The drivers of happiness inequality
Suggestions for promoting social cohesion

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Abstract

The goal of this paper is to identify and quantify the contribution of a set of covariates in affecting levels and over time changes of happiness inequality. Using a recent decomposition methodology, we focus on the increase in happiness inequality observed in Germany between 1992 and 2007 in the German Socio-Economic Panel (GSOEP) database, deriving the following findings. First, trends in happiness inequality are mainly driven by composition effects, while coefficient effects are negligible. Second, among composition effects, education has an inequality-reducing impact, while changes in labour market conditions and demographic composition contribute to explain the rise in happiness inequality. Third, the increase in income inequality cannot be considered as a driver of the increase in happiness inequality, while the increase in average income has a reducing impact. A clear cut policy implication of our paper is that policies enhancing education and labour market performance are crucial to reduce happiness inequality and the potential social tensions arising from it.

Keywords: happiness inequality, happiness inequality, income inequality, education, decomposition methods.

JEL Codes: I31, I28, J17, J21, J28.

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1. Introduction

Economists in the last decades have widely investigated happiness levels and their drivers.[1] The motivation for our paper is to extend the analysis from happiness levels to happiness inequality. As well-known, unlike income, happiness is not transferable. While policy makers can evaluate whether to redistribute income across individuals, it is not possible to transfer happiness across individuals. Probably for this reason, the literature concerning happiness inequality at the individual level is lacking, with only few recent exceptions such as Stevenson and Wolfers (2008), Van Praag (2011), Dutta and Foster (2011), and Guven et al. (2009). A wider macroeconomic literature is instead available, which exploits cross-country data (Veenhoven, 1990 and 2005).

The original contribution of our paper consists in identifying at the micro level the individual determinants of both levels and over time changes of happiness inequality. We make use of a decomposition methodology introduced by Firpo et al. (2007) and further developed in Fortin et al. (2011). By using the Recentered Influence Function (RIF) regressions (Firpo et al. 2009), this methodology represents a generalization of the Oaxaca-Blinder procedure (Blinder, 1973; Oaxaca, 1973), since it can be applied to any distributional parameter other than the mean. The methodology allows splitting the total change in happiness inequality into two aggregate effects, the first related to the overall changes in the distribution of happiness inequality determinants in the population (*composition effect)*, the second related to the overall changes in the return of

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[1] Actually, the investigation of the determinants of happiness has been one of the most salient topics of economists since the Classics, for instance Malthus (1798). Subsequently, the relevance of the wealth-happiness nexus was investigated, among others, by Marshall (1890), Veblen (1899) and, more recently, Scitovsky (1976) and Hirsch (1976). Nowadays, the wide availability of databases including measures of happiness provides abundant empirical evidence for testing hypotheses stemming from the happiness debate.

such determinants (*coefficient*, or *structure*, *effect*). Once the aggregate decomposition has been carried out, it is also possible to compute a more detailed decomposition, subdividing both the composition and coefficient effects into the contribution of each covariate.[2]

Identifying and quantifying the contribution of each driver on levels and over time changes of happiness inequality matters from a policy point of view, since it allows policy makers to intervene on the reduction of social tension (Tullock, 1971, Brown 1996, Gurr 1996), through policies aimed at affecting drivers of happiness inequality. Further, this methodology allows disentangling the impact of those determinants that can be directly redistributed by the policy maker, like income and wealth, from the impact of determinants that cannot be directly redistributed, such as education and employment status.[3]

The measurement and the analysis of happiness is becoming more and more important in the political arena as well. For instance, the UK government planned to evaluate happiness of people with wellbeing indicators since Autumn 2011, consistently with the statements of the Prime Minister Cameron who argues that "his goal in politics is to help make a better life for people" and "noted that government should be properly focused on quality of life as well as economic growth".[4] From a scientific standpoint, a similar argument is proposed by Stiglitz, Sen and Fitoussi (2009). In their report on the measurement of economic performance and social progress, the authors underline the importance of using indicators of self-assessed life satisfaction: "These measures, while not replacing conventional economic indicators,

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[2] The approach has been already used to account for changes in wage inequality in several empirical contributions (Firpo et al., 2007, 2011; Chi and Li, 2008; Schirle, 2009).

[3] Van Praag (2011) comments that ".. most of [the] determinants [of well-being] cannot be redistributed but they are relevant for well-being, and inter-individual differences in those non-income determinants may cause feelings of well-being inequality as well".

[4] See http://algarvedailynews.com/news/4007-uk-happiness-assessment-in-hand accessed on July 27, 2011. In July 2012 the first experimental results of the Programme "Measuring National Well-being" has been released by the UK Office for National Statistics (ONS, 2012).

provide an opportunity to enrich policy discussions and to inform people's view of the conditions of the communities where they live. More importantly, the new measures now have the potential to move from research to standard statistical practice" (p.41).

The focus of the paper is on the German case, using the German Socio-Economic Panel (GSOEP). The analysis is composed by two main steps. In the first step we investigate for two time periods (1992-93-94 and 2005-06-07) the determinants of cross sectional happiness inequality, in terms of variance and Gini index, by means of RIF regressions. In the second, we identify and quantify the role played by each single covariate in shaping the evolution over time of happiness inequality, in terms of the two indicators considered.

The first step of the analysis shows that education, income, being employed, having a saving account, being a house owner and being married are negatively correlated to happiness inequality, while being unemployed, living in the East and being a prime age individual are positively correlated. Further, being female and having children do not affect inequality

As for the second step of the analysis, the decomposition procedure, we derive the following main findings. First, most of the dynamics of happiness inequality is explained by the composition effect, while the coefficient effect is negligible, suggesting that the returns to drivers are invariant over time. Second, the increase in education level has a reducing effect on happiness inequality. Third, changes in labour market conditions (mainly being unemployed) strongly contribute to the increase in inequality. Fourth, the increase in income inequality in Germany cannot be considered as a driver of the increase in inequality, confirming the findings of Stevenson and Wolfers (2008), while the increase in average income entails a reduction in the dispersion of happiness, consistently with Clark et al. (2012).

Additional roles are played by a demographic effect, since the increase in the middle age cohort share of the population is associated with an increase in happiness inequality, and by the decline in the share of individuals with a saving account, underlying the importance of financial well-being.

Since happiness inequality is a driver of social tensions, we conclude by suggesting that education and labour market policies, apart from the well known effects emphasized in the macroeconomic and labour literature, entail an additional impact on happiness inequality, reducing social unrest.

It is important to stress that we are not claiming that the analysis of happiness inequality has to replace other dimensions of inequality that are currently used by policy makers when deciding redistributive measures (income, wages and so on). Consistently with the report of Stiglitz, Sen and Fitoussi (2009), we argue that happiness inequality can represent an additional dimension that policy makers might take into account.

The paper is divided into six sections. In section 2 we discuss the related literature, while in section 3 we illustrate our sample and provide descriptive findings. In section 4 we outline analytical features of the decomposition approach. In section 5 we present econometric findings. In section 6 we discuss further the findings of the paper, while the seventh section concludes.

2. Related literature

Happiness inequality has mainly been addressed from a macroeconomic standpoint, using cross-country data. Chin-Hon-Foei (1989) documents a positive correlation between economic fluctuations and happiness inequality for European countries in the period 1975-84. Veenhoven (1990 and 1995) observes that happiness is more equally distributed in more economically stable and developed countries.

Conversely, the micro analysis of happiness inequality is relatively poor from both an empirical and a theoretical point of view. Using individual data, Stevenson and Wolfers (2008) document that happiness inequality has substantially decreased in the US from 1970 to 2006. However, since the early 1990s, there is an upward trend, which does not compensate the massive decrease occurred in the previous decades. Stevenson and Wolfers (2008) explain the falling trend in happiness inequality in terms of a strong erosion of the race and gender happiness gaps. They also show that trends in income inequality and happiness inequality are rather different.

Dutta and Foster (2011) adopt the approach of Allison and Foster (2004) for ordinal variables to measure happiness inequality in the US. They find patterns similar to those observed by Stevenson and Wolfers (2008).

From a theoretical point of view, Van Praag (2011) argues that the "reference effect", i.e. the fact that individuals evaluate their conditions taking into account those of their peers, has to be taken into account in order to define properly the concept of well-being inequality.

From a different perspective, Guven et al. (2009) document that the husband-wife happiness gap has positive impact on the likelihood of separation, thereby assessing a specific case where happiness inequality reduces cohesion in a "small society" such as the household.

So far we have reviewed the happiness inequality literature. However, two additional streams of the literature are related to our paper, concerning the relation between income inequality and happiness, and between happiness inequality and social cohesion, respectively.

