DISCUSSION PAPER SERIES

IZA DP No. 7153

The Drivers of Happiness Inequality: Suggestions for Promoting Social Cohesion

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January 2013

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zur Zukunft der Arbeit
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Discussion Paper No. 7153
January 2013

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IZA Discussion Paper No. 7153
January 2013

ABSTRACT

The Drivers of Happiness Inequality: Suggestions for Promoting Social Cohesion*

This paper identifies and quantifies the contribution of a set of covariates in affecting levels and over time changes of happiness inequality. Using a decomposition methodology based on RIF regression, we analyse the increase in happiness inequality observed in Germany between 1992 and 2007, using 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 the increase in unemployment contributes to the rise in happiness inequality. Third, the increase in average income has a reducing impact on happiness inequality, while the raise in income inequality cannot be considered as a driver of happiness inequality trends. A clear cut policy implication is that policies enhancing education and economic performance contribute to reduce happiness inequality and the potential social tensions arising from it.

JEL Classification: I31, I28, J17, J21, J28

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

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* We are grateful to Elena Giachin for her support in the construction of the database. We thanks Nicole Fortin for clarifications about the methodology, Joseph Deutsch, Francisco Ferreira, Claudia Senik, Jacques Silber, Alois Stutzer, Ruut Veenhoven, Bernard Van Praag and Rainer Winkelmann for their suggestions, as well as the participants to the IZA workshop on redistribution and well-being (Lausanne, 2011), the ECINEQ conference (Catania, 2011), the AIEL conference (Pescara, 2010), the "Health, Happiness, Inequality" workshop (Darmstadt, 2010), the Scitovsky conference 2012 (University of Cassino), the SIE conference (Matera, 2012). We also thank the editor and two anonymous referees. Usual disclaimer applies.

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. 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), and Dutta and Foster (2011). 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 Fortin et al. (2011), based on the Recentered Influence Function (RIF) regressions (Firpo et al. 2009). This methodology represents a generalization of the Oaxaca-Blinder procedure, 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 to such determinants (*coefficient*, or *structure*, *effect)*. It is also possible to compute a more detailed decomposition, subdividing both the composition and coefficient effects into the contribution of each covariate.[2]

[1] The investigation of the determinants of happiness has been one of the most salient topics in economics 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).

[2] The approach has been already used to investigate wage inequality trends (Chi and Li, 2008; Firpo et al., 2011).

Identifying and quantifying the contribution of each driver on levels and over time changes of happiness inequality matters from a policy perspective, since it allows policy makers to intervene on the reduction of social tension through policies aimed at affecting drivers of happiness inequality (Tullock, 1971; Brown, 1996; Gurr, 1994). Further, it is possible to disentangle 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, since 2011 the UK government planned to evaluate happiness of people with wellbeing indicators and to focus 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, 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 happiness inequality, in terms of variance and Gini index, by means of RIF

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[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. Furthermore, in 2012 the first experimental results of the Programme "Measuring National Well-being" has been released by the UK Office for National Statistics (2012).

regressions. In the second, we identify and quantify the role played by each single covariate in shaping the evolution over time of happiness inequality, by means of the decomposition method.

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, basically the whole dynamics of happiness inequality is explained by the composition effect, while the coefficient effect is negligible, suggesting that returns to drivers are substantially invariant over time. Second, the increase in education level has a reducing effect on happiness inequality. Third, the increase in the unemployment rate 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 recent evidence provided by 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 policies aimed at fostering education and economic performance, in terms of lower unemployment rate and higher average income, reduce happiness inequality and 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 (income, wages, consumption) generally used for the planning of redistributive measures. 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 describe our sample and provide descriptive findings. In section 4 we outline analytical features of the decomposition approach. In section 5 we present the econometric findings, while the sixth 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 2005) observes that happiness is more equally distributed in countries that are more economically stable and developed.

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.

Similar findings for the US have been derived by Dutta and Foster (2011), which adopt the approach of Allison and Foster (2004) for ordinal variables

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 considered in order to define properly the concept of well-being inequality.[5]

So far we have reviewed the happiness inequality economic 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 (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 to the relation between income inequality and happiness inequality, a unified theoretical framework in the microeconomic literature is still lacking. On the one hand, in a simplified utilitarian framework 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, 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, 1973).

