EQUALITAS
Economics of Inequality and Poverty Analysis

EQUALITAS Working Paper No. 69

Personal Wellbeing and Intergenerational Mobility in Spain

Amaia Palencia - Esteban

Pedro Salas - Rojo

July, 2020

Personal Wellbeing and Intergenerational Mobility in Spain

Amaia Palencia-Esteban

Universidade de Vigo (Spain), ECOBAS and EQUALITAS

E-mail: apalencia@uvigo.es

Pedro Salas-Rojo

Universidad Complutense de Madrid (Spain), ICAE and EQUALITAS

E-mail: pedsalas@ucm.es

Abstract

This paper explores the relation between personal wellbeing and intergenerational income, occupational and educational mobility. First, using recent data for Spain (2017), we employ innovative Statistical Learning techniques to impute fathers' income and estimate intergenerational income mobility. Second, by means of several recently developed graphical tools and OLS specifications, we find the relation between wellbeing (measured with self-reported life satisfaction and happiness) and all measures of intergenerational mobility to be non-significant. This implies that improving or worsening one's fathers' economic, educational or professional status does not have permanent effects on personal wellbeing. In line with the literature, we find other socio economic factors, such us being married or enjoying a good health, to be positively related to higher levels of personal wellbeing.

Keywords: Wellbeing, Intergenerational Mobility, Life Satisfaction, Statistical Learning.

JEL Code: I14, I31, J62

1. Introduction

Ever since the Easterlin Paradox was proposed (Easterlin, 1974), the empirical evidence has confirmed that happiness does not necessarily increase with national income (DiTella and MacCulloch, 2006; Stevenson and Wolfers, 2013; Easterlin, 2016). But, what happens when we focus on an individual perspective? Answering this question, an increasing number of studies have studied the relation between personal wellbeing and many different economic or social factors such as health, social status, educational level and relevant aspects of childhood (Steptoe et al, 2015; Michalos, 2017; Churchill et al, 2019). This paper contributes to this literature by exploring the connection between the personal wellbeing of Spanish citizens (2017) and several approaches to intergenerational income, occupational and educational mobility.

The previous research on the relation between intergenerational mobility and wellbeing has led to inconclusive results. Some authors have found upward mobility to be associated with higher subjective wellbeing, with downward mobility producing the opposite effect (Clark et al, 2008; Clark and D'Angelo, 2013; Nikolaev and Burns, 2014; Hadjar and Samuel, 2015; Zhao et al, 2017). The intuition behind these results is linked to psychological permanent rewards derived from achieving a higher socio economic status, which ultimately imply the fulfillment of expectations, personal self-realization or higher consumption capabilities. However, further research has also found that these positive and negative mobility effects are transitory and dissipate with time (Di Tella et al, 2006; Guilbert and Paul, 2009). According to the hedonic adaptation theory, as individuals move along the socio economic ladder, they quickly adjust to their new status. In this manner, wellbeing improvements derived from intergenerational mobility have a non-lasting effect, as they only appear immediately after the mobility takes place, disappearing afterwards. Finally, other authors (Zhang and de Graaf, 2016; Iveson and Deary, 2017) find intergenerational mobility and personal wellbeing to be unrelated, with no effects attributed neither to the short nor the long term.

Using data from the Centro de Investigaciones Sociológicas (CIS; 2017), we analyze the relation between personal wellbeing (measured with life satisfaction and personal happiness) and intergenerational income, educational and occupational mobility in Spain. Considering three different approaches to mobility allows us to test whether the potential wellbeing effects are obtained through different channels. However, the CIS database does not provide information on fathers' income, hindering a direct approach to intergenerational income mobility. Overcoming this limitation, we employ the Statistical Learning techniques recently proposed in Bloise et al (2020) and, by means of the Two Samples Two Stages Least Squares methodology (Bjorklund and Jantti, 1997), we use three waves of the Encuesta de Presupuestos Familiares (1980/81, 1990/91 and 2000/01) to impute the fathers' income into the CIS database. This way, we are able to measure intergenerational income mobility in Spain, allowing us to study its relation with personal wellbeing.