As for the relation between income inequality and happiness levels, two bottom lines emerge from this literature (see, e.g., Alesina et al., 2004; Graham and Felton, 2006): i) the more income inequality is perceived as a signal of an unfair society, the more happiness is negatively affected by income inequality; ii) the higher the perception of vertical mobility, the lower the sense of unfairness generated by inequality.

Shifting the focus from levels to inequality of happiness, a unified theoretical approach that investigates the relation between income inequality and happiness inequality at the micro level is still lacking. On the one hand, in a simplified utilitarian approach where happiness depends only on personal or household income, an increase in income inequality would generate – under standard microeconomic assumptions - an increase in happiness inequality. In a richer setting, one might claim that the gap from the income of the reference group might generate positive effects on happiness inequality also because of envy issues (Van Praag, 2011). Furthermore, in a framework where jobs characterized by high incomes are also associated to higher work satisfaction and greater capability in evaluating the working time as enjoying and stimulating, an increase in income inequality might generate a more than proportional impact on happiness inequality, since all these non pecuniary factors are supposed to enlarge differences between the wealthy and the poor (Scitovsky, 1974).

On the other hand, income inequality may be paradoxically perceived as even positive by the poor, reducing happiness inequality, since it can be considered as a signal of what they might achieve in the future, the so called tunnel hypothesis effect (Hirschman, 1973).[5] In these cases, expectations of vertical mobility are such that income divide does not translate into happiness divide and economic inequality may be not at odd with social cohesion.

The only available empirical evidence concerning income inequality and happiness inequality are carried out in a macroeconomic framework, by means of cross-country analysis. For instance, Ovaska and Takashima (2010) observe that income inequality positively affects happiness inequality.

[5] See Senik (2004), Jiang et al. (2009) and Becchetti and Savastano (2010) for empirical evidence.

As for the relation between happiness inequality and social cohesion, both "discontent theories" and "expected utility theories" of social protest predict a positive relation between happiness gaps and social unrest. According to "discontent theories", lack of happiness has a strong effect on social upheaval (e.g. Brown, 1996, Gurr, 1996). According to "expected utility theories", rational individuals participate in rebellious actions only if the costs are lower than the expected gain (Tullock, 1971). However, expected gains are reasonably proxied by the satisfaction gap between happy and unhappy people times the probability of riot success, suggesting that the happiness gap has a crucial effect on social unrest (Guimaraes and Sheedy, 2010).

3. Sample and descriptive findings

The GSOEP is one of the most widely used panel databases containing information on life satisfaction (see, e.g., Frijters et al. 2004a and 2004b). We select for our inquiry two time periods, the first one including the years 1992, 1993, and 1994, and the second one the years 2005, 2006, and 2007. This time span is homogeneous from a social and political point of view, being posterior to the German reunification. Excluding the individuals for which at least one variable of the analysis is missing, we end up with 24,560 observations for the first time period and 34,339 for the second period.

The main variable of interest, Life Satisfaction, is measured in the GSOEP database as a 0-10 categorical ordered variable.[6] In this work we assume the cardinality of this variable (see section 5 for a justification of this assumption) and this enables us to

[6] The GSOEP question is "How satisfied are you with your life, all things considered?". The responses are rated from 0 (completely dissatisfied) to 10 (completely satisfied). It is important to stress that, while the stream of literature which we follow is focussed on the analysis of "happiness inequality", available data are concerned with individuals' life satisfaction, a concept closely related, but that might be not identical to happiness. In the interpretation of the results this caveat should be taken into account. However in the literature the two terms are often used as synonyms and results on their determinants are substantially unchanged in surveys where both questions (on life satisfaction and happiness) appear. As well, it is not unusual in the happiness literature to make mixed use of happiness and life satisfaction data. For instance, in the World Database of Happiness (Veenhoven, 209) for some of the countries data comes from life satisfaction questions. Also Clark et al. (2012) uses different data sources, some on happiness data and some on life satisfaction data.

evaluate some standard measures of distribution inequality, viz. variance and Gini index.

On average, in Germany happiness decreased over time from 6.955 to 6.790 (-2.5%), while happiness inequality increased over the period, since the variance increased by 7.9%, from 3.221 to 3.474 and the Gini index increased by around 7%, from 0.137 to 0.146.[7] These trends are consistent with those observed for happiness in the World Database of Happiness (Veenhoven, 2009), which documents an increase in inequality in Germany.[8] As observed above, a similar trend in the same time period is observed in the US by Stevenson and Wolfers (2008). It is also worth noting that, according to the World Database of Happiness, in most of the developed countries happiness inequality has decreased (Clark et al, 2012). In such a framework, the German case represents a peculiar and interesting case to study.

In order to find out which are the driving forces of happiness inequality we focus on those covariates the literature has shown to be important determinants (age, income level, income inequality, relative income, education, marital status and having children, employment status, saving status and house ownership). In particular, to measure the income variable, we consider the yearly equivalent household disposable income, adjusted by the OECD price deflator (base year 2007). As for income inequality, we make use of two dummy variables, the first one concerning the individuals with an income lower than 60% of median income, the second regarding those with an income greater than 200% of the median. Relative income is also considered in order to control for the influence of the reference group (Van Praag, 2011). It is derived by computing the median income of the reference group (individuals with the same gender, age class, education, Lander), and then deriving

[7] Note that there is evidence of a significant drop in self reported life satisfaction as an individual is in the panel for a long period (Frijters and Beatton, 2008). However, our results are not affected by this problem, since we analyze data in a cross section perspective.

[8] In particular, standard deviation of happiness increases from 1.77 in 1993 (source: SOEP), to 2.22 in 2007 (source: European Social Survey, ESS).

the share of individuals under (above) the 60% (200%) of the median income of the reference group median.[9] Table A1, in Appendix, provides definitions of these covariates, while Table 1 reports covariates' mean values in the two considered time periods.[10]

The main trends observed in the GSOEP sample are the following: a) the population is getting older and more educated; b) the shares of widowed, separations, divorces, (included in the variable 'no more married') increase, as well as the share of households without children, while the share of marriages decreases; c) the average income level increases, as well as the income inequality, since the share of individual under (above) the 60% (200%) of the median income raise;[11] d) on average, the share of individuals under (above) the 60% (200%) of the median income of the reference groups increase; e) the employment rate is basically stable (slightly higher in the second period) while the unemployment rate increases, and the share of retired decreases; f) the share of house owners increases slightly over time, while g) the share of individuals having a saving account gets lower.

Can the rise in happiness inequality be explained by the above mentioned changes in covariates and to what extent? In the following section we outline the methodological approach which allows answering to these questions.

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[9] One might suspect that the variables being poor (rich) and being relatively poor (rich) are highly correlated. Actually, this is not the case, since the correlation is around 0.4, and hence this does not prevent to use both set of variables in the model specification.

[10] For an overview of findings on happiness determinants see, among others, Frey and Stutzer (2002a), Dolan et al. (2008), and Clark et al. (2006).

[11] The increase in income inequality in the nineties is consistent with the documented increase in wage inequality in both East and West Germany (Gernandt and Pfeiffer, 2007, Dustmann et al., 2008).

4. The decomposition approach and its application to happiness data

4.1. Methodological problems

In this section we briefly summarize the methodological problems concerning the happiness literature, both in general and with respect to inequality issues. Other methodological issues regarding the Gini index as a measure of happiness inequality are instead discussed in section 5.

In the happiness literature, two main issues deserve to be mentioned. First, there are no a priori reasons to assume that scales used for self reported happiness are homogenous across different individuals, suggesting extreme caution when making interpersonal comparisons (Harsanyi, 1955). Second, evaluation of happiness inequality requires the assumption of cardinality of self reported happiness.

As for the first issue, several authors observe that scale heterogeneity does not prevent the use of happiness data in empirical analysis. Cantril (1965) finds that individual evaluations on the 0-10 scales are quite comparable. Di Tella and McCulloch (2006) argue that, even in presence of heterogeneity in individual scales, there are no a priori reasons to believe that such heterogeneity is systematically affected by drivers of happiness. In the same vein, Frey and Stutzer (2002a) admit the existence of heterogeneity in the scales used for self-reported happiness, but argue that this does not invalidate regression results, since they expect such heterogeneity to be random.

Beegle et al. (2012) provide a clear example of frame of reference bias, and tests empirically the validity of the Frey and Stutzer (2002a) argument by means of the vignette approach. The authors' findings confirm the presence of heterogeneity in individual scales, but also reject the hypothesis that such heterogeneity alters results of the standard regressions.

The second methodological issue concerns the fact that the happiness variable is usually reported in an ordinal scale, while the analysis of happiness inequality requires a cardinal concept, since we want to detect not only if an individual is happier than another, but also how much she/he is happier.