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[5] From a different perspective, Guven et al. (2012) 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.

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, i.e. the so called "tunnel effect" (Hirschman, 1973).[6] 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 odds with social cohesion.

Besides the few microeconomic studies discussed above, the relationship between income inequality and happiness inequality have been mainly investigated in a macroeconomic framework, by means of cross-country analysis. For instance, Ovaska and Takashima (2010) observe that income inequality positively affects happiness inequality.

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, 1994). 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, 2012).

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., 2004). 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. The time span is homogeneous from a social and political

[6] See Senik (2004), and Becchetti and Savastano (2010) for empirical evidence.

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.

In the GSOEP database, the main variable of interest, Life Satisfaction, is reported as a 0-10 categorical ordered variable.[7] In this work we assume the cardinality of this variable (see section 4 for a justification of this assumption) and this enables us to evaluate some standard measures of distribution inequality, viz. variance and Gini index.

On average, in Germany the average level of 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.[8] These trends are consistent with those reported on the World Database of Happiness, which documents an increase in inequality in Germany.[9] 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 developed countries happiness inequality has decreased (see also Clark et al, 2012). In such a framework, the German case represents a peculiar and interesting case to study.

In order to identify the drivers of happiness inequality we focus on the standard covariates used in happiness studies (age, income level, income inequality, relative income, education, marital status and having children, employment status, saving

[7] 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 related literature focuses on the analysis of "happiness inequality", GSOEP data report individuals' life satisfaction, a concept closely related but not identical to happiness. Note, however, that in the literature the two terms are often used as synonyms and results on their determinants are substantially the same (see for instance Clark et al, 2012).

[8] 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.

[9] See http://worlddatabaseofhappiness.eur.nl. In particular, standard deviation of happiness increases from 1.77 in 1993 (source: SOEP), to 2.22 in 2007 (source: European Social Survey).

status and house ownership). In particular, for 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 whose income level is lower than 60% of median income, the second regarding those whose income level is greater than 200% of the median income.

To investigate the influence of the reference group (Van Praag, 2011), we also consider the relative income. It is obtained by computing the median income of the reference group (individuals with the same gender, age class, education, Lander), and then deriving the share of individuals under (above) the 60% (200%) of the median income of the reference group.[10]

Table A1, in Appendix, provides definitions of the covariates, while Table 1 reports covariates' mean values in the two considered time periods.[11] The main trends observed in the GSOEP sample are the following: a) 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) average income level increases, as well as income inequality, since the share of individual under (above) the 60% (200%) of the median income raises;[12] d) on average, the share of individuals under (above) the 60% (200%) of the median income of the reference groups increases; 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 the share of individuals having a saving account gets lower.

[10] 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.
[11] For an overview of findings on happiness determinants see Frey and Stutzer (2002).
[12] The increase in income inequality is consistent with the observed increase in wage inequality in Germany (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 analysis of happiness. Other methodological issues regarding the Gini index as a measure of happiness inequality are instead discussed in section 5.

Two main issues deserve to be mentioned within the happiness literature. 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. 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 can be compared. Di Tella and McCulloch (2006) argue that, even in presence of heterogeneity in individual scales, such heterogeneity is not systematically affected by drivers of happiness. In the same vein, Frey and Stutzer (2002) 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) test empirically the validity of the Frey and Stutzer (2002) 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 how much an individual is happier than another.

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). Further, Clark et al. (2009) observe that doctors implicitly believe in cardinality when asking to their patients how much a given part of the body hurts after a touch.

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*

Let 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 happiness level is given by $Y_i = Y_{i1} \cdot T_i + Y_{i0} \cdot (1 - T_i)$, where $T_i = 1$ 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 Oaxaca-Blinder (henceforth OB) decomposition allows to break down the overall difference in means over time, $\Delta_O^{\mu} = \mu_1 - \mu_0$, 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}. This kind of decomposition is usually denoted as "aggregate" decomposition. By means of the OB decomposition, it is also possible to identify the contribution of each covariate to these two aggregate effects, the "detailed" decomposition.