Our results prove that the relation between wellbeing and intergenerational mobility is not significant, so the potential effects derived from improving or worsening ones' situation with respect to one's ascendants are not permanent in Spain. This conclusion is obtained from two different independent analyses. First, the new graphical tools developed by Jenkins (2019, 2020) show that personal wellbeing levels are neither higher nor more unequally distributed for individuals who experience a given type of intergenerational mobility (upward or downward) with respect to the immobile. Indeed, its distribution is quite homogeneous across all mobility categories considered. Second, all regressions and robustness checks performed to account for several sociodemographic factors confirm the absence of a significant relation between our variables of interest. Still, and in line with previous literature, we find that factors such as enjoying good health or being married are positively connected to both life satisfaction and personal happiness. These results are remarkably robust to different specifications and sample restrictions.

The contribution of this article is three-fold. First, we use innovative Statistical Learning algorithms to estimate intergenerational income mobility in Spain (2017). Given the incomplete and imperfect nature of the data, these computing techniques increase the accuracy of our imputations and estimations. Being the scarcity of intergenerational valid data the norm, this paper proves the adequacy of this methodology and sets the ground for future empirical analysis. Second, we present and apply the new analytical tools proposed by Jenkins (2019, 2020), which had not been implemented before for analyzing wellbeing in Spain. Third, our results contribute to the general wellbeing debate by confirming previous findings: the absence of a permanent relation between personal life satisfaction and happiness with intergenerational mobility.

The reminder of the paper is structured as follows. Section 2 presents the main database and variables employed in the analysis. Section 3 studies intergenerational income, educational and occupational mobility in Spain, while Section 4 relates several mobility measures to subjective wellbeing. Section 5 concludes.

2. Data

The data comes from the module "Social Inequality and Social Mobility in Spain", a survey conducted by the Centro de Investigaciones Sociológicas (CIS) in 2017 based on the design explained in Marrero et al (2017) and Betancort et al (2019).[1] The 2482 observations obtained

[1] The CIS is a dependent entity of the Spanish Ministry of Presidency whose main task consists on improving the scientific knowledge of the Spanish society. The database, the questionnaire and details of the sample design are available at: http://www.cis.es/cis/opencm/ES/2_bancodatos/estudios/ver.jsp?estudio=14350.

from a stratified multi-stage sampling procedure are representative for the Spanish population by age and gender. To exclusively include individuals participating in the labor market, and also following the intergenerational mobility literature, in this paper the sample is restricted to those aged between 30 and 60 years.

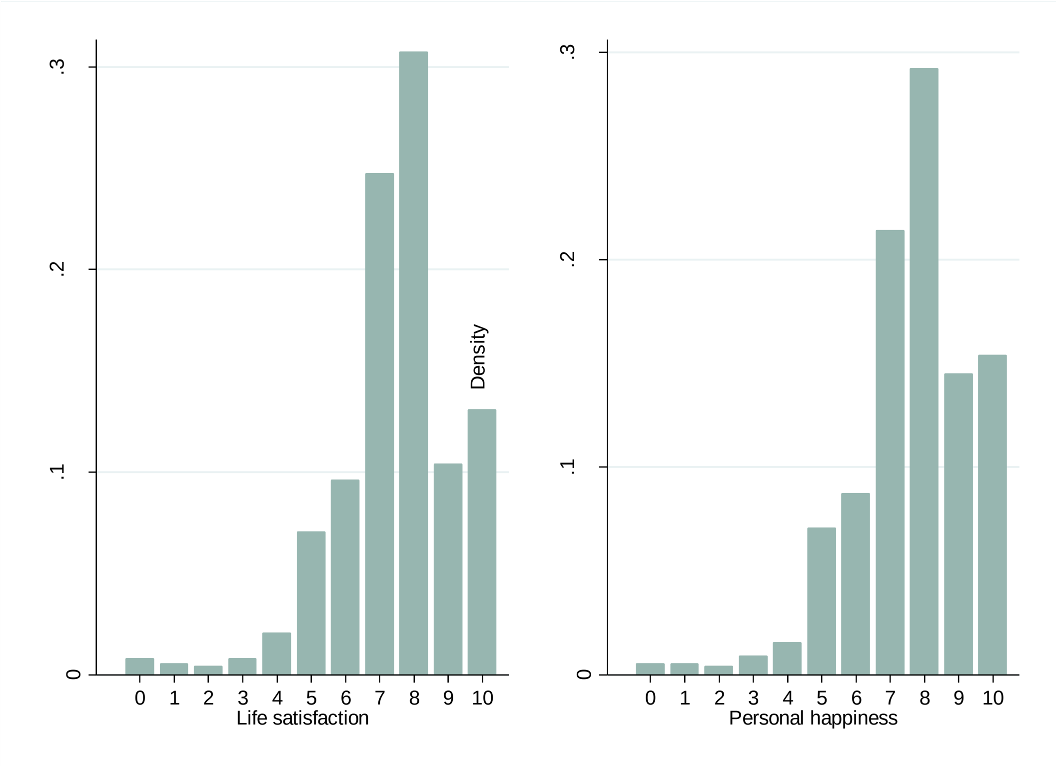
This section presents the variables employed in our analysis. First, we explain how life satisfaction and personal happiness are used to accurately measure the subjective wellbeing of the respondents.We then present the variables employed to calculate intergenerational mobility: household income and the education and occupation of the individuals and their fathers. Finally, we introduce several social and demographic aspects that account for the remaining relevant factors that, according to the literature, affect personal wellbeing.