Several works pointed out that considering happiness as either cardinal or ordinal leads to similar results in a regression framework (Ferrer-I-Carbonell and Frijters, 2004; Van Praag and Ferrer-i-Carbonell, 2004, 2006; Van Praag, 2007).[12] Further, Clark et al. (2009) observe that doctors implicitly reveal to believe in cardinality when asking to their patients how much a given part of the body hurts after a touch (and base on an implicit comparison of other patients' declarations their evaluation of the relevance of the pain). As a matter of fact, doctors and psychologists also use cardinality in the self assessed health (SAH) literature with measures that are precise predictors of future mortality and morbidity (Idler and Benyamini, 1997).

More in general, especially in social sciences, ordinal categorical variables are often treated as cardinal. Based on the reported evidence, we treat our dependent variable, self-reported happiness, as cardinal.

4.2. *Decomposition methodology*

In this subsection we illustrate the decomposition methodology applied to happiness inequality.

Let Y be the self reported degree of happiness. Let also Y_{i1} be the happiness of an individual i observed in period 1, and Y_{i0} the corresponding value in period 0. For each individual i the observed degree of happiness is $Y_i = Y_{i1} \cdot T_i + Y_{i0} \cdot (1 - T_i)$, where

[12] Van Praag (2007, p. 18) argues that *"All these specifications amount to different specifications of the labeling system of the underlying indifference curves, but the indifference curves themselves are unchanged and are these indifference curves which are estimated, either by Ordered Probit, Logit or what else."*

$T_i = 1$ if individual *i* is observed in period 1, and 0 otherwise. Finally, let X be a vector of *K* individual covariates, which are observed in both periods.

The conditional mean of *Y* on *X* at time *t*=0,1 can be written as $E(Y|X, T = t) = X\beta_t$, where β_t is the vector of regression coefficients, which can be estimated by OLS.

The Oaxaca-Blinder (henceforth OB) decomposition (Blinder, 1973; Oaxaca, 1973) allows to break down the overall difference in means, $\Delta_O^\mu = \mu_1 - \mu_0$, into two components, one related to the changes in the returns of the set of covariates, the *coefficient* or *structure effect*, Δ_S^μ, and the other linked to the changes in the distribution of these covariates, the *composition effect*, Δ_X^μ. These two effects can be easily derived by adding and subtracting a counterfactual mean, for instance $E(X\,|\,T=1)\beta_0$, as in the following:

$$\begin{aligned} \Delta_O^\mu &= \mu_1 - \mu_0 = E(X \mid T = 1)\beta_1 - E(X \mid T = 0)\beta_0 \pm E(X \mid T = 1)\beta_0 = \\ &= E[X \mid T = 1](\beta_1 - \beta_0) + (E[X \mid T = 1] - E[X \mid T = 0])\beta_0 = \Delta_S^\mu + \Delta_X^\mu \end{aligned} \tag{1}$$

thus yielding the "aggregate" decomposition.

By means of the OB decomposition, it is also possible to identify the contribution of each covariate to these two effects, the "detailed" decomposition:

$$\begin{aligned} \Delta_S^\mu &= E[X|T=1](\beta_1 - \beta_0) = \sum_{k=1}^{K} E[X_k|T=1](\beta_{1,k} - \beta_{0,k}) \\ \Delta_X^\mu &= (E[X|T=1] - E[X|T=0])\beta_0 = \sum_{k=1}^{K} \{E[X_k|T=1] - E[X_k|T=0]\}\beta_{0,k} \end{aligned}$$

where X_k and $\beta_{t,k}$ are the *k*-th elements of the vector of covariates and of the vector of regression coefficients, respectively.

Fortin et al. (2011) extend the aggregate and the detailed decomposition of the mean provided by Oaxaca-Blinder to any distributional parameter other than the mean, ν, like median, quantiles, variance or Gini index. We define this method as FFL decomposition.

The basic idea is to estimate a linear regression where Y is replaced by the recentered influence function (RIF) of the parameter ν, $RIF(y;\nu)$. The RIF is obtained by adding the distributional parameter of interest to the influence function $IF(y;\nu)$. The influence function (Hampel, 1974) is a statistical tool, used to assess the robustness of a distributional statistic to the presence of outliers, which detects the contribution (also defined as *influence*) of each observation to the distributional parameter of interest. As an example, the influence function of the variance is $(y-\mu)^2-\sigma^2$, and the RIF is $\sigma^2+\left[(y-\mu)^2-\sigma^2\right]=(y-\mu)^2$. Hence, each observation is replaced by its squared difference from the mean.[13]

An useful property of the $RIF(y;\nu)$ is that its expected value coincides with the statistic of interest. Hence, using the law of iterated expectations, it is possible to write:

$$\nu = E[RIF(Y;\nu)] = E_X\{E[RIF(Y;\nu)|X]\} \tag{2}$$

In its simplest form, the conditional expectation of the $RIF(y;\nu)$ can be written as a linear function of the covariates, yielding the RIF regression (Firpo et al, 2009):

$$E[RIF(Y;\nu)|X] = X\gamma^{\nu} \tag{3}$$

where the parameters γ_t^{ν} can be estimated by OLS.

[13] For the influence function of the Gini coefficient see Monti (1981).

Similarly to the case of the mean, it is possible to decompose the overall difference over time of ν, $\Delta_O^\nu = \nu_1 - \nu_0 = \Delta_S^\nu + \Delta_X^\nu$, where, analogously to the Oaxaca-Blinder decomposition, the coefficient and composition effects can be written as:

$$\begin{aligned} \Delta_S^\nu &= E[X|T=1]' (\gamma_1^\nu - \gamma_0^\nu) \\ \Delta_X^\nu &= (E[X|T=1] - E[X|T=0])' \gamma_0^\nu \end{aligned} \tag{4}$$

Note, however, that the above decomposition holds only in the case of a linear specification of the conditional expectation (2). Barsky et al. (2002) show that, in the case of the mean, the OB decomposition is biased.

Fortin et al. (2011) observe that this bias can occur also for other distributional statistics. Hence, they suggest a solution based both on the Di Nardo et al. (1996) reweighing procedure and on the RIF regression. By reweighing the distribution of X's in period 0 to have the same distribution as in period 1, it is possible to estimate the counterfactual mean $\overline{X}_{01}$, as well as the counterfactual coefficients $\hat{\gamma}_{01}^\nu$ from the regression of $RIF(Y_0;\nu)$ on the reweighted sample.

Hence, in line with (1), by adding and subtracting the counterfactual estimated RIF-regression $\overline{X}_{01}\hat{\gamma}_{01}^\nu$ it is possible to decompose the overall change as:

$$\Delta_O^\nu = \left[\overline{X}_1 \hat{\gamma}_{01}^\nu - \overline{X}_{01} \hat{\gamma}_{01}^\nu\right] + \left[\overline{X}_{01} \hat{\gamma}_{01}^\nu - \overline{X}_0 \hat{\gamma}_0^\nu\right]. \tag{5}$$

Equation (5) is defined as the "reweighted-regression" decomposition. However, this decomposition entails both a specification and a reweighting error. Then, the "pure" composition effect is estimated as:

$$\Delta_{X,p}^\nu = \left(\overline{X}_{01} - \overline{X}_0\right)\hat{\gamma}_0^\nu \tag{6}$$

and the "pure" coefficient effect as:

$$\Delta^{\nu}_{S,p} = \overline{X}_1\left[\hat{\gamma}^{\nu}_1 - \hat{\gamma}^{\nu}_{01}\right] \qquad (7)$$

In practice, the decomposition is carried out by means of two OB decompositions (Fortin et al., 2011):

1) a decomposition in which we consider the sample at period 1 and the counterfactual sample to get the pure structure effect. The composition effect of this decomposition is the *reweighting error*;
2) a decomposition with the counterfactual sample and the sample at period 0, which allows deriving the pure composition effect. The structure effect of this decomposition is the *specification error*.

As a final remark, note that other decomposition methodologies of happiness inequality have been considered in the literature. Ferrer-i-Carbonell and Van Praag (2003) decompose the variance of income satisfaction by means of a stepwise regression. They also consider the standard variance decomposition between and within East and West Germany. Dutta and Foster (2011) measure the gross contribution of gender, race and region to happiness inequality, by using the methodology to measure inequality for ordinal variables proposed by Allison and Foster (2004). However, both approaches do not allow to decompose the overall change in happiness inequality into the coefficient and covariate effects. Stevenson and Wolfers (2008) propose to decompose happiness inequality based on the decomposition approach introduced by Lemieux (2002). This methodology allows only to identify the aggregate contribution of changes in regression coefficients, distribution of covariates, and residuals, while the detailed decomposition, i.e. the contribution of each covariate, is not identified.

By contrast, the methodology proposed here allows to identify the contribution of each covariate to the changes in happiness inequality.

