Figure 1.1: Van Praag et al. (2003a) Two-Layer Model

This model is very general, and allows to distinguish the differentiated effects of a variable of interest has on the different dimensions of individual life and, through these dimensions, quantify the overall result/effect. Inspired by this approach, we attempt the following:

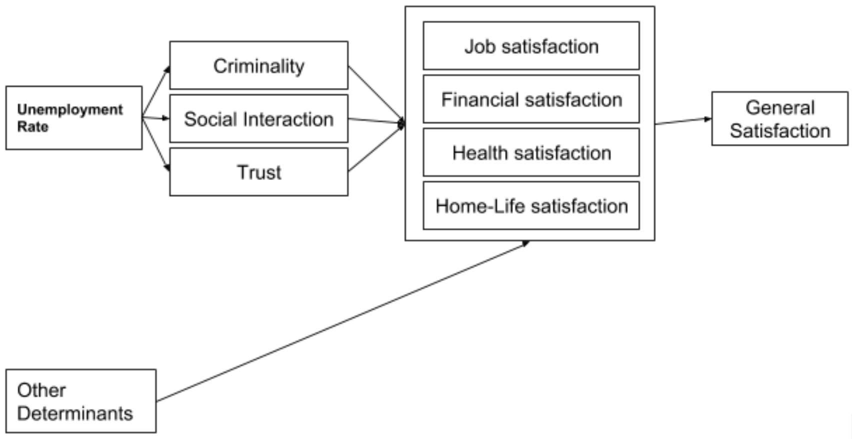

Figure 1.2: Three-Layer Model

Why do we use these 3 transmission channels only? Certainly, many factors could govern the transmission of unemployment effects to domain satisfactions. Some researchers have pointed out these three as one of the the most important ones. For instance, 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. On the other hand, crime often ranks at the top of public concern. Cohen (2008) provides new evidence on crime's effect on life satisfaction using a combination of victimization and subjective survey data. He finds heterogeneous effects of different measures of criminality. At countyâĂŘlevel, crime rates and perceived neighborhood safety have little impact on overall life satisfaction. In contrast, the effect of a home burglary on life satisfaction is quite largeâĂŤnearly as much as moving from excellent health to good health.

On the relationship between unemployment and crime, Raphael and Winter-Ebmer (2001) use U.S. state data and estimate the effect of unemployment on the rates of seven felony offenses, controlling extensively for state-level demographic and economic factors and estimate specifications that include state-specific time trends, state effects, and year effects. They find significantly positive effects of unemployment on property crime rates that are stable across model specifications, and that estimates suggest that a substantial portion of the decline in property crime rates during the 1990s is attributable to the decline in the unemployment rate. However, their evidence for violent crime is considerably weaker.

1.4 Overview of the paper and main results

Our paper can be seen as an attempt of a structural estimation of the effects of aggregate unemployment measures on individual SWB and their channels using simultaneous equation methodology. This approach has received little attention on happiness research.

Before identifying the mechanisms of the relation between unemployment and happiness we provide evidence regarding the effect of individual employment status and aggregate unemployment on SWB. We identify some degree of heterogeneity in the effect of aggregate unemployment rates, mainly depending on whether individuals themselves are employed or unemployed.

Using linear simultaneous equations model, we obtain the effects of unemployment mediated by selected transmission channels: crime, trust on our peers and social interactions. We justify the choice of linear models by transforming the overall SWB verbal answers to a new scale, where the cardinality assumption is much more sensitive. To achieve this, our results exploit external data from the European Social Survey (ESS), and use a combination of the Continuum Approach and the Reference Distribution Method.

These effects can also be obtained indirectly from the mediated effect of employment on different life domains satisfaction. Our results shows that employment affect different domains in a highly heterogeneous way. However, it is interesting to notice that the effect of unemployment on overall SWB through the level of trust and crime (insecurity) can be recovered from the desagreggated model. Even more appealing is the fact that we cannot do the same for social interactions. We consider our results evidence in favor of new questions on the surveys focusing individual satisfaction with their social life.

We obtain further evidence of how unemployment affects well-being by estimating 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.

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, its consequences on our peers and the underlying mechanisms, we used the 190–2001 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. In particular, we have kept this wave since it has information about several "Domain Satisfaction", that is information of individual satisfaction in specific spheres of life. 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 life satisfaction, which we include in our analysis. It specifically ask respondents about job satisfaction, satisfaction with their financial situation, subjective assessment of their health and satisfaction with home life. Regarding subjective health the survey ask "All in all, how would you describe your state of health these days?" And respondents are given the option to answer "Very good", "Good" , "Fair" , "Poor" or "Very Poor". On the other hand, respondents have give a numerical valuation between 1 and 9 to their own Satisfaction with financial situation, Job Satisfaction, and Satisfaction with home life, where 1 is dissatisfied and 9 is satisfied.

In order to be transparent, it must be said we exclude health satisfaction as determinant of overall SWB in our first layer, due to the impossibility of transform this ordinal measure into a cardinal one in the $[0, 10]$ interval.

The data also allow us 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".

However, as is explained in detail in the result section, we transform the data to using a combination of the Continuum Approach and the Reference Distribution Method to translate this data up to a numerical scale and obtain different thresholds for each country.

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).

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 reduction in their income, but also (ii) a psychological effect takes place in many situations. However, the sign of the effect of the unemployment of other could go either positive or negative, as we have suggested before. Further, we recognize this effect could be heterogeneous. We construct aggregate measures of unemployment from the same data source. The main level of aggregation will be the region (measure by NUTS 3-digit code, collected by variable `X048C`), although we will also compute aggregate measure for each socio-economics group in each country (unempB (coded by the variable `x046` to explore further heterogeneity.