2.1 Dependent variables.

Personal wellbeing is preferably measured with the self-reported life satisfaction (Diener et al, 1985; Kahneman and Thaler, 2006; Molina et al, 2011; Powdthavee et al, 2015; Iveson and Deary, 2017; Shuck and Steiber, 2018; Mahler and Ramos, 2019). Despite we acknowledge remarkable levels of subjectivity in this variable, ample evidence demonstrates that it provides meaningful, reliable and valid information about individuals' wellbeing. In general, life satisfaction is related to long-term factors used by the individuals to make a broad judgement on the quality of their lives. Among those factors, the literature highlights psychological positive aspects such as the self-fulfillment of personal ambitions and expectances, and all the benefits derived from stable social interactions. In this paper, we measure life satisfaction by collecting the answers to the following question: *do you consider yourself to be satisfied with your life?*. The discrete categorical possible answers range between 0 (completely unsatisfied) and 10 (completely satisfied).

In addition, to test the robustness of our results, we repeat the whole analysis with the self-reported happiness. This variable is obtained through the question: do you consider yourself to be a happy person? with the possible answers again ranging between 0 (completely unhappy) and 10 (completely happy). However, the long lasting effects that happiness has over personal wellbeing are unclear, as this variable is related to external shocks such as unemployment, divorces or deaths of relatives (Oswald and Powdthavee, 2008). In this manner, happiness is more connected to the current personal situation rather than to a general perspective of wellbeing. Consequently, we consider life satisfaction as our main dependent variable, leaving the study of personal happiness for robustness checks. Figure 1 plots their distribution, confirming that, despite the conceptual differences, they are rather similar.

Figure 1: Density of life satisfaction and happiness (Source: CIS).



2.2 Intergenerational mobility variables.

As already mentioned in the introduction, the literature has found inconclusive results on the relation between both factors. On the one side, some authors claim that both factors are non-connected (Zhang and de Graaf, 2016; Iveson and Deary, 2017). On the other side, other authors find the relation to be significant, but disagree on whether the effects of mobility in wellbeing are permanent (Guilbert and Paul, 2009) or transitory (Di Tella et al, 2006). In this study, we get the wider possible picture and avoid focusing on just one type of mobility by following Clark and D'Angelo (2009), Molina et al (2011) and Nikolaev and Burns (2014) and measuring the effects of intergenerational income, occupational and educational mobility in Spain.

Measuring intergenerational income mobility requires two vectors: one that collects fathers' income and another that includes income of the children (Blinder, 1976; Solon, 1992; Zimmerman, 1992). Unfortunately, the CIS (2017) database does not include information on fathers' incomes, so the well-known Two States Two Samples Least Squares methodology is implemented to impute it from previous surveys[2] (Bjorklund and Jantti, 1997). The implementation of this technique, despite not particularly difficult, requires a separated

[2] Particularly, we use three waves of the Encuesta de Presupuestos Familiares (EPF): 1980/81, 1990/91 and 2000/01. The details and statistics proving the validity of this imputation proceeding are presented in Section 3.

explanation, which is assessed in section 3. Then, for now, we present the main statistics of the income that the respondents report in the CIS database.