5. The econometric analysis: results

The econometric analysis is divided into two parts. In the first one, we investigate the cross-sectional impact of standard happiness drivers on happiness inequality, for the two time periods considered, by means of the RIF regressions. We make use of two inequality indices, the variance, which represents a standard measure of distributional inequality, and the Gini index, as robustness check. In the second step, we apply the decomposition analysis to quantify the relevance of composition and coefficient effects in affecting the observed changes in happiness inequality.

As for the Gini index, there are at least two main additional methodological concerns. The first minor regards the fact that happiness is not "transferable", while the Gini index is usually defined over transferable variables. However, it has been observed that this interpretation may be too literal (Petrie and Tang, 2008), hence the transferability of a variable is not essential for the definition and the measurement of inequality with the Gini index.

The second concern is more crucial. When dealing with bounded variables, as happiness, the measurement of inequality by means of the Gini index is underestimated. In fact, the hypothetical situation in which one individual owns the total amount of happiness is not attainable, since the happiness variable is upper limited (Petrie and Tang, 2008; Erreygers, 2009). This means that with bounded variables the theoretical maximum level of inequality is smaller that the one derived with transferable variables.

One possible solution is to standardize the Gini index by using the maximal attainable Gini index for bounded variables, as suggested by Petrie and Tang (2008) to measure health satisfaction inequality.[14] For the purpose of this paper, this option is

[14] To provide an intuition about the standardized Gini index, assume a population of 10 individuals in which the sum of happiness levels is 40. In such a case, Petrie and Tang (2008) identify the

not feasible since the influence function for a standardized Gini index is not available in the statistic literature.

However, we claim that applying the FFL decomposition to the Gini index can anyway represent an interesting robustness check for the analysis computed on the variance, for three main reasons. First, we empirically observe that the dynamics of the standardized Gini coefficients is very close the that of the Gini index, with an increase in happiness inequality of about 6%. Second, we find that the Gini index underestimates the standardized Gini index of around 45% in both periods, suggesting that the underestimation does not differ over time. Third, it is important to stress that the numerator of the Gini index is the same as the one of the standardized Gini index, the only difference being the denominator, i.e. the two indexes are the same apart from a scale factor.

In such a framework, we argue that the composition and coefficient effects are meaningful, even if they have to be interpreted as the impact of each single covariate or coefficient on the variation of the Gini index, and not of the standardized Gini index. Interestingly, as we will show in the following sections, the results derived by applying the FFL decomposition to the Gini index are very close to the ones derived for the variance.

5.1. First step: RIF regressions and the identification of the drivers of cross sectional happiness inequality

Table 2 reports the results of the RIF regressions for the two periods examined separately (1992-93-94 and 2005-06-07), for the variance and for the Gini index. Coefficients measure the impact of each covariate on the inequality measure considered. While there are many contributions concerning the determinants of

maximum of the reachable happiness inequality as the case where 4 people were associated to the maximum level of happiness (10) and the other 6 to a value of happiness equal to zero.

happiness levels, there is very little evidence about the determinants of happiness inequality. For this reason, this first step of the analysis represents an important finding of the paper *per se*.

With regard to the contribution of each single covariate on the variance of happiness, education has a significant and monotonically negative impact, regardless the period observed (see Table 2 and Section 5 for a more detailed discussion of this finding). An intuition of what is behind this econometric result is given by the analysis of the histograms of the happiness distribution for low, medium and high education levels (Figure 1): the comparison between low and high education happiness distribution clearly shows that higher education is related to a reduction in the density of both the left and the right tail (i.e. individuals with very low or very high satisfaction scores). This evidence is also consistent with the fact that the happiness variance decreases in the level of education, and that this relation is steeper in 2005-07 (Figure 2). It is also worth noting that happiness inequality widened among educational groups in the US as well (Stevenson and Wolfers, 2008).

As for the income level, it is interesting to note that the higher the income the lower the happiness inequality, and the relation is highly significant and does not change much overtime. Moving to our measure of income inequality, it comes out that being poor (having an income lower than 60% of the median income) entails an increase in happiness inequality, effect that increases over time, while being rich (above the 200% of the median) has no effect on happiness inequality.

Similar findings are derived when considering being poor or rich with respect to the reference group, with the former having a positive impact and the latter a non significant impact on happiness inequality.

As for the employment status, being employed reduces inequality, while being unemployed has a positive effect, and the effect of being retired is never significant. As it can be seen in Figure 3, trends of variance indexes computed by employment status in the two periods examined resemble those of corresponding RIF regression coefficients.

With regard to the effect of age on happiness inequality, we observe a concave trend, first increasing until the 45-54 age class, then decreasing. The effect is always significant only for individuals aged from 35 to 54, i.e. happiness in these age categories displays a large variability that increases over time. The reverse U-shape of the relation between age and happiness inequality is consistent with the time pressure explanation that concerns mainly prime aged individuals (Engfer, 2009).[15] There is also a remarkable increase in the age effect for the elderly, in 2005-07, with respect to 1992-94. The reverse U-shape effect can also be seen in Figure 4, where variance indexes by age classes are reported.

Living in the East Länders increases inequality, but the effect decreases over time. The disabled worker status has a negative impact on both indices.[16] Note that its effect falls dramatically in 2005-07 in variance regression estimates.

Being divorced or separated, with respect to being single, has a significant positive effect on inequality in both periods. Having no children significantly increases happiness inequality only in the second period.

Finally, having a saving account reduces happiness inequality, as expected, effect that is partially counterbalanced by a negative effect related of being a home owner.

As robustness check in Table 2 we also report the RIF regression using the Gini index. It is reassuring to note that there are no important differences with respect to the coefficients computed in the variance analysis, i.e. same signs and statistical

[15] Our finding closely resembles the often documented U-shaped relationship between age and happiness levels (among others, Frijters and Beatton, 2008 and Van Landeghem, 2008).

[16] Note that disability has gradually become in Germany a shock absorber in the labour market. In principle, d*isability benefits* are provided by the German system to workers of all ages not able to carry on a regular employment. See Börsch-Supan and Wilke (2004) for details on this issue.

significance, and similar magnitude once taking into account the different scale between the two inequality indexes.

5.2. *Second step: Decomposition results*

The results of the decomposition analysis of the Variance are reported in Table 3, which includes also the decomposition results for the Gini index as robustness check. As a general remark, it is important to underline that the composition effect almost entirely explains the variation of variance over time, while coefficient effect is never significant, as well as the contribution of almost all covariates to the coefficient effect.[17] This suggests that the effects of the determinants of happiness inequality remain stable over time. Hence, we focus our comments on the analysis of the composition effect.

From an economic point of view, three main findings emerge. First, education negatively affects the variation of happiness inequality. Had only the shares of education levels changed over time, the variance of happiness inequality would have decreased by 0.028 (11% of the overall between period change). In order to ease the comprehension of the composition effect, note that it is computed using equation (6), which includes two elements. The first is the over time change of the covariate composition[18] and the second is the coefficient at time zero. In the case of education, the composition effect is negative since increase in the shares of medium and high education, as documented in Table 1, is multiplied by a negative coefficient as it can be seen from RIF regression results (Table 2). It is also worth noting that this result is

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[17] Note also that the errors components are not statistically different from zero, meaning that the linear approximation holds true and that the reweighing procedure works fine.

[18] Actually this term is equal to the difference between X_{01}, the counterfactual composition of covariates at time 0 weighted in order to have the same distribution as in time 1, and X_0.. Note that since the reweighting error is close to zero and not statistically different from zero then $X_{01} \rightarrow X_1$. More in general, to derive both composition and coefficient effects reported in Table 3, one needs the counterfactual mean of each covariate and the counterfactual coefficient. In order to not burden the paper, we do not report these figures, as usual in the related literature (see, for instance, Firpo et al. 2011 and Fortin et al., 2011). However, they are available on request.

robust to the definition of the education variables. We also used the variable 'year of education' in terciles categories, and results (available upon request) were even stronger.

Second, interesting results come out from the labour market variables. The increase in unemployment rates over time (from 7.1% to 9.7%) has a strong and positive impact on the evolution of happiness inequality (more than 30% of the variance variation), due to the fact that unemployed coefficient is negative (Table 2).

Third, the increase in average income between the two time periods entails a negative impact on happiness inequality (-7% of the total variance variation). This is consistent to what Clark et al. (2012), whose findings based on the World Values Survey suggest that "raising the incomes of all will not increase the happiness of all, but will reduce its variance".