2.3 Channels and mediators

In the present discussion we are not only interested on the effects of employment on several dimension of our SWB, but also we pretend to elucidate the mechanisms that underline this relation. For that reason we construct measures of criminality, trust among people and social interaction or density of social capital.

For the measure of criminality we exploit the information contained in a question asking individuals whether criminals live in their neighbor. From this information we built a regional indicator of criminality which is based on the proportion of people within a regional area that respond affirmative to this questions (`crimeR`).

To construct and indicator of the density of social interaction we use both the level of involvement of individuals in voluntary work and their membership to organizations. The way we aggregate individual information to obtain a regional indicator is straight forward: we compute whether or not individual does voluntary work and whether or not is registered as a member of some association. Then we compute the regional proportion of individuals who belong to some association or do voluntary work. Finally, we aggregate both indicators with equal weight. The resulting variable is call `SI`.

Finally we also built an indicator of the level of trust between peers. We use the information contained in the question "Most people can be trusted". As before, we compute the proportion of the people who answer "Most people can be trusted", which is the option that indicate people do trust others. The variable we work with is called `Trust`

Then, to partial out the effect of unemployment on these mediating variables we also construct several variables who are known to determine the levels of trust, insecurity and social interactions. Among them we include GDP, Inflation, average education, average age, degree of drug addiction in the population (`drugAddR`), size of the region (obs), resistance to inmigration (`resistImmR`), and the importance individuals give to friends (`friendImpR`) and politicians (`politImpR`). All the variables are built using date from EVS, but per-capita GDP and inflation, which 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 Other determinants of happiness

The reader familiar with the literature of happiness is encourage to skip this section.

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. (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.

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

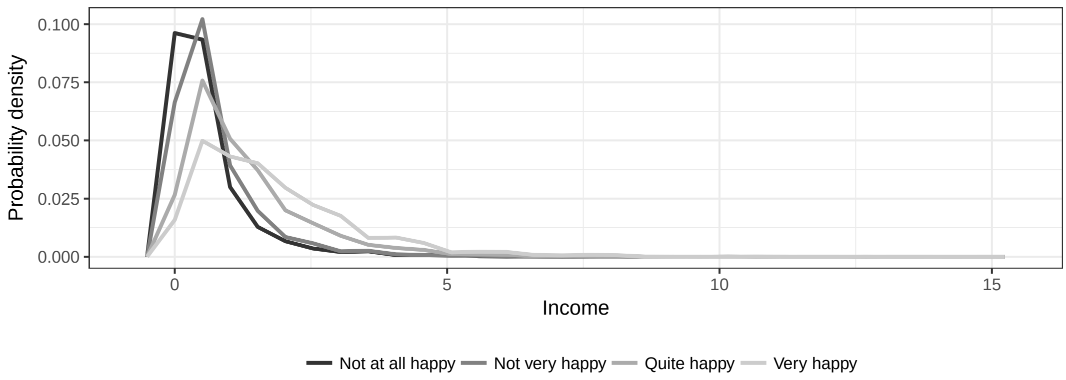

Figure 2.1: Happiness distribution by income.

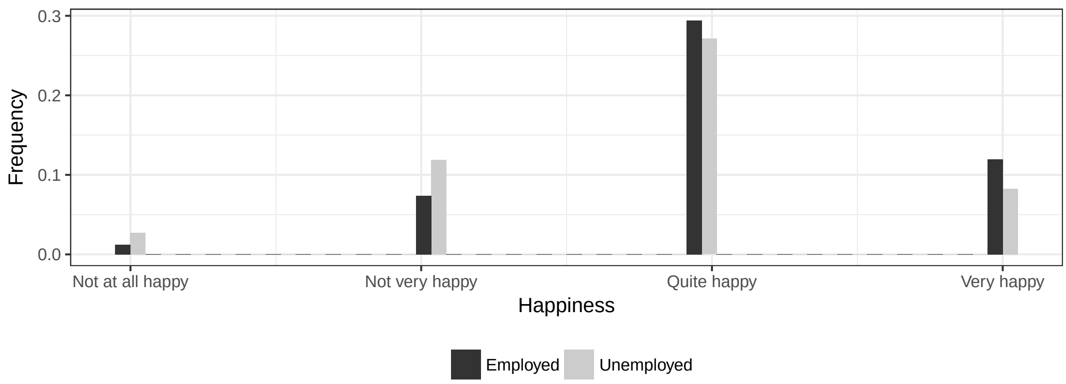

Figure 2.2: Happiness distribution by occupational status.

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.

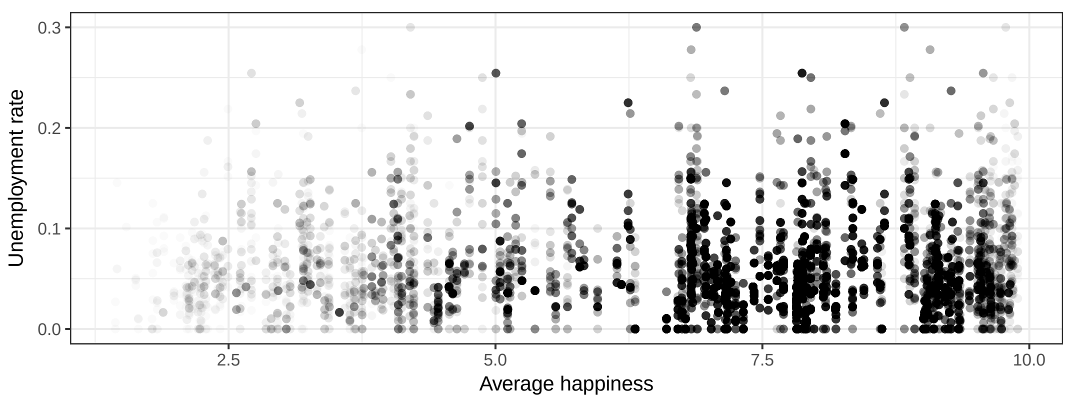

Figure 2.3: Happiness distribution and aggregate unemployment rate.