Fortin et al. (2011) extend the aggregate and the detailed decomposition of the mean provided by Oaxaca-Blinder to any distributional parameter, 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 standard 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 $(y_i-\mu)^2-\sigma^2$, and the RIF is $\sigma^2+\left[(y_i-\mu)^2-\sigma^2\right]=(y_i-\mu)^2$. Hence, the RIF of the variance is equal for each observation to the 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. Using the law of iterated expectations, it is possible to express the distributional parameter ν in terms of the conditional expectation of the RIF on the covariates X:

$$\nu=E[RIF(Y;\nu)]=E_X\{E[RIF(Y;\nu)|X]\} \tag{1}$$

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):

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

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

Then, it is possible to decompose the overall difference over time of ν, $\Delta_O^{\nu}=\nu_1-\nu_0$, into a coefficient ($\Delta_S^{\nu}$) and composition effect (Δ_X^{ν}), $\Delta_O^{\nu}=\Delta_S^{\nu}+\Delta_X^{\nu}$, effects that can be written as:

[13] For the influence function of the Gini coefficient see Monti (1991).

$$\Delta_S^{\nu} = E[X|T=1]'\left(\gamma_1^{\nu} - \gamma_0^{\nu}\right)$$
$$\Delta_X^{\nu} = \left(E[X|T=1] - E[X|T=0]\right)'\gamma_0^{\nu} \tag{3}$$

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. 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.

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:

$$\Delta_O^{\nu} = \left[\overline{X}_1\hat{\gamma}_{01}^{\nu} - \overline{X}_{01}\hat{\gamma}_{01}^{\nu}\right] + \left[\overline{X}_{01}\hat{\gamma}_{01}^{\nu} - \overline{X}_0\hat{\gamma}_0^{\nu}\right]. \tag{4}$$

Equation (4) is defined as the "reweighted-regression" decomposition. However, this decomposition entails both a specification and a reweighting error. Hence, the "pure" composition effect is estimated as:

$$\Delta_{X,p}^{\nu} = \left(\overline{X}_{01} - \overline{X}_0\right)\hat{\gamma}_0^{\nu} \tag{5}$$

and the "pure" coefficient effect as:

$$\Delta_{S,p}^{\nu} = \overline{X}_1\left[\hat{\gamma}_1^{\nu} - \hat{\gamma}_{01}^{\nu}\right] \tag{6}$$

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

1) a decomposition with 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, such as Ferrer-i-Carbonell and Van Praag (2003), Dutta and Foster (2011) and Stevenson and Wolfers (2008). The main step forward of the methodology proposed in this paper is that it allows identifying the composition and structure 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 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, the major issue concerns the fact that since happiness is a bounded variable the Gini index underestimates happiness inequality.[14] In fact, the hypothetical situation in which one individual owns the total amount of happiness is

[14] Another related issue is 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.

not attainable, since the happiness variable is upper limited (Petrie and Tang, 2008; Erreygers, 2009).

Petrie and Tang (2008) suggest to standardize the Gini index by using the maximal attainable Gini index for bounded variables.[15] For the purpose of this paper, this option is not feasible since the influence function for a standardized Gini index is not available in the statistical literature.

However, 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 index is very close to that of the Gini index: in both cases happiness inequality increase by 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 change over time. Third, the numerator of the Gini index is the same as the one of the standardized Gini index, i.e. the two indexes are the same apart from a scale factor.

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 those 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 separately (1992-93-94 and 2005-06-07), for the variance and for the Gini index. The coefficients of the RIF regression measure the impact of each covariate on the inequality measure

[15] As an example, assume a population of 10 individuals in which the sum of happiness levels is 40. The maximum attainable happiness inequality is reached if 4 people were associated to the maximum level of happiness (10) and the other 6 to a value of happiness equal to zero.

considered. Given the little evidence about the determinants of happiness inequality, the 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 (Table 2). An intuition of what is behind this result is given by the analysis of the histograms of the happiness distribution for low, medium and high education levels (Figure 1): it emerges that higher education is associated to a reduction in the density of 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, relation that becomes steeper in 2005-07 (Figure 2). It is also worth noting that a similar pattern of happiness inequality among educational groups has been observed in the US as well (Stevenson and Wolfers, 2008).

As for the income level, there is evidence of an inverse relationship between income and happiness inequality, relation that is highly significant and does not change much overtime. Considering 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 relative income variables, i.e. being poor or being 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 happiness inequality, while being unemployed has a positive effect. The effect of being retired is never significant. Figure 3 shows that trends of variance indexes computed by employment status in the two periods resemble those of the corresponding RIF regression coefficients.