Fourth, the increase in income inequality has a little impact on happiness inequality. In particular, the increase in the share of poor generates a significant positive impact that, however, accounts only for the 3% of the total variance variation, while the increase in the share of rich has a non statistically significant impact. The finding implies that the strong increase in wage and income inequality observed in Germany (Dustmann et al 2008, Gernandt and Pfeiffer, 2007) – and in our data as well - cannot be considered as one of the driving forces of the increase in happiness inequality, because of the small size of the impact. This also suggests that the non-pecuniary drivers of happiness, such as the distribution of education, age, and employment status (conditional on income) are behind the increase in happiness inequality. Our result is also consistent with the findings derived by Stevenson and Wolfers (2008) for the US: different dynamics over time are observed for income and happiness inequality, suggesting - also for the US case - the importance of the role of non-pecuniary drivers in shaping the evolution of happiness inequality. Since income inequality can be computed in different ways, we have carried out a robustness using the RIF of the variance of income, equal to $(y_i - \mu)^2$, which represents for each individual the square distance to the mean in that period, and hence can be considered as the individual contribution to the income inequality.[19] From Table 4 it comes out that results are very similar to those in Table 3: the impact of income inequality is quite small and explain only the 2% of the total variance variation (3% in Table 3).

Another interesting finding is that relative income positively affects in a more relevant way the increase of happiness inequality. More specifically, the over time change in being relatively poor explains 14% of the variance variation, while being relatively rich has no effect. This evidence can be considered as a preliminary test of Van Praag (2011), which stresses the importance of relative living conditions to address happiness inequality issues. However, note that this result might depend on the way the reference group has been computed.

Furthermore, the reduction in the share of those who have a saving account positively affects happiness inequality. This is due to the fact that, according to the RIF regression in Table 2, having a saving account is associated to lower inequality, and since the share of individuals with a saving account decreased over time the impact of this variable on the evolution of inequality is positive. Note however that, the other proxy for financial conditions and wealth, house ownership, is slightly significant in the decomposition, negative, and much smaller in magnitude.

Demographic changes are noticeable only for the 35-45 and 45-54 age classes, which have both a positive effect on the evolution of the happiness inequality (15% of total Variance variation over time), consistently with findings emerging from RIF regressions in Table 2. Further, from descriptive statistics in Table 1 it emerges that the

[19] Note that to compute this variable we forced the mean income to be the same in both period, since variance, as is well known, is not scale independent. That is to say that variance could increase only due to the raise in mean income.

size of these cohorts increased, because of the ageing of the German population and of the baby boomers. Hence, the rising inequality is explained by the higher population share ageing from 35 to 54 years, which displays higher happiness inequality, as confirmed also by Figure 4. As explained above, these findings could be related to time pressure effects.

As far as marital and familiar status, being married is the only covariate with a significant and positive impact on the dynamics of happiness inequality (with respect to the omitted category, 'never been married'). RIF regressions show that this variable is associated with lower levels of inequality. Hence, since the share of married individuals strongly decreases, the impact on inequality is positive and explains about 14% of the total change in the variance. A smaller impact is derived for being disabled, whose share increased only slightly over time.

Finally, the slight decrease in the share of those who live in the East Länders entails a negative effect on the variation of happiness inequality, since living in this area is positively associated to higher inequality (Table 2).[20] Since the socio-economic differences between West and East Germany are still pronounced, especially at the beginning of the period considered, we have also carried out two separate decomposition exercises for the two macro regions. The findings for the whole country are mainly driven by the West Germany.[21] This could be due to the small number of observations for East Germany (around 20% of the total), which might affect the significance of composition or coefficient effects. Since a more in-depth analysis of the drivers of happiness inequality in East Germany is beyond what achievable with our data, we discard this issue in what follows.

[20] A reasonable interpretation is that individuals in East Germany - after the fall of the communist regime and in a more competitive and less protected environment - suffer more from relative comparisons.

[21] Decomposition results for West Germany are very close to those derived for the whole country. The results computed separately for West and East Germany are available from the authors upon request.

In Table 3 we also report the decomposition results when using the Gini index as distributional measure. Interestingly, the main results are very close to the ones derived by using the variance, providing robustness to the analysis. In fact, using the Gini index we can confirm that changes in the index over time are mainly due to changes in covariates and not to changes in coefficients. Moreover, we derive results substantially similar to what previously observed, including the negative impact of education, the overall slight negative impact of income inequality, the positive impact of being unemployed and the inverse U-shape impact of age. Further, also the shares of happiness inequality trends explained by the changes in the covariates are very close to the ones derived for the variance.

5.3 Further result discussion

The negative composition impact of education on the dynamics of happiness inequality is one of the main finding of the paper, which deserves further investigation. In Table 5 we report the results of two separate logit regressions, to detect which covariates affect the probability of falling in the upper or lower tail of happiness distribution. We recode as Low happiness a degree of happiness lower or equal to 5, while High happiness corresponds to a degree higher than 8. Overall, results are consistent with previous findings: education affects negatively the probability to fail in the low happiness, while it is not significant with respect to the probability to being fully satisfied.

A general interpretation for the negative impact of higher education on the low tail of inequality is that education enables individuals to increase their set of "functionings" and, through them, to enhance their "capabilities", using the terms introduced by Sen (1999). Then, it is reasonable to relate the increase of functionings, and the enhancement of capabilities, to higher happiness. All this considered, assuming that an important part of happiness inequality is explained by fat low tails (higher share of individuals with very low happiness scores), we can argue that education, by enlarging the set of functionings and capabilities, reduces the probability that individuals lack of sufficient resources to avoid the "low satisfaction trap". For instance, more educated individuals are more likely to find satisfactory and well remunerated jobs, are relatively more able to care about their health and benefit more from leisure since they can appreciate a wider range of cultural products, as documented by Hayward et al. (2005).

However, the impact of education on the probability to being fully satisfied is not statistically significant. How can this less expected effect be interpreted? Our claim is that education raises aspiration levels and therefore, everything else being equal, the gap between realisations and aspirations.[22] In such a framework, the positive spillovers related to education and aspirations could be offset by the gap between realisations and aspirations.

Going back to the decomposition results, how can we explain the reducing impact of education on happiness inequality, and the relation between education and inequality that becomes stronger over time (Figure 2)? Since what we are measuring in the decomposition is a direct effect of education, net of the indirect effect via income generated by "returns to schooling", our findings can hardly be explained by the rise in skill wage differentials due to global integration and technological change occurred in the labour markets since the nineties. A possible interpretation for the increasing direct effect of education on happiness inequality might concern the higher and increasing capability of educated individual to enjoy the leisure time. This in turn can be related to the diffusion of the web and of new technologies which provides,

[22] The point is well resumed by Frey and Stutzer (2002b), and further discussed by Ferrante (2009), among others.

especially for skilled individuals, both an amount of additional information (together with an increase in its speed of circulation) and new tools to enjoy leisure and culture.

7. Conclusions

The contribution of our paper to the happiness literature lies in the investigation of determinants of both levels and over time changes of happiness inequality, and in the decomposition of happiness inequality changes in composition and coefficient effects. By applying the methodological approach proposed by Fortin et al. (2011) to the German case in the period 1992-2007, we find what follows.

First, most of the dynamics of happiness inequality is explained by the composition effect, while changes in coefficient effects are almost nil, documenting the invariance across time of what factors (and how much they) make individuals happier.

Second, happiness inequality has risen mainly due to the deterioration of labour market conditions and to a demographic effect (the increase in the middle age cohort population share). These changes have been less than compensated by the increase of the share of highly educated individuals which entails a negative effect on the dynamics of inequality. Further, the increase in income inequality cannot be considered as one of the driver of the increase in happiness inequality, consistently with the US case (Stevenson and Wolfers, 2008), while increase in income levels reduces inequality, confirming the findings of Clark et al. (2012).

We claim that the analysis of the drivers of happiness or happiness inequality may be useful in terms of policies as well. Indeed, policy makers can take into account, in addition to standard economic variables such as income and wage levels and inequality, also pieces of information related to happiness inequality, when deciding redistributive policies.

From the application on the German case, our main policy suggestion is that education is a crucial factor for social cohesion. Education has a direct effect in reducing happiness inequality and such effect has become steeper over time. The economic literature has deeply investigated the impact of this variable on individual earnings and as a factor of macroeconomic conditional convergence. As far as we know, this is the first time that such variable, net of its role on personal income, has been found to affect happiness inequality and, as such, to be a driver of social cohesion.

Beyond education, we also documented that labour market conditions have a direct smoothing effect on happiness inequality. This evidence provides straightforward policy implications: measures aiming at increasing (decreasing) the employment (unemployment) rate generate, apart from the clear cut effects on economic performance, additional spillovers in terms of reduction of happiness inequality and, in turn, of enhanced social cohesion.