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,

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

where $\mathbb{1}_{\mathbf{A}}(\cdot)$ denotes the indicator function of a set $\mathbf{A}$, the usage of $\le$ 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 $h^*_i \ge 3$.

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:

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

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

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

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

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

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

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

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., 2003b). 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

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

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

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

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

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

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

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

which, when solved, yields that

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

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, $q = 1, \ldots, Q$, be the associated location scalars and probabilities. For an ordered probit model, the associated probability of category j then is

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

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

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

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 subsections 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 cardinality of our SWB. Then we regress the transformed SWM on several individual-specific and aggregate variables to check the robustness of our baseline specification. Further, we explore the magnitude of the multiplier effect by different regions. Finally, we explore the mechanisms that relate unemployment to happiness.

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 the hypothesis that $Q = 1$ cannot be rejected at any reasonable significance levels. In particular, we obtain three pairs of corresponding thresholds, $(-4.82, -4.75)$, $(-3.94, -3.87)$, and $(-2.11, -2)$, demonstrating that the two sets of thresholds are particularly close to each other.

Our result 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 of our main dataset we use the reference distribution method to assign numerical values for every verbal response.

For instance, Figure A.1 and Figure A.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.

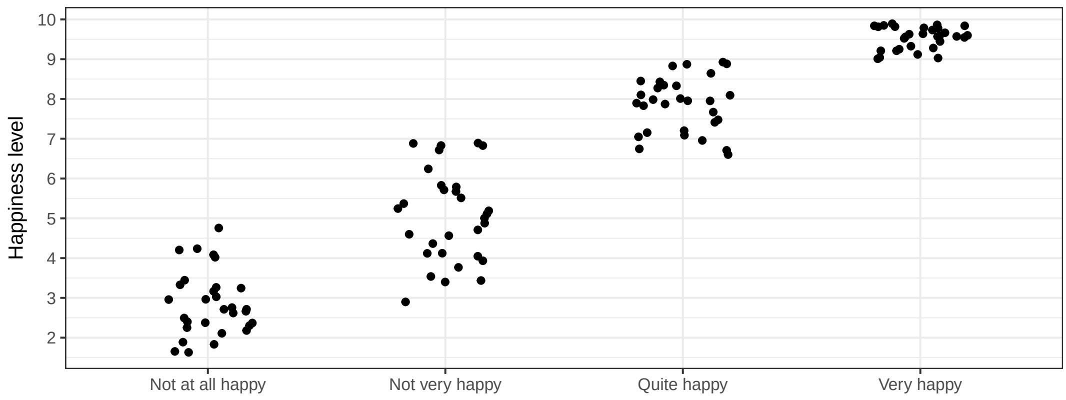

Figure 4.1: Numerical values assigned to happiness levels across countries using the continuum approach in conjunction with the reference distribution method.

4.3 Baseline model

Table 1 constitutes our base line model where in addition to individual determinants of SWB, we also include variables such as the unemployment rate, 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).

Results in Table 1 resemble most the the previous findings found by the literature on the individual determinants on happiness. First, the OLS results show that being unemployed lowers subjective well being by 0.17 points in a $[0, 10]$ scale (remember we have transformed data into that scale). The estimate is somewhat lower in magnitude than those found previously (Clark and Oswald, 1994; Helliwell, 2003), but it is in agreement with the literature in terms of the direction of the relationship. 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 previous findings (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 as expected: we observe a positive relation between income and SWB (Graham and Pettinato, 2004; Shields and Price, 2005). Being married shows a positive effect 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 from $K = 3$ up to the order $K = 7$, and each time we have 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. In terms of the estimates in comparison to the previous three approaches in **??**, one can observe several differences. First, the effect of marriage of somewhat higher using the SNEOP, particularly for large K when the errors distribution becomes better approximated. Similarly, the negative estimate of unemployment is also higher in magnitude in the case of SNEOP. Lastly, a particularly strong change can be observed in terms of both linear and quadratic terms of income, with the SNEOP again providing estimates of higher magnitude. Thus, this provides some evidence that accounting for heterogeneity in terms of errors distribution can provide potential sizable improvements.

Next, the result regarding estimated errors distribution central moments, testing procedures, and Hermite polynomial coefficient estimates are provided in Table A5. Noteworthy, almost all the polynomial coefficients are strongly significant across all orders K, suggesting that arbitrarily approximating a distribution can provide substantial improvements in the model fit. On the other hand, the null hypothesis of orders K and $K-1$ yielding equivalent results is strongly rejected in all the considered cases with the p-value being less than 0.05 each time.

Table 1: Estimation of SWB using individual and aggregate level data

	OLS	POLS
`Constant`	1.88*** (0.03)	-0.23*** (0.03)
`age`	-0.02*** (0.00)	-0.03*** (0.00)
`sex`	0.02*** (0.01)	0.03*** (0.01)
`educ`	0.01*** (0.00)	0.01*** (0.00)
`married`	0.24*** (0.01)	0.29*** (0.01)
`unemp`	-0.17*** (0.01)	-0.21*** (0.02)
`selfemp`	0.00 (0.01)	0.01 (0.01)
`retired`	-0.08*** (0.01)	-0.10*** (0.01)
`unempR`	0.23*** (0.08)	0.32*** (0.10)
`unempC`	-0.00 (0.17)	-0.02 (0.21)
`unempB`	-0.18 (0.13)	-0.15 (0.16)
`incomeMedium`	0.11*** (0.01)	0.12*** (0.01)
`incomeHigh`	0.17*** (0.01)	0.21*** (0.01)
`GDPpc`	0.03*** (0.00)	0.03*** (0.00)
`Infl`	-0.00 (0.00)	-0.00 (0.00)
`age2`	0.02*** (0.00)	0.03*** (0.00)

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

Lets turn the attention to aggregates variables. For the unemployment rates, the relation of the country level and the socio-economic group appear to be non-significant. The relationship between unemployment rate of reference group and overall happiness is negative, but non-significant, while the relation with the regional unemployment is positive. We need to be careful about the interpretation of these estimates as the variables unemployment varies between (0,1). The effect of regional unemployment is not quite counterintuitive. It could be explaine using the "social-norm" hypothesis -individuals care more about closer peers than for random people in the region. However, we believe that this could be the by product of multiple effects going in opposite directions.