With regard to the effect of age on happiness inequality, we observe a reverse U-shape trend, first increasing until the 45-54 age class, then decreasing. This trend is consistent with the time pressure explanation that concerns mainly prime age individuals, and can be observed also in Figure 4, where variance indexes by age classes are reported.[16]

Living in the East Länders increases inequality, but the effect decreases over time. Being a disabled worker has a negative impact on both indices, impact that increases strongly over time.[17] Being married significantly decreases happiness inequality in both periods, and its impact decreases over time, while being divorced or separated, with respect to being single, has a significant positive effect on inequality only in the second period. Similarly, having no children significantly increases happiness inequality only in the second period. Finally, having a saving account and, to a lesser extent, being a home owner reduces happiness inequality.

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 relevant differences with respect to the coefficients computed in the variance analysis, i.e. same signs and statistical 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, the composition effect almost entirely explains the variation of

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[16] Our finding closely resembles the well known U-shaped relationship between age and happiness levels (see among others Frijters and Beatton, 2012).

[17] 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.

the variance over time, while coefficient effect is never significant, as well as the contribution of almost all covariates to the coefficient effect.[18] 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 the impact of specific covariates, 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 variation).[19] To ease the interpretation of the composition effect, note that it is computed using equation (5), which includes two elements. The first is the overtime change of the covariate composition[20] and the second is the coefficient at time zero. In the case of education, the composition effect is negative, since the increase in the shares of medium and high education (Table 1) is multiplied by a negative coefficient, as it can be seen from RIF regression results (Table 2). This result is 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.[21]

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[18] Note also that the reweighting and the specification errors are not statistically different from zero, meaning that the linear approximation holds true and that the reweighing procedure works fine (Fortin et al., 2011).

[19] This value is the sum of the composition effects for medium and higher education dummies.

[20] Actually this term is equal to the difference between X_{01}, the counterfactual composition of covariates at time 0 weighted 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 significant, then $X_{01} \rightarrow X_1$. More in general, to exactly derive both composition and coefficient effects reported in Table 3, one needs the counterfactual mean of each covariate and the counterfactual coefficient. In order not to burden the paper, we do not report these estimates, as usual in the related literature (see, for instance, Firpo et al., 2011 and Fortin et al., 2011). They are available upon request.

[21] For a further discussion concerning the impact of education see the working paper version (Becchetti et al, 2011), where we showed that being more educated reduces the probabilities of being unsatisfied as well as the probability of being fully satisfied. The former result is quite expected: being more educated reduces the probability that individuals lack of sufficient pecuniary and cultural resources to avoid the "low satisfaction trap". As for the latter, more unexpected, our claim is that education might raise aspiration levels and therefore, everything else being equal, the gap between realisations and aspirations (see among others Ferrante, 2009).

Second, interesting results emerge 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 the average level of income between the two time periods entails a negative impact on happiness inequality (-7% of the total variance variation). This is consistent to Clark et al. (2012), whose recent findings based on the World Values Survey dataset 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 3% of the total variance variation, while the increase in the share of rich is not statistically significant. This evidence suggests that the strong increase in wage and income inequality observed in Germany (Dustmann et al., 2008) 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) have to be taken into account to explain the changes 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 the important role of non-pecuniary drivers in shaping the evolution of happiness inequality.

As robustness check, as alternative measure of income inequality we make use of the RIF of the variance of income, equal to $(y_i - \mu)^2$, which represents the individual contribution to the income variance.[22] Results are reported in Table 4, and are very similar to those in Table 3: the impact of income inequality is small and explain only 2% of the total variance variation (3% in Table 3). Further, all other findings are in line to what observed in Table 3.

Relative income positively affects the increase in happiness inequality. More specifically, the overtime change in the share of the 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.[23]

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. The other proxy for financial conditions and wealth, house ownership, is instead 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 happiness inequality (15% of total variance variation over time). This is consistent with findings emerging from RIF regressions in Table 2 and from descriptive statistics in Table 1, which show that the size of these cohorts increased because of the ageing of the German population and of the baby boomers. As explained above, these findings could be related to time pressure effects.

[22] Note that to compute this variable we forced the mean income to be the same in both periods, since variance is not scale independent.
[23] However, this result might depend on the way the reference group has been computed.