The literature on intergenerational income mobility has generally focused on personal income to analyze the transmission of opportunities from fathers to sons and daughters (Jantti and Jenkins, 2013). However, we believe that household income should be the variable considered when relating income mobility to life satisfaction and personal happiness. Using household income does not only control for assortative mating, but also collects more information about consumption and saving possibilities within the family unit. Clearly, solely relying on personal income would not account for some relevant aspects of household economies, and could lead to biased results in the context of personal wellbeing.

Thereby, in this article we use household income, which includes all sources of income perceived by the household where the respondent lives net of taxes and transferences. Still, for comparative reasons, we account for the number of household members performing a per capita adjustment. We divide the total household income by the squared root of the household size, as this is the method traditionally used for inequality studies in Spain (see Perrote et al, 2003).[3]

Table 1 shows the summary statistics of the household per capita adjusted income by age cohorts. The relative similitude of the mean values and the standard deviations goes in line with the permanent income hypothesis. Regarding income inequality, the Gini coefficient associated to the household income distribution gets to 0.320 points, which is close to the 0.315 Gini that Ayala (2016) calculated for Spain in 2014. Same as Cabrera et al (2020), we conclude that the CIS database provides accurate estimates of the Spanish income distribution.[4]

Table 1: Summary Statistics of the Household per capita adjusted income, by cohorts.

Age	Mean annual household adjusted income	SD. of the annual household adjusted income
30-40	1977.12	1142.26
41-50	2025.81	1126.53
51-60	1823.82	1192.18

SD. Stands for Standard Deviation.

[3] We have eliminated the individuals with missing income, keeping a restricted sample of 781 observations. To prove that this restriction does not bias the results, and given that occupation and education present few missing values, intergeneration mobility of those two variables has been studied using both the restricted and the unrestricted sample, which includes 1190 observations. As explained in the results sections, this sample restriction does not affect our main results.

[4] All monetary units used in the paper are adjusted to 2017 euros.

Regarding intergenerational occupational mobility, we focus on the occupational change between the respondents and their fathers.[5] The CIS employs the ISCO-08 classification, providing occupations disaggregated up to the 3-digit level. However, occupational mobility matrices require a more aggregated dimension as the occupational groups must reflect certain professional status or skills, so that moving from one group to another may imply substantial changes in a person's life wellbeing. With this aim, and following Cabrera et al (2020), we use the ISCO-08 skills classification to produce four different categories that do not only represent diverse skill levels, but also involve different class status, working conditions and associated wages. First, we have unqualified workers (ISCO-08=9); second, semi-qualified and qualified labourers (ISCO-08=4-8); third, technicians and support professionals (ISCO-08=3); fourth, managers and professionals (ISCO-08=1-2*)*.

Table 2 presents the summary statistics of the occupational distribution of the respondents and their fathers. The structural change in the Spanish labor market is evident: while 32.23% of respondent have high skill occupations (ISCO-08=1-3), this ratio only reaches 22.92% for the fathers. Still, the main difference lies in the semi-qualified and qualified workers, as their proportion is much smaller for the respondents than for their fathers. Complementarily, Table A1 in the Appendix presents the summary statistics for the unrestricted sample, confirming that these statistics are maintained.

Table 2: Summary Statistics of the occupation of the respondents and their fathers.

	Respondents	Fathers
ISCO-08=9, Unqualified workers (1)	14.47%	6.27%
ISCO-08=4-8, Semi-qualified and qualified workers (2)	53.27%	70.81%
ISCO-08=3, Technicians and support professionals (3)	13.19%	9.73%
ISCO-08=1-2, Managers and professionals (4)	19.04%	13.19%
Mean	2.36	2.29
Standard Deviation	0.95	0.77

[5] Considering mothers' occupation would substantially reduce the sample size due to the late incorporation of women into the Spanish labor market. In fact, a big share of the respondents' mothers carried household informal works.

Finally, intergenerational educational mobility analyzes how the education of the respondents relates to their fathers'. In the CIS database, the educational categories are defined following the ISCED classification (UNESCO, 2012) but, again, we recode the levels of studies to create four groups. First, those with zero or primary education (ISCED=0-1); second, those with lower-secondary education (ISCED=2); third, those with upper secondary education and post-secondary (ISCED=3-4); forth, those with tertiary education (ISCED=5-8).