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

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 unemployment rates and one's own unemployed status with aggregated unemployment rates. Table 2 presents the results (the full results can be found in A6). The important result the unemployment of the reference group impacts negatively for both groups, but it is non-significant for employed people. Moreover, this regression shows that for unemployed people the "social norm" hypothesis is only evident at unemployment country-level.

Table 2: Estimation on SWB including interactions between unemployment rates and employment status

	OLS	POLS
`unempB:emp`	-0.09 (0.14)	-0.06 (0.18)
`unempR:emp`	0.35*** (0.09)	0.47*** (0.11)
`unempC:emp`	-0.18 (0.18)	-0.22 (0.22)
`unemp:unempB`	-0.84** (0.37)	-0.81* (0.45)
`unemp:unempR`	-1.11*** (0.28)	-1.19*** (0.34)
`unemp:unempC`	1.42*** (0.46)	1.61*** (0.56)

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

4.4 Mechanisms

In this section we show our results of the transmission channels and the way how domain satisfactions relates to overall happiness. Nevertheless, we consider important to explain the way we try to model these channels.

$$SWB_{ir} = f(DS_{1,ir}, ..., DS_{K,ir}; u_{ir}) \tag{4.1}$$

$$DS_{j,ir} = g(\mathbf{Z}_r, \mathbf{X}_{j,ir}; \boldsymbol{\epsilon}_{j,ir}) \tag{4.2}$$

$$\mathbf{Z}_r = h(\text{unemployment}_r, \mathbf{W}_r; \boldsymbol{\xi}_r) \tag{4.3}$$

where SWB_{ir} is the overall measure of invididual SWB for individual i at region r; $DS_{j,ir}$ is the domain satisfaction j (with $j = 1, ..., K$) for individual i at region r; $\mathbf{Z}_r$ represents a vector of transmission channels (crime, social interaction and trust); $\mathbf{X}_{j,ir}$ is a vector of individual-region specific characteristics for domain statisfaction j; $\mathbf{W}_r$ are other observable determinants of transmission channels. Finally, u_{ir}, $\boldsymbol{\epsilon}_{j,ir}$, ;$\boldsymbol{\xi}_r$ are stochastic unobserved components assumed to be orthogonal. The system (4.1)-(4.3) is a general semi-structural model. However, our approach consider $f(.)$, $g(.)$, $h(.)$ as linear functions, taking advantage that we transform our ordinal measure of SWB into a cardinal measure in the $[0, 10]$ interval and the fact we have data for 3 domain satisfaction on the same scale.

Table 3, shows the effect of the main mechanism of unemployment on the overall SWB of individuals happiness. The estimations of the whole system can be found in the appendix. Results are very intuitive. First of all, as Table A7 shows, the regional unemployment rate increase crime and social interactions, while reduce trust between people. The only results that one would argue is that regional unemployment increase the level of social interactions. However, it is common for people to bound more with their peers in hard times.

At the same time, Table 3 shows that crime has a negative effect on the overall SWB of individuals, which it was expected and it has been observed previously. In addition, we can observe that both the level of trust in our peers and the social interactions of the regions affects positively the happiness levels, which has also been observed by several studies (Helliwell, 2003).

Table 3

	Happy
`crimeR`	-0.35*** (0.08)
`trustR`	0.38* (0.22)
`siR`	0.72*** (0.22)
`unempR`	-1.19*** (0.25)

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

Another interesting finding is that now the direct effect of unemployment rate on individual SWB is negative (recall that we found positives coefficients in our baseline result Table 1. This negative results it seem to us more intuitive, as people should be psychological affected by the fate of their close peers and at the same time a higher unemployment rate increase their concern about their own risk of moving to unemployment. This provides further evidence unemployment does affect happiness through the mediators we include in our analysis.

Next, Table 4 pictures the indirect effect of unemployment through different mechanisms. The first line of results shows the effect of unemployment through social interactions, trust, and crimes, respectively, on the individual happiness. The effects are computed by multiplying the partial effects of those channels in the happiness equation times the partial effect of regional unemployment in the channel equations. The following three lines are produced by replacing happiness with alternative satisfaction measures. The last line uses Table 5 to produce a weighted sum of the previous three rows. That is, we introduce an additional layer of unemployment effect on happiness. In this manner, we obtain an alternative set of unemployment effects on happiness through the three channels (social interactions, trust, and crime).

In particular, we observe unemployment has a positive impact on individual SWB through social interactions. And increase in of 1 p.p of unemployment produces an increase in happiness of 0.007 points in the [0,10] scale of happiness. This mechanisms resembles to some extent to the social norm (Clark et al., 2010): as we are all worse, we are all worse together, and that make us feel better. It is also interesting to notice that the absolute effect of unemployment through social interactions is remarkably more important than the other two mechanisms we consider here.