As for marital and familiar status, only the variable being married has a significant and positive impact on the dynamics of happiness inequality (with respect to the omitted category, 'never been married'). RIF regression coefficients show that this variable is associated with lower levels of inequality. Hence, since the share of married individuals strongly decreases over time, 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 living 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).[24] 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.[25] This could be due to the small number of observations for East Germany (around 20% of the total), which might affect the significance of the estimates. 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.

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 covariate composition and not in coefficients. Moreover, we derive results

[24] 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.

[25] 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.

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. Finally, also the contributions of each covariate as share of the total variation of the Gini index are very close to the ones derived for the variance.

6. 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 returns of determinants of happiness.

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). The latter finding is something that should be taken into account when analysing the consequences of the Easterlin paradox that focuses only on the relation between income growth and happiness levels (see Clark et al, 2012).

This overall evidence provides straightforward policy implications: measures aiming at increasing education and economic performance, i.e., higher incomes and lower unemployment rate, generate 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 variance and 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	-0.028	-0.38		-0.304	-4.81	***	-0.001	-0.49		-0.009	-5.42	***
Medium_education	-0.356	-3.74	***	-0.209	-2.18	**	-0.013	-5.35	***	-0.011	-4.56	***
High_education	-0.433	-3.71	***	-0.386	-3.51	***	-0.015	-5.04	***	-0.021	-7.17	***
Age18_24	-0.317	-2.29	**	-0.250	-1.92	*	-0.011	-3.06	***	-0.009	-2.78	***
Age35_44	0.275	2.57	***	0.524	5.45	***	0.013	4.78	***	0.023	9.16	***
Age45_54	0.817	6.94	***	0.953	8.93	***	0.025	8.48	***	0.040	14.54	***
Age55_64	0.108	0.77		0.195	1.56		0.003	0.79		0.011	3.37	***
Disable	0.875	6.22	***	1.498	13.33	***	0.032	9.11	***	0.054	18.29	***
Married	-0.394	-3.39	***	-0.182	-1.96	*	-0.011	-3.90	***	-0.011	-4.38	***
No more married	0.131	0.91		0.314	2.87	***	0.006	1.66	*	0.006	2.16	**
No child in the HH	0.058	0.61		0.264	3.38	***	0.002	1.04		0.009	4.66	***
Income level	-0.015	-3.05	***	-0.016	-4.78	***	-0.001	-5.20	***	-0.001	-6.86	***
Poor	0.230	1.76	*	0.479	4.38	***	0.008	2.33	**	0.015	5.14	***
Rich	0.286	1.40		0.243	1.54		0.010	1.94	*	0.006	1.37	
Rel. poor	0.516	4.47	***	0.262	2.81	***	0.015	5.13	***	0.010	4.30	***
Rel. rich	-0.102	-0.61		0.049	0.37		-0.007	-1.73	*	-0.001	-0.43	
Living in the East	0.654	6.64	***	0.179	2.28	**	0.039	15.90	***	0.016	7.75	***
Employed	-0.344	-3.19	***	-0.604	-5.95	***	-0.010	-3.65	***	-0.015	-5.74	***
Unemployed	3.011	18.44	***	2.221	15.97	***	0.079	19.32	***	0.072	19.95	***
Retired	-0.225	-1.49		-0.218	-1.45		-0.004	-1.12		-0.003	-0.70	
Owner	-0.293	-3.85	***	-0.131	-1.93	*	-0.012	-6.18	***	-0.009	-5.13	***
Saving Acc.	-0.878	-9.40	***	-1.052	-15.31	***	-0.028	-11.85	***	-0.033	-18.60	***
Constant	4.359	20.48	***	4.380	23.57	***	0.175	33.06	***	0.177	36.51	***
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	0.2808	5.53 ***	-0.0650	-0.60	0.007692	5.853 ***	0.0005	0.20
Reweighing error	-0.0121	-0.4246			0.0003	0.334		
Specification error	0.0493	0.43346			0.0006	0.247		
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	coeff	coeff	coeff
Female	-0.0009	-0.0923	0.0000	-0.0034
Medium education	-0.0084 *	-0.0436	-0.0003 ***	-0.0016
High education	-0.0175 ***	-0.0358	-0.0006 ***	-0.0029
Age18_24	0.0059	0.0468	0.0002 *	0.0013
Age35_44	0.0154 *	-0.0140	0.0007 ***	0.0007
Age45_54	0.0254 ***	-0.1022	0.0008 ***	0.0005
Age55_64	-0.0002	-0.1076	0.0000	-0.0008
Disable	0.0169 **	0.0805	0.0006 ***	0.0030 ***
Married	0.0379 *	0.3206	0.0011 ***	0.0063
No more married	0.0029	0.0775	0.0001	0.0013
No child in the HH	0.0025	0.1186	0.0001	0.0037
Income level	-0.0269 **	0.2523	-0.0010 ***	0.0055
RIF Income variance	0.0054 *	-0.0369	0.0002 *	-0.0008 *
Rel. poor	0.0388 ***	-0.1202	0.0011 ***	-0.0029
Rel .rich	0.0008	-0.0094	-0.0001	0.0002
Living in the East	-0.0103 ***	-0.1046	-0.0006 ***	-0.0050 ***
Employed	-0.0027	-0.0725	-0.0001	-0.0020
Unemployed	0.0888 ***	-0.1039	0.0023 ***	-0.0016
Retired	0.0079	0.0403	0.0002	0.0008
Owner	-0.0093 ***	0.0825	-0.0004 ***	0.0004
Saving Acc.	0.1004 ***	-0.0743	0.0031 ***	-0.0027
Constant		-0.1636		0.0005
TOT	0.2727 ***	-0.0618	0.0074 ***	0.0006
Reweighing error	-0.0128		-0.0002	
Specification error	0.0549		0.0009	
Index change	**0.2530** ***		**0.0087** ***	
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.