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Tables

Table 1. Changes in the mean of covariates over time

	1992-93-94	2005-06-07
Female	0.505	0.531
Low Educated (*ISCED 1-2*)	0.196	0.127
Medium Educated (*ISCED 3-4*)	0.566	0.591
High Educated (*ISCED 5-6*)	0.238	0.282
Age 18_24	0.105	0.085
Age 25_34	0.263	0.195
Age 35_44	0.225	0.282
Age 45_54	0.208	0.242
Age 55_64	0.199	0.196
Disabled	0.079	0.095
Married	0.615	0.523
No more married	0.131	0.159
Children in the household	0.640	0.666
Income level (in thousands)	21.079	22.699
Poor (income lower than 60% if the median)	0.156	0.189
Rich (income greater than 200% of the median)	0.061	0.078
Relatively poor (<60% of reference group income)	0.233	0.306
Relatively rich (>200% of reference group income)	0.071	0.086
Living in the East	0.209	0.204
Employed	0.734	0.748
Unemployed	0.071	0.097
Retired	0.106	0.075
House owner	0.446	0.481
Having a saving account	0.815	0.695

GSOEP Weighted data. For variable definitions see Table A1 in the Appendix.

Table 2. RIF Regressions for the two periods, for the Variance and the Gini index.

	Variance						Gini					
	1th Period			2th Period			1th Period			2th Period		
	coeff	t-stud		coeff	t-stud		coeff	t-stud		coeff	t-stud	
Female	-0.020	-0.27		-0.303	-4.76	***	-0.001	-0.44		-0.009	-5.28	***
Medium_education	-0.356	-3.70	***	-0.202	-2.09	**	-0.013	-5.30	***	-0.011	-4.52	***
High_education	-0.435	-3.68	***	-0.359	-3.22	***	-0.014	-4.94	***	-0.020	-7.01	***
Age18_24	-0.322	-2.31	**	-0.246	-1.87	*	-0.010	-3.04	***	-0.009	-2.76	***
Age35_44	0.276	2.55	***	0.525	5.41	***	0.013	4.78	***	0.023	9.09	***
Age45_54	0.818	6.87	***	0.955	8.86	***	0.025	8.46	***	0.040	14.38	***
Age55_64	0.101	0.71		0.206	1.63		0.003	0.78		0.011	3.34	***
Disable	0.892	6.28	***	1.500	13.25	***	0.032	9.15	***	0.054	18.27	***
Married	-0.389	-3.31	***	-0.178	-1.90	*	-0.011	-3.81	***	-0.010	-4.29	***
No more married	0.141	0.97		0.321	2.91	***	0.006	1.73	*	0.006	2.21	**
No child in the HH	0.077	0.80		0.276	3.49	***	0.003	1.21		0.010	4.90	***
Income level	-0.005	-1.01		-0.008	-2.41	***	0.000	-3.15	***	0.000	-4.36	***
Poor	0.301	2.29	**	0.557	5.07	***	0.009	2.89	***	0.017	5.85	***
Rich	-0.148	-1.02		-0.282	-2.40	***	-0.004	-1.07		-0.007	-2.36	***
Rel. poor	0.535	4.61	***	0.262	2.78	***	0.015	5.28	***	0.010	4.14	***
Rel. rich	-0.206	-1.68	*	0.031	0.30		-0.006	-2.00	*	-0.004	-1.31	
Living in the East	0.673	6.75	***	0.170	2.13	**	0.039	15.93	***	0.016	7.68	***
Employed	-0.345	-3.17	***	-0.610	-5.96	***	-0.010	-3.64	***	-0.015	-5.72	***
Unemployed	3.047	18.46	***	2.251	16.05	***	0.079	19.37	***	0.073	20.02	***
Retired	-0.254	-1.67	*	-0.232	-1.53		-0.005	-1.29		-0.003	-0.79	
Owner	-0.291	-3.78	***	-0.119	-1.73	*	-0.012	-6.12	***	-0.009	-4.93	***
Saving Acc.	-0.889	-9.42	***	-1.058	-15.26	***	-0.028	-11.87	***	-0.033	-18.58	***
Constant	4.189	19.51	***	4.226	22.76	***	0.171	32.13	***	0.173	35.88	***
Obs.	24,560			34,339			24,560			34,339		
R^2	0.06			0.07			0.09			0.11		

*stands for statistically different from zero at 10%, ** at 5%, *** at 1%. For variable definitions see Table A1 in the Appendix.

Table 3. Decomposition of Life Satisfaction inequality changes: composition and coefficient effects, for Variance and Gini index.

	Variance						Gini					
	Composition			Coefficients			Composition			Coefficients		
	coeff	t		coeff	t		coeff	t		coeff	t	
Female	-0.0007	-0.24		-0.0990	-0.85		0.0000	-0.33		-0.0035	-1.21	
Medium_education	-0.0087	-2.00	**	-0.0394	-0.20		-0.0003	-2.63	***	-0.0016	-0.34	
High_education	-0.0193	-2.30	**	-0.0264	-0.27		-0.0007	-2.87	***	-0.0028	-1.22	
Age18_24	0.0060	1.81	*	0.0476	1.87	*	0.0002	2.29	**	0.0013	2.00	*
Age35_44	0.0150	1.83	*	-0.0097	-0.11		0.0007	3.60	***	0.0008	0.37	
Age45_54	0.0250	2.80	***	-0.0941	-0.72		0.0008	3.28	***	0.0006	0.22	
Age55_64	-0.0002	-0.10		-0.0924	-1.05		0.0000	-0.11		-0.0005	-0.23	
Disable	0.0167	2.33	**	0.0821	1.30		0.0006	2.68	***	0.0031	2.17	**
Married	0.0373	2.07	**	0.2973	1.59		0.0011	2.38	***	0.0057	1.25	
No more married	0.0030	0.51		0.0786	0.84		0.0001	0.95		0.0014	0.68	
No child in the HH	0.0019	0.47		0.1090	0.62		0.0001	0.83		0.0033	0.80	
Income level	-0.0179	-2.30	**	0.0409	0.22		-0.0008	-3.26	***	0.0027	0.53	
Poor	0.0077	1.00		-0.0474	-0.45		0.0003	1.37		-0.0009	-0.36	
Rich	0.0073	1.44		-0.0157	-0.59		0.0003	1.86	*	-0.0004	-0.63	
Rel. poor	0.0372	3.03	***	-0.1124	-0.92		0.0011	3.31	***	-0.0026	-0.92	
Rel .rich	-0.0022	-0.68		-0.0016	-0.07		-0.0002	-1.66	*	0.0003	0.43	
Living in the East	-0.0107	-2.25	**	-0.1075	-1.56		-0.0006	-2.68	***	-0.0050	-3.27	***
Employed	-0.0027	-0.88		-0.0811	-0.37		-0.0001	-0.94		-0.0022	-0.42	
Unemployed	0.0886	4.21	***	-0.1080	-1.58		0.0023	4.49	***	-0.0017	-1.07	
Retired	0.0070	0.92		0.0359	0.98		0.0001	0.67		0.0007	0.83	
Owner	-0.0098	-2.48	***	0.0853	0.91		-0.0004	-3.34	***	0.0004	0.19	
Saving Acc.	0.1002	4.83	***	-0.0817	-0.40		0.0031	5.91	***	-0.0029	-0.59	
Constant				0.0748	0.13					0.0043	0.31	
TOT	3.3820	0.01		5.5258	0.01		0.7358	3.95	***	0.000	0.33394	
Reweighing error	-0.0121	-0.4246					0.0003	0.3339				
Specification error	0.0493	0.43346					0.0006	0.247		0.001	0.24695	
Index change	**0.2530**	**3.38**	***				**0.0087**	**4.15**	***			
Obs	58899						58899					

*stands for statistically different from zero at 10%, ** at 5%, *** at 1%. Standard errors are computed bootstrapping the whole decomposition procedure (100 replications), as in Firpo et al. (2009). For variable definitions see Table A1 in the Appendix.

Table 4. Decomposition of Life Satisfaction inequality changes: composition and coefficient effects, for Variance and Gini index. Robustness check.