Table 4: Computed estimates of mediated effects of unemployment

	Social Interaction	Trust	Crime
Overall SWB	0.76	-0.13	-0.09
Job Satisfaction	-0.55	0.21	-0.32
Financial Satisfaction	0.36	-0.52	0.30
Satisfaction at Home	0.47	-0.60	-0.37
Indirect Effect on overall SWB	0.10	-0.15	-0.08

In fact, from Table 4 we can see that as unemployment increase, it creates better conditions for the increase of criminal activities, which negatively affects our SWB. Finally, we observe employment produce a negative effect on happiness through our levels of trust in our peers. We believe that people generally associate trust with monetary issues, thus unemployment could deeply deteriorate the feelings of individuals on this regard.

Then, following the same procedure we estimate by simultaneous equations the effects of unemployment (and each of its mediators) on three different life domains: job satisfaction, satisfaction with their financial situation, satisfaction with home life. All the estimation can be found in Table A8, Table A9 and Table A10 respectively.

Table 4 shows the estimations of the mediated effects of unemployment. The first thing it should be noticed is that the mechanisms through which unemployment affects happiness are different for each life domain. While the impact of unemployment on trust affects negatively individual financial satisfaction and satisfaction at home it has a positive effect on job satisfaction and the opposite is true about the social interaction mechanisms. The only result we do not consider intuitive is the effect of unemployment on financial satisfaction through crime. It seems impossible to explain a positive effect of crime on SWB, while the relation between unemployment and crime is negative, although Cohen (2008) finds heterogeneous effects for the different measures of criminality on life satisfaction.

Finally, Table 5 computes the weights of each life domain on each individual overall SWB. We observe that homelife has the largest effect on the overall SWV, while both job satisfaction and subjective assessment of the financial situation are both positive and significative. Once we have computed these weights, we can obtain the overall effect of unemployment through the considered life domains. This result can be find in the last line of Table 4.

We believe this results are highly informative. First we observe that the effect of unemployment through trust and crime is the same wheter we consider the direct effects on overall SWB or we computed from the indirect effects on several life domains. However, although the sign is the same, we obtain different effects of unemployment though social interaction:

0.76 in the first case and 0.1 in the second case.

As we consider the social interaction as a way of drawing satisfaction from relating with others, we believe that such personal dimensions of life as the ones considered here are not enough to obtain satisfactory conclusions of individuals overall well-being. In this sense, we consider our results evidence in favor of new questions on the surveys focusing individual satisfaction with their social life.

Table 5: Decomposition/Aggregation of Happiness

	Happiness decomposition
`Constant`	5.28*** (0.04)
`homelife`	0.22*** (0.00)
`finhh`	0.05*** (0.00)
`jobsat`	0.04*** (0.00)

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

To address the follow-up question regarding sensitivity to the definition of unemployment, we broaden its definition and include those only with part time jobs. The effects of the same three channels as before now become $(0.45, -0.04, -0.34)$, which is significantly different from both of the methods used before.

4.5 Modified Oaxaca-Blinder Decomposition

An alternative approach to discuss the mechanism is through the counter factual analysis. We plan to use a modified version of Oaxaca-Blinder decomposition to achieve it.

We have two different groups: employed ($j = 0$) and unemployed ($j = 1$). The object is to decompose the difference of the probabilities of being happiness level of k between these two groups. In particular, we try to answer this challenge through social classes: upper and lower.

It is clear from our baseline analysis that social classes will affect individual's happiness. In particular, being upper class brings positive effect on happiness. The general intuition behind this is that if the employment status affect the chance of belonging to a certain class, then we establish an indirect link between employment and happiness. Here we aim to discover what will happen to the probability of being happiness level k, if employed individuals with one class face the same chance of belonging to this class as their unemployed counterparts.

Consider explanatory variable $X^j, j = 0, 1$ for each group, we want to compare $P^j(H^j = k)$, $k = 0, 1, 2, 3$, $j = employed, unemployed$. To this end, we will treat one of these two groups as standard. Now consider a perdition $\{A_e\}_e$ of the support of X^j.

Notice that

$$P^j(H^j = k) = \sum_e P^j(H^j = k|X^j \in A_e)P(X^j \in A_e) \tag{4.4}$$

Let

$$P^{j,s}(H^j = k) = \sum_e P^j(H^j = k|X^j \in A_e)P(X^s \in A_e) \tag{4.5}$$

where $j \neq s$, is the counter-factual part since it has a counter-factual interpretation. That is the probability of happiness equal to degree k of j population if their component distribution is distributed as population s.

The decomposition is then:

$$P^j(H^j = k) - P^s(H^s = k) = (P^j(H^j = k) - P^{j,s}(H^j = k)) + (P^{j,s}(H^j = k) - P^s(H^s = k)) \tag{4.6}$$

The first part is called counter-factual component difference. It is the difference that could been observed if the only difference between these two population is their component distribution.

The second part is called counter-factual structural effect. It is the difference that could be observed if the two population have the same component distribution.

In our application, the two groups are employed and unemployed. The perdition we have is social class: upper class or lower class.

The meaning of counter-factual component difference is the probability difference that can be explained by the different probabilities of being one class (say upper class) between employed and unemployed individuals. That is employment status influence the happiness through social class by letting the probabilities of being one certain class different between employed and unemployed.

The meaning of counter-factual structural effect is the probability difference that can be explained by the difference conditional on the two population belong to the same class. This can be interpreted as the employment status will change the happiness through social class by letting the probability of $happiness = k$ under the same class different.

In practice, we only need to estimate the conditional probability $P^j(H^j = k|X^j \in A_e)$ for different groups, as $P^j(H^j = k)$,$P(X^j \in A_e)$ can be simply the empirical probability. We extend our core variables (as shown in the baseline model) by adding social class explanatory variables with restriction to each perdition. Using a standard ordinal probit model, we could obtain the estimated conditional probabilities for each group.

The following table presents the modified O-B decomposition results for social class perdition.