Figures

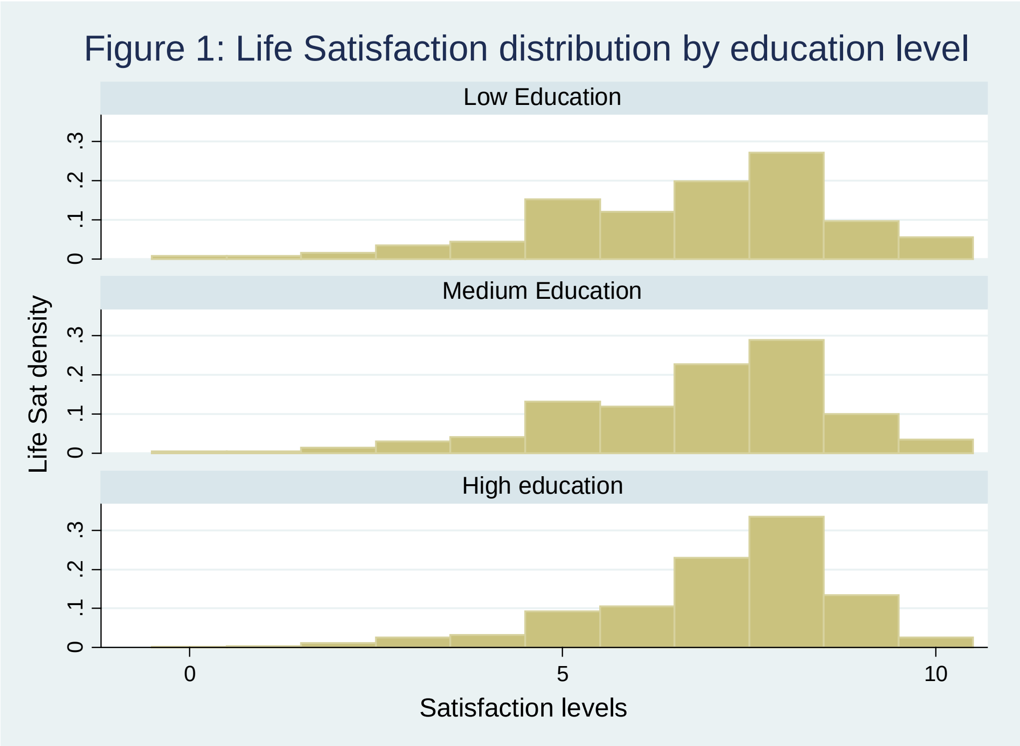

Figure 1: Life Satisfaction distribution by education level
Low Education
Medium Education
High education
Life Sat density
0
.1
.2
.3
0
5
10
Satisfaction levels