	Variance				Gini			
	Composition		Coefficients		Composition		Coefficients	
	coeff	t	coeff	t	coeff	t	coeff	t
Female	-0.0009	-0.31	-0.0923	-0.82	0.0000	-0.44	-0.0034	-1.23
Medium_education	-0.0084	-1.82 *	-0.0436	-0.27	-0.0003	-2.42 ***	-0.0016	-0.41
High_education	-0.0175	-2.34 ***	-0.0358	-0.40	-0.0006	-3.23 ***	-0.0029	-1.26
Age18_24	0.0059	1.51	0.0468	1.61	0.0002	1.85 *	0.0013	1.62
Age35_44	0.0154	1.78 *	-0.0140	-0.16	0.0007	3.17 ***	0.0007	0.34
Age45_54	0.0254	2.99 ***	-0.1022	-0.80	0.0008	3.66 ***	0.0005	0.17
Age55_64	-0.0002	-0.10	-0.1076	-1.13	0.0000	-0.12	-0.0008	-0.37
Disable	0.0169	2.22 **	0.0805	1.44	0.0006	2.53 ***	0.0030	2.42 ***
Married	0.0379	1.96 *	0.3206	1.48	0.0011	2.41 ***	0.0063	1.25
No more married	0.0029	0.46	0.0775	0.89	0.0001	0.87	0.0013	0.70
No child in the HH	0.0025	0.60	0.1186	0.70	0.0001	0.97	0.0037	0.95
Income level	-0.0269	-2.30 **	0.2523	0.72	-0.0010	-3.05 ***	0.0055	0.67
RIF Income	0.0054	1.68 *	-0.0369	-1.60	0.0002	1.86 *	-0.0008	-1.71 *
Rel. poor	0.0388	3.03 ***	-0.1202	-1.41	0.0011	3.58 ***	-0.0029	-1.40
Rel .rich	0.0008	0.21	-0.0094	-0.33	-0.0001	-0.52	0.0002	0.30
Living in the East	-0.0103	-2.65 ***	-0.1046	-1.37	-0.0006	-2.87 ***	-0.0050	-3.00 ***
Employed	-0.0027	-0.89	-0.0725	-0.34	-0.0001	-0.91	-0.0020	-0.40
Unemployed	0.0888	4.18 ***	-0.1039	-1.56	0.0023	4.46 ***	-0.0016	-1.04
Retired	0.0079	1.08	0.0403	1.10	0.0002	0.92	0.0008	0.93
Owner	-0.0093	-2.40 ***	0.0825	0.79	-0.0004	-3.14 ***	0.0004	0.18
Saving Acc.	0.1004	5.12 ***	-0.0743	-0.40	0.0031	6.56 ***	-0.0027	-0.60
Constant			-0.1636	-0.22			0.0005	0.03
TOT	58.4302	0.14	54.9281	0.15	0.7358	3.95 ***	0.000	0.33394
Reweighing error	-0.0128	-0.42			-0.0002	-0.21		
Specification error	0.0549	0.45			0.0009	0.31		
Index change	**0.2530**	**3.38** ***			**0.0087**	**4.15** ***		
Obs	58899				58899			

*stands for statistically different from zero at 10%, ** at 5%, *** at 1%. Standard errors are computed bootstrapping the whole decomposition procedure (100 replications), as in Firpo et al. (2009). For variable definitions see Table A1 in the Appendix.

Table 5. Determinants of the probability of falling in the life satisfaction distribution tails

	Low happiness			High happiness		
	Marg.eff.	t		Marg.eff.	t	
Female	-0.008	-1.45		0.020	4.34	***
Medium_education	-0.037	-4.94	***	0.000	0.00	
High_education	-0.047	-5.11	***	0.003	0.35	
Age18_24	-0.025	-2.27	**	0.028	3.11	***
Age35_44	0.067	8.15	***	-0.043	-6.45	***
Age45_54	0.097	10.80	***	-0.049	-6.64	***
Age55_64	0.029	2.68	***	-0.015	-1.66	*
Disable	0.118	12.18	***	-0.048	-4.61	***
Married	-0.017	-2.04	**	0.031	4.15	***
No more married	0.015	1.49		0.010	1.08	
No child in the HH	0.019	2.80	***	-0.002	-0.36	
Income level	-0.005	-10.93	***	0.001	2.79	***
Poor	0.002	0.20		-0.002	-0.17	
Rich	0.052	2.83	***	-0.005	-0.45	
Rel. poor	0.012	1.62		-0.006	-0.84	
Rel .rich	-0.001	-0.05		0.013	1.26	
Living in the East	0.099	18.33	***	-0.112	-17.31	***
Employed	-0.013	-1.61		0.006	0.87	
Unemployed	0.139	12.87	***	-0.051	-4.01	***
Retired	0.012	1.14		0.000	0.00	
Owner	-0.037	-6.81	***	0.021	4.54	***
Saving Acc.	-0.077	-12.09	***	0.019	3.19	***
Constant	-0.083	-4.99	***	-0.234	-18.05	***

*stands for statistically different from zero at 10%, ** at 5%, *** at 1%. The high happiness is defined as LifeSatisfaction>8, while the low happiness as LifeSatisfaction<=5. For variable definitions see Table A1 in the Appendix.

Figures

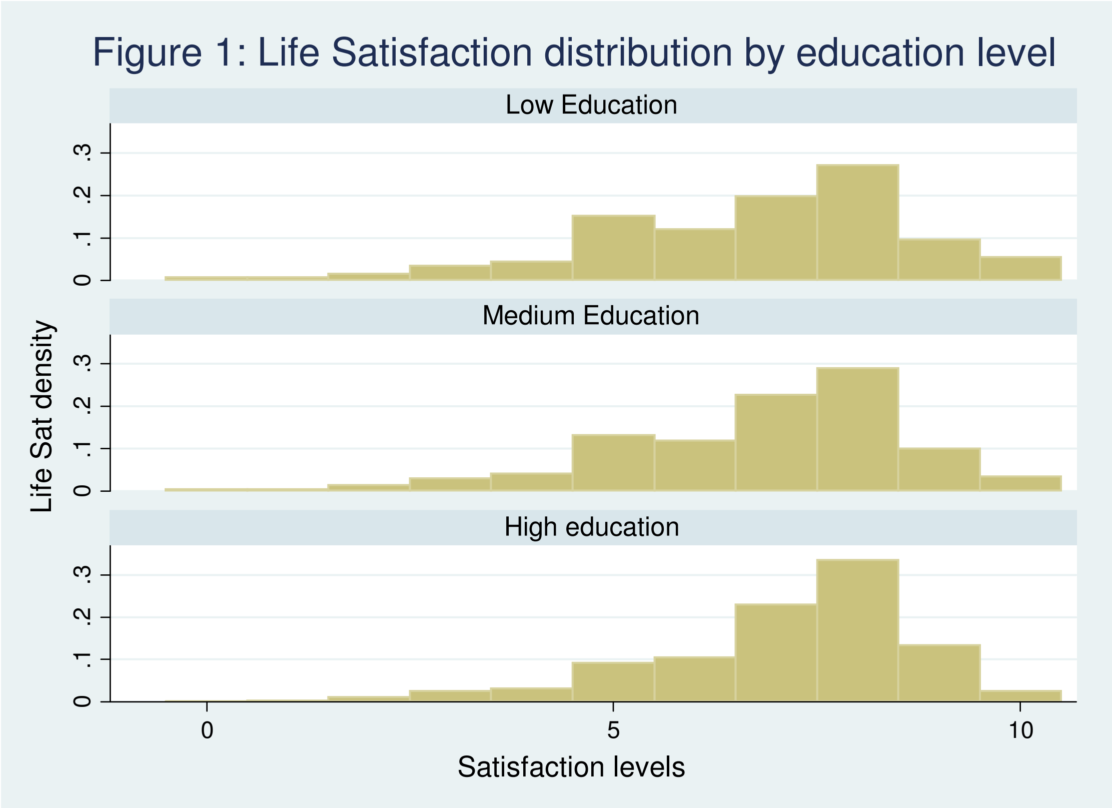

Figure 1: Life Satisfaction distribution by education level
Low Education
Medium Education
High education
Life Sat density
0
.1
.2
.3
0
5
10
Satisfaction levels

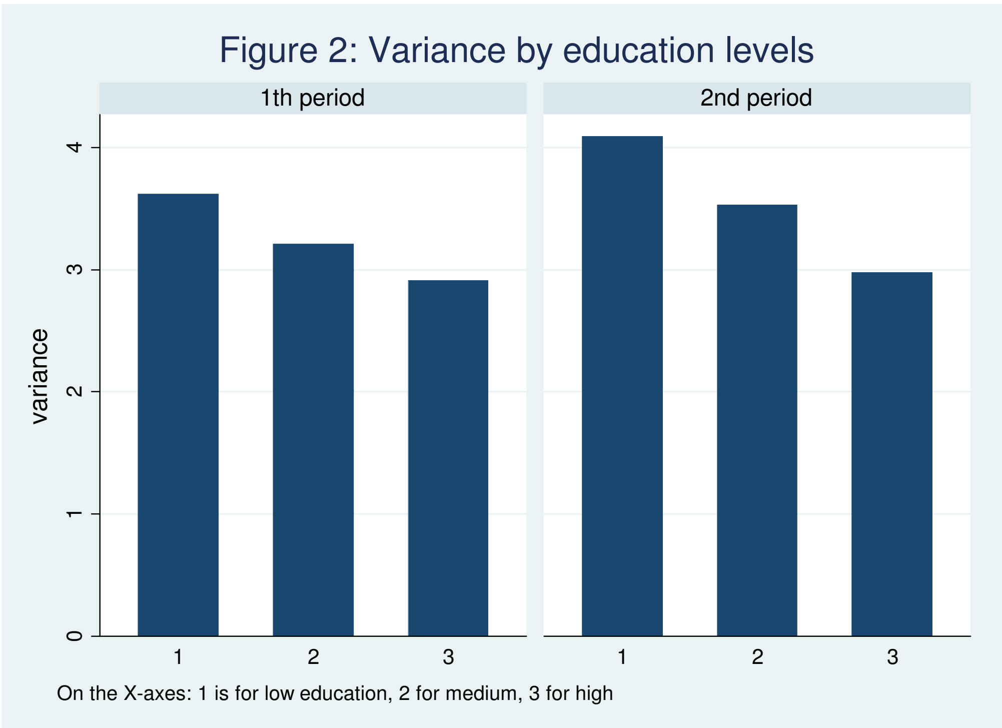

Figure 2: Variance by education levels
1th period
2nd period
variance
0
1
2
3
4
1
2
3
1
2
3
On the X-axes: 1 is for low education, 2 for medium, 3 for high