Table 6: O-B Decomposition

	Pr(Happiness=0)	Pr(Happiness=1)	Pr(Happiness=2)	Pr(Happiness=3)
employed	0.02922	0.12379	0.60729	0.23970
unemployed	0.08898	0.29449	0.47140	0.14513
Counter-factual Part	0.03632	0.14136	0.59329	0.22903
Total Difference	-0.05976	-0.17071	0.13589	0.09458
Component Difference	-0.00710	-0.01757	0.01400	0.01067
Structural Effect	-0.05266	-0.15314	0.12189	0.08391

For social classes, we conclude that employment status might not effect happiness via this channel. The component difference are quite close to zero, compare to the employed probabilities, the counter-factual part are slightly higher in low happiness levels (0 and 1) and lower in high happiness levels (2 and 3). But all of the differences are small and could be negligible.

One drawback of this approach is the lack of testing tool. We can not tell, say whether the component difference is significant for happiness is of level 0.

4.6 Random Parameters Model

Finally, we focus on the effects of the unemployment rate of different socio-economic groups (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 to be their own socio-economic group). Instead we assume them to also care about all socio-economics groups, 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 7 we do not reject that the standard deviation of the lower classes is equal to 0, both for skill and unskilled workers). Table 7 shows only the the coefficients that were randomized, to see the full specification check the Appendix.

Table 7

	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 7 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.

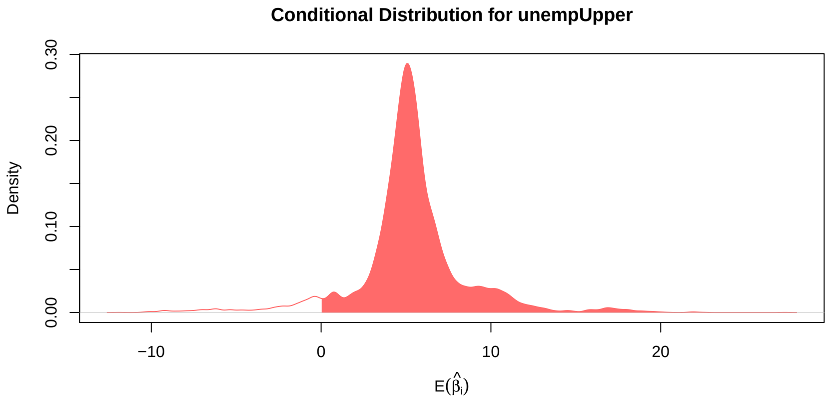

Figure 4.2: Distribution of the Partial Effect of Unemployment rate of the Upper working class

We consider these results very illustrative. 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. 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.

4.7 Causality

One of the most important concerns in economics and econometrics is whether we are able to interpret coefficients of a regression as a causal relationship. In this sense, should we interpret our results as causal effects? Even though are model is an attempt of structural estimation, unfortunately, heterogeneity and the likelihood of having excluded or forgotten another important channels makes that our results are subject to omitted variable bias.

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 explanatory variables that imply individual decisions, thus reverse causality or simultaneity problems could be present. Thus, since we do not have at hand external information (an instrumental variable that controls for these variables), it is impossible to identify the estimated parameters as causal effects. Other reason could be related to 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. Last but not least, another possible problem of why we cannot interpret our results as causal effects, is that our variables selected as transmission channels are not the unique possible transmission mechanisms, also our exclusion restrictions may not be suitable. Therefore, given these limitations we have to be cautious about the causal interpretations in our work.

4.8 Extensions and further research

(a) **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 in our system.

Another important point could be to include health domain satisfaction as overall life satisfaction. In order to this, it is relevant to have in the data base a complementary variable of health self assesment in $[0, 10]$ interval, in order to apply continuum approach or distribution reference approach.

5 Conclusion

The ultimate goal of this paper was to quantify the effects of unemployment of one individual on others' SWB. Our approach is to use a semi-structural linear model that relates the effect of unemployment rate at region-level with overall happiness, but through different domain satisfactions, as Van Praag et al. (2003b) suggest. Besides, we focus the discussion on three of the important channels that specialized literature points out: criminality, social interaction and trust.

We use a linear simultaneous equation model to obtain the effects of unemployment mediated by several variables: crime, trust on our peers and social interactions. We justify the choice of linear models by transforming the overall SWB verbal answers to a new scale, where the cardinality assumption is much more sensitive. To achieve this, our results exploit external data from the European Social Survey (ESS), and use a combination of the Continuum Approach and the Reference Distribution Method.

These effects can also be obtained indirectly from the mediated effect of employment on different life domains satisfaction. Our results shows that employment affect different domains in a highly heterogeneous way. However, it is interesting to notice that the effect of unemployment on overall SWB through the level of trust and crime (insecurity) can be recovered from the desagreggated model. Even more appealing is the fact that we cannot do the same for social interactions. We consider our results evidence in favor of new questions on the surveys focusing individual satisfaction with their social life.

We obtain further evidence of how unemployment affects well-being by estimating 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. Finally, it should be said that our estimates are sensitive to the definition of unemployment, and even though we estimate a semi-structural system, our estimates should not be interpreted as causal effects.