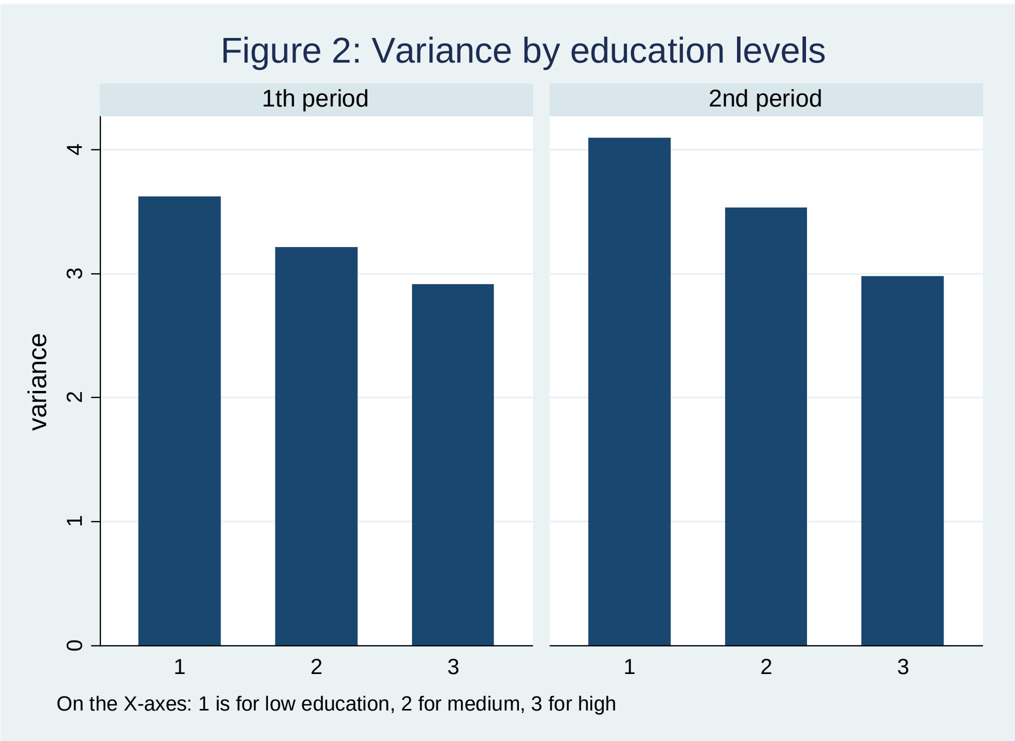

Figure 2: Variance by education levels
1th period
2nd period
variance
0
1
2
3
4
1
2
3
On the X-axes: 1 is for low education, 2 for medium, 3 for high

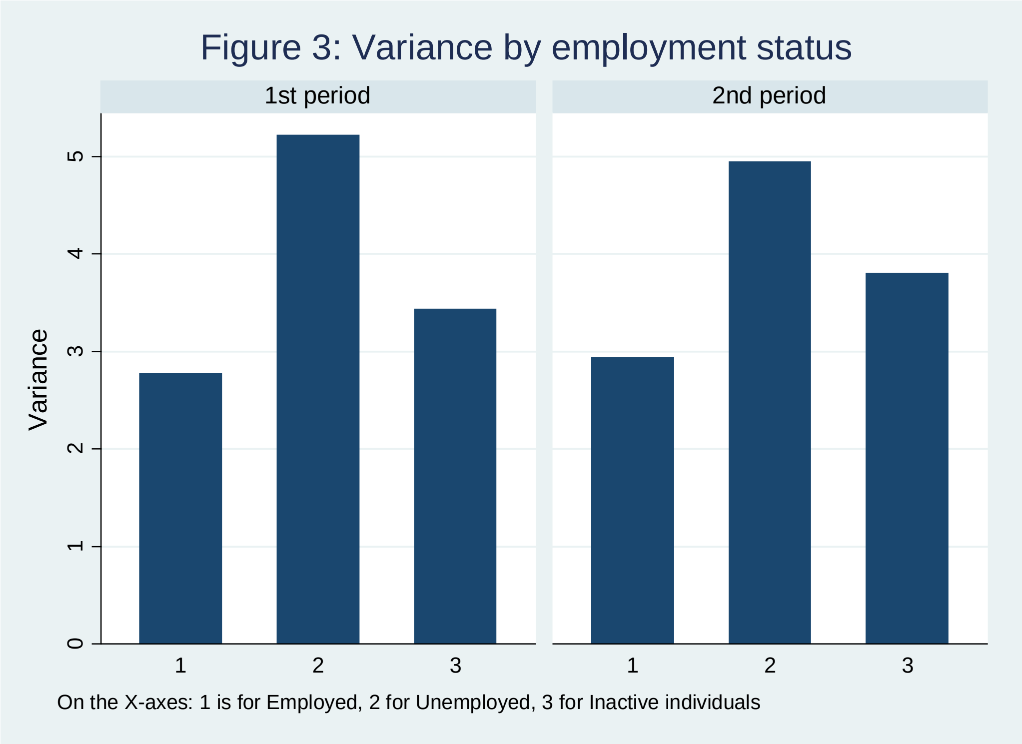
Figure 3: Variance by employment status
1st period
2nd period
Variance
0
1
2
3
4
5
1
2
3
1
2
3
On the X-axes: 1 is for Employed, 2 for Unemployed, 3 for Inactive individuals