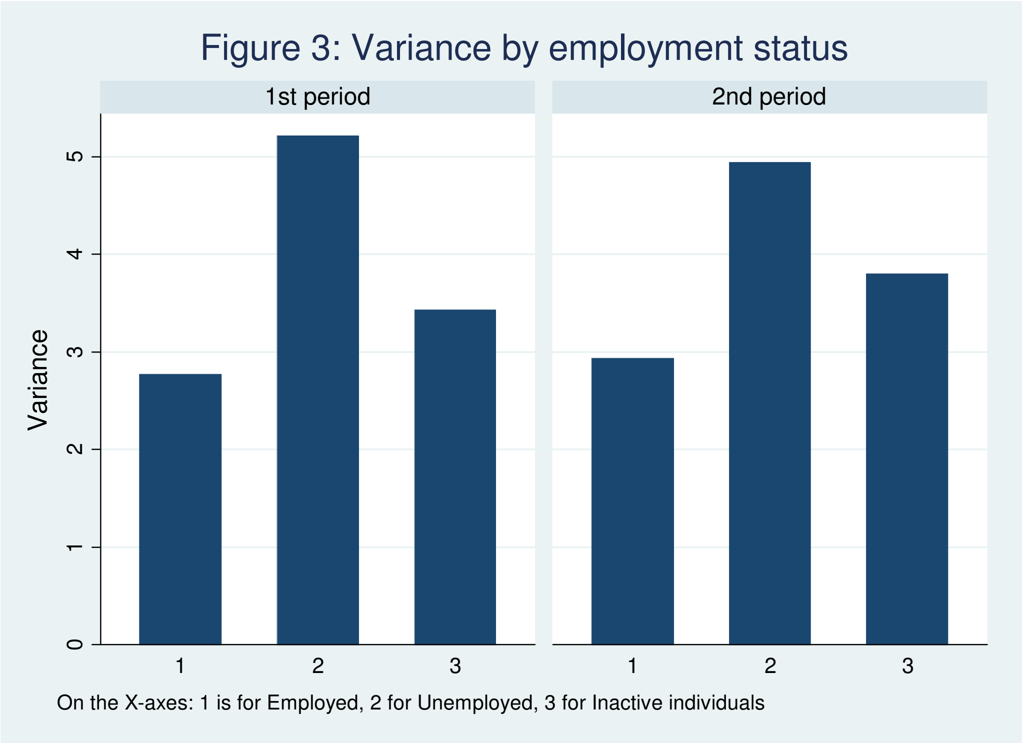

Figure 3: Variance by employment status
1st period
2nd period
Variance
0
1
2
3
4
5
1
2
3
1
2
3
On the X-axes: 1 is for Employed, 2 for Unemployed, 3 for Inactive individuals

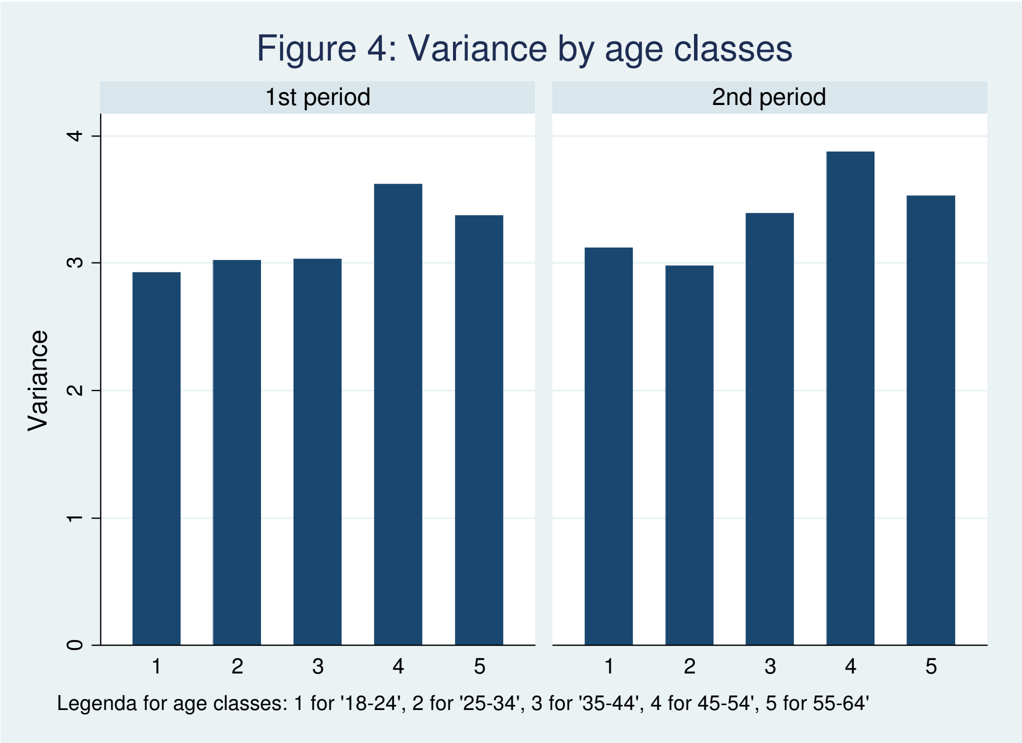

Figure 4: Variance by age classes
1st period
2nd period
Variance
0
1
2
3
4
1
2
3
4
5
1
2
3
4
5
Legenda for age classes: 1 for '18-24', 2 for '25-34', 3 for '35-44', 4 for 45-54', 5 for 55-64'

Appendix

Table A1: Definitions of the variables	
Male	Dummy variable equal to one if respondent is male
East	Dummy variable equal to one if respondent lives in the East
Age 17-24	Dummy variable equal to one if respondent's age is between 17 and 24
Age 25-34	Dummy variable equal to one if respondent's age is between 25 and 34
Age 35-44	Dummy variable equal to one if respondent's age is between 35 and 44
Age 45-54	Dummy variable equal to one if respondent's age is between 45 and 54
Age 55-64	Dummy variable equal to one if respondent's age is between 55 and 64
Low educ	ISCED category 1-2
Medium educ	ISCED category 3-4
High educ	ISCED category 5-6
Inc_1	Dummy variable equal to one if the respondent's income is in the first income quintile of the pooled sample (1991, 1992, 2006, 2007)
Inc_2	Dummy variable equal to one if the respondent's income is in the second income quintile of the pooled sample (1991, 1992, 2006, 2007)
Inc_3	Dummy variable equal to one if the respondent's income is in the third income quintile of the pooled sample (1991, 1992, 2006, 2007)
Inc_4	Dummy variable equal to one if the respondent's income is in the fourth income quintile of the pooled sample (1991, 1992, 2006, 2007)
Inc_5	Dummy variable equal to one if the respondent's income is in the fifth income quintile of the pooled sample (1991, 1992, 2006, 2007)
Rel. Poor	Being in the bottom quartile of the relative pooled income distribution
Rel. Rich	Being in the top quartile of the relative pooled income distribution
Unemployed	Dummy variable taking value of one if the respondent is unemployed
Employed	Dummy variable taking value of one if the respondent is employed
Disabled	Dummy variable equal to one if respondent is Disable
Retired	Dummy variable taking value of one if the respondent is retired
Married	Dummy variable taking value of one if the respondent is married
No more married	Dummy variable taking value of one if the respondent is separated
No child	Dummy variable equal to one if there are no child livign in the household
Saving Account	Dummy variable taking value of one if the respondent has a saving account
Owner	Dummy variable taking value of one if the respondent is house owner