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Appendix

A Figures

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

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

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

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

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)	-0.05*** (0.01)
`age2`	0.02*** (0.00)	0.02*** (0.00)	0.05*** (0.01)
`income`	0.25*** (0.04)	0.28*** (0.04)	0.21*** (0.06)
`income2`	-3.09*** (0.53)	-3.74*** (0.57)	-3.55*** (0.85)
`sex`	0.07*** (0.01)	0.08*** (0.02)	0.08*** (0.02)
`educ`	-0.00 (0.00)	-0.00 (0.00)	0.01*** (0.00)
`married`	0.21*** (0.02)	0.21*** (0.02)	0.54*** (0.04)
`unemp`	-0.20*** (0.03)	-0.22*** (0.03)	-0.43*** (0.06)
`selfemp`	-0.08** (0.03)	-0.10*** (0.03)	-0.06 (0.05)
`retired`	-0.01 (0.03)	-0.02 (0.03)	-0.07 (0.05)
`unempR`	-0.09 (0.22)	-0.10 (0.24)	-0.18 (0.42)
`unempC`	2.00*** (0.42)	2.03*** (0.45)	2.19*** (0.72)
`unempB`	-0.76*** (0.16)	-0.90*** (0.17)	-1.68*** (0.44)
`relincR`	-0.01 (0.04)	-0.04 (0.04)	-0.17 (0.13)
`relincC`	0.01 (0.04)	0.04 (0.04)	0.38*** (0.10)
`relincB`	-0.05* (0.03)	-0.05* (0.03)	0.03 (0.09)
`GiniR`	-0.52* (0.29)	-0.52* (0.31)	1.44*** (0.46)
`GiniC`	-1.13*** (0.29)	-1.68*** (0.31)	-4.90*** (0.51)
`GiniB`	0.31 (0.25)	0.50* (0.27)	1.49*** (0.38)
`GDPpc`	0.02*** (0.00)	0.02*** (0.00)	0.07*** (0.00)

Note: standard errors in parenthesis. Statistical significance at the 1%, 5%, and 10% level is marked by ***, **, and *, respectively. The order of the estimated SNEOP model is $K = 7$.

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. In the case of the testing against OP (ordered probit) and the corresponding model of order $K-1$, parentheses contain the corresponding p-values following from the χ^2_{K-2} and χ^2_1 distributions, respectively.

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

	OLS	POLS
`Constant`	1.88*** (0.03)	-0.23*** (0.03)
`age`	-0.02*** (0.00)	-0.03*** (0.00)
`sex`	0.02*** (0.01)	0.03*** (0.01)
`educ`	0.01*** (0.00)	0.01*** (0.00)
`married`	0.24*** (0.01)	0.29*** (0.01)
`unemp`	-0.10*** (0.03)	-0.14*** (0.04)
`selfemp`	0.01 (0.01)	0.01 (0.01)
`retired`	-0.08*** (0.01)	-0.10*** (0.01)
`incomeMedium`	0.11*** (0.01)	0.12*** (0.01)
`incomeHigh`	0.17*** (0.01)	0.21*** (0.01)
`GDPpc`	0.03*** (0.00)	0.03*** (0.00)
`Infl`	-0.00 (0.00)	-0.00 (0.00)
`age2`	0.02*** (0.00)	0.03*** (0.00)
`unempB:emp`	-0.09 (0.14)	-0.06 (0.18)
`unempR:emp`	0.35*** (0.09)	0.47*** (0.11)
`unempC:emp`	-0.18 (0.18)	-0.22 (0.22)
`unemp:unempB`	-0.84** (0.37)	-0.81* (0.45)
`unemp:unempR`	-1.11*** (0.28)	-1.19*** (0.34)
`unemp:unempC`	1.42*** (0.46)	1.61*** (0.56)

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

Table A7

	Happy	Crime	Trust	Soc. inter
`Constant`	-25.89 (8420.19)	17.20 (1354.41)	-2.13NA	-0.37 (1345.54)
`crimeR`	-0.35*** (0.08)	—	—	—
`trustR`	0.38* (0.22)	—	—	—
`siR`	0.72*** (0.22)	—	—	—
`GDPpc`	-0.00 (0.00)	-0.00*** (0.00)	0.00*** (0.00)	-0.00*** (0.00)
`Infl`	0.00 (0.00)	0.00*** (0.00)	-0.00*** (0.00)	0.00*** (0.00)
`age`	-0.06 (0.06)	—	—	—
`sex`	0.04*** (0.01)	—	—	—
`educ`	0.01*** (0.00)	—	—	—
`married`	0.57*** (0.13)	—	—	—
`unemp`	-0.30*** (0.02)	—	—	—
`selfemp`	-0.00 (0.04)	—	—	—
`retired`	-0.07 (0.22)	—	—	—
`unempR`	-1.19*** (0.25)	0.25*** (0.01)	-0.35*** (0.01)	1.06*** (0.01)
`unempC`	0.67** (0.29)	—	—	—
`unempB`	-0.73*** (0.26)	—	—	—
`incomeMedium`	0.26*** (0.02)	—	—	—
`incomeHigh`	0.43*** (0.02)	—	—	—
`I(age2)`	0.00 (0.00)	—	—	—
`factor(wave)2`	33.84 (8420.19)	-16.88 (1354.41)	1.64NA	1.80 (1345.54)
`factor(wave)3`	33.97 (8420.19)	-16.81 (1354.41)	1.54NA	1.82 (1345.54)
`factor(wave)4`	34.02 (8420.19)	-17.39 (1354.41)	1.56NA	3.59 (1345.54)
`drugAddR`	—	0.72*** (0.00)	—	—
`obsR`	—	0.00*** (0.00)	-0.00 (0.00)	-0.00*** (0.00)
`educR`	—	-0.02*** (0.00)	0.02*** (0.00)	-0.03*** (0.00)
`ageR`	—	-0.00*** (0.00)	0.01*** (0.00)	-0.01*** (0.00)
`resistImmR`	—	—	-0.26*** (0.00)	0.25*** (0.00)
`friendImpR`	—	—	0.58*** (0.01)	-0.42*** (0.01)
`politImpR`	—	—	0.13*** (0.00)	-0.13*** (0.00)