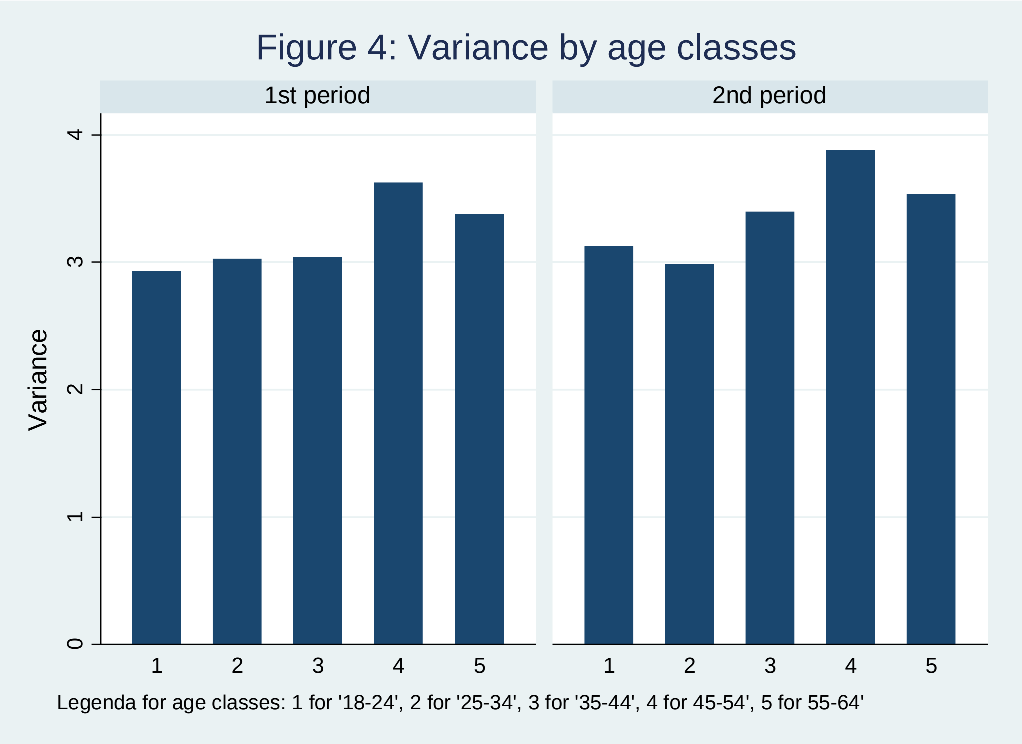
Figure 4: Variance by age classes
1st period
2nd period
Variance
0
1
2
3
4
1
2
3
4
5
1
2
3
4
5
Legenda for age classes: 1 for '18-24', 2 for '25-34', 3 for '35-44', 4 for 45-54', 5 for 55-64'

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
Income level	Yearly equivalent income of the household
Poor	Having an income lower than 60% of the median
Rich	Having an income higher than 200% of the median
Rel. Poor	Having an income lower than 60% of the median of the income of the reference group
Rel. Rich	Having an income greater othan 200% of the median of the income of the reference group
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, divorced or 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