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

Table A8

	Job sat.	Crime	Trust	Soc. inter
Constant	12.30*** (3.14)	0.32*** (0.01)	-0.50*** (0.01)	1.43*** (0.01)
crimeR	-1.27*** (0.17)	—	—	—
trustR	-0.61* (0.37)	—	—	—
siR	-0.52 (0.39)	—	—	—
GDPpc	0.02*** (0.00)	-0.00*** (0.00)	0.00*** (0.00)	-0.00*** (0.00)
Infl	-0.00*** (0.00)	0.00*** (0.00)	-0.00*** (0.00)	0.00*** (0.00)
age	-0.27 (0.17)	—	—	—
sex	0.04 (0.04)	—	—	—
educ	0.02*** (0.00)	—	—	—
married	0.37* (0.20)	—	—	—
unemp	-0.52** (0.24)	—	—	—
selfemp	0.22*** (0.04)	—	—	—
retired	-1.42* (0.82)	—	—	—
unempR	-1.24** (0.50)	0.25*** (0.01)	-0.35*** (0.01)	1.06*** (0.01)
unempC	2.53*** (0.70)	—	—	—
unempB	-2.11*** (0.66)	—	—	—
incomeMedium	0.40*** (0.03)	—	—	—
incomeHigh	0.72*** (0.03)	—	—	—
I(age2)	0.00 (0.00)	—	—	—
factor(wave)3	-0.33*** (0.06)	0.06*** (0.00)	-0.10*** (0.00)	0.02*** (0.00)
factor(wave)4	-0.24*** (0.05)	-0.52*** (0.04)	-0.08** (0.04)	1.79*** (0.04)
drugAddR	—	0.72*** (0.00)	—	—
obsR	—	0.00*** (0.00)	-0.00 (0.00)	-0.00*** (0.00)
educR	—	-0.02*** (0.00)	0.02*** (0.00)	-0.03*** (0.00)
ageR	—	-0.00*** (0.00)	0.01*** (0.00)	-0.01*** (0.00)
resistImmR	—	—	-0.26*** (0.00)	0.25*** (0.00)
friendImpR	—	—	0.58*** (0.01)	-0.42*** (0.01)
politImpR	—	—	0.13*** (0.00)	-0.13*** (0.00)

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

Table A9: Satisfaction with financial situation of household

	Fin. sat. in hh.	Crime	Trust	Soc. inter
Constant	42.60*** (14.46)	0.11*** (0.02)	-0.15*** (0.02)	1.21*** (0.02)
crimeR	-0.72 (0.78)	—	—	—
trustR	-2.37** (1.08)	—	—	—
siR	-1.82 (1.23)	—	—	—
GDPpc	0.14*** (0.03)	-0.02*** (0.00)	0.01*** (0.00)	-0.01*** (0.00)
Infl	0.00*** (0.00)	0.00*** (0.00)	-0.00 (0.00)	-0.00*** (0.00)
age	-2.10*** (0.77)	—	—	—
sex	-0.12 (0.09)	—	—	—
educ	0.00 (0.01)	—	—	—
married	4.89*** (1.79)	—	—	—
unemp	-0.51* (0.27)	—	—	—
selfemp	0.48** (0.24)	—	—	—
retired	-6.84*** (2.50)	—	—	—
unempR	-1.86 (1.97)	-0.42*** (0.03)	0.22*** (0.03)	-0.20*** (0.03)
unempC	20.45*** (4.30)	—	—	—
unempB	-7.82*** (2.57)	—	—	—
incomeMedium	1.66*** (0.32)	—	—	—
incomeHigh	2.43*** (0.30)	—	—	—
I(age2)	0.02*** (0.01)	—	—	—
drugAddR	—	0.59*** (0.01)	—	—
obsR	—	0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)
educR	—	0.01*** (0.00)	0.02*** (0.00)	-0.01*** (0.00)
ageR	—	0.00*** (0.00)	-0.00*** (0.00)	-0.01*** (0.00)
resistImmR	—	—	-0.12*** (0.01)	0.24*** (0.01)
friendImpR	—	—	0.43*** (0.01)	0.02** (0.01)
politImpR	—	—	0.26*** (0.01)	-0.30*** (0.01)

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

Table A10: Satisfaaction with home life

	Home life	Crime	Trust	Soc. inter
Constant	57.83*** (18.93)	0.11*** (0.02)	-0.15*** (0.02)	1.21*** (0.02)
crimeR	0.88 (1.01)	—	—	—
trustR	-2.74** (1.37)	—	—	—
siR	-2.38 (1.65)	—	—	—
GDPpc	0.13*** (0.04)	-0.02*** (0.00)	0.01*** (0.00)	-0.01*** (0.00)
Infl	0.00*** (0.00)	0.00*** (0.00)	-0.00 (0.00)	-0.00*** (0.00)
age	-2.81*** (1.00)	—	—	—
sex	-0.05 (0.12)	—	—	—
educ	-0.02 (0.02)	—	—	—
married	7.31*** (2.36)	—	—	—
unemp	-0.15 (0.35)	—	—	—
selfemp	0.59* (0.35)	—	—	—
retired	-8.91*** (3.22)	—	—	—
unempR	-1.96 (2.57)	-0.42*** (0.03)	0.22*** (0.03)	-0.20*** (0.03)
unempC	18.20*** (5.65)	—	—	—
unempB	-8.90*** (3.44)	—	—	—
incomeMedium	1.29*** (0.39)	—	—	—
incomeHigh	1.43*** (0.37)	—	—	—
I(age2)	0.03*** (0.01)	—	—	—
drugAddR	—	0.59*** (0.01)	—	—
obsR	—	0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)
educR	—	0.01*** (0.00)	0.02*** (0.00)	-0.01*** (0.00)
age2	—	0.00*** (0.00)	-0.00*** (0.00)	-0.01*** (0.00)
resistImmR	—	—	-0.12*** (0.01)	0.24*** (0.01)
friendImpR	—	—	0.43*** (0.01)	0.02** (0.01)
politImpR	—	—	0.26*** (0.01)	-0.30*** (0.01)

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

Table A11: Random parameters model

	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.