Table 3: Summary Statistics of the education of the respondents and their fathers.

	Respondents	Fathers
ISCED=0-1, Primary education (1)	29.96%	67.09%
ISCED=2, Low secondary education (2)	12.80%	10.50%
ISCED=3-4, Upper secondary education (3)	29.58%	9.86%
ISCED=5-8, Post secondary (4)	27.66%	12.55%
Mean	2.55	1.67
Standard Deviation	1.18	1.08

Table 3 presents the summary statistics of the educational distribution of the respondents and their fathers, reflecting the expansion of the compulsory secondary education. While the share of individuals with just primary education is reduced by more than a half, those with post-secondary education doubled their proportion. Indeed, upper secondary education experienced the biggest change: 29.58% of the respondents hold tertiary degrees when only 9.86% of the fathers did. Table A2 in the Appendix presents the statistics for the unrestricted sample, showing that these proportions remain unchanged.

2.3 Control variables.

We also include several control variables to account for some social and demographic aspects that the literature finds to be related with personal wellbeing. In particular, we consider respondents' age and squared age (controlling for life cycle and its potential non linearities), gender (binary), civil status (being married or not), having children (binary) and self-assessed poverty (it ranges from 0, the richest, to 10, the poorest). Table 4 shows the summary statistics of the control variables of the restricted sample, while Table A3 in the Appendix provides those describing the unrestricted sample.

Table 4: Summary Statistics of the control variables.

	Mean	Standard Deviation
Age	44.79	8.36
Gender (Men=1)	0.50	0.50
Civil Status (Married=1)	0.59	0.49
Kids (Have kids=1)	0.73	0.46
Poverty (0=poorest, 10=richest)	4.82	1.41

Finally, depending on the type of intergenerational mobility considered, the regressions also include the respondents' actual income quintile, occupational group or the educational level as controls. This is, when we include educational mobility as an independent variable, we also use the highest level of education achieved by the respondent as a regressor, substituting it by the occupational status when studying the effect of occupational mobility. This way, the coefficients capturing the impact that different types of intergenerational mobility have on wellbeing are not conditioned by the occupational, educational or income group to which the respondent belongs.

3. Intergenerational Mobility in Spain

This section explores intergenerational mobility in Spain. We begin by explaining the Statistical Learning methods and the auxiliary data used to compute intergenerational income mobility, as the lack of father's income information in the CIS database requires performing a precise imputation. Then, we calculate the intergenerational income elasticity and the corresponding transition matrix, and end up studying occupational and educational mobility.

Imputation Methods

Computing intergenerational income mobility requires income information from both cohorts, but fathers' income is not available in the CIS (2017) nor in any other modern Spanish database. This lack of data is not endemic to Spain, as it is prevalent in many other develop and in most of developing economies, hindering the study of intergenerational income mobility. Overcoming this data limitation, Bjorklund and Jäntti (1997) proposed the Two Samples Two Stages Least Squares (TSTSLS) methodology, which is based on a two-sample instrumental variable estimator (Angrist and Krueger, 1992; Arellano and Meghir, 1992). This technique has repeatedly been used in the intergenerational mobility literature, such as in Cervini-Pla (2015) for Spain, Barbieri et al (2019) for Italy, Bloise et al (2020) for US and South Africa.

The TSTSLS estimation requires two different samples. The main sample contains individual's current income and socioeconomic information about their fathers, but not the information on fathers' income. The second or auxiliary sample comes from an earlier survey and must contain incomes and the same socioeconomic information as the main sample, but for previous cohorts. The main idea of this procedure consists on considering individuals in the auxiliary sample as pseudo-parents, estimating their income conditioned on the selected common set of socioeconomic factors. The resulting fitted income values are then imputed into the main sample by matching the fathers' and pseudo-fathers' socioeconomic information present in both surveys. Formally, consider equation (1):

$$y_i^s = \alpha + \beta y_i^f + \varepsilon_i \quad (1)$$

Where y_i^s is the logarithm of the sons' permanent individual income, y_i^f is the logarithm of fathers' permanent earnings, α is the mean income of sons' and ε_i is an error term that collects individual's income not explained by the fathers'.[6] As the CIS dataset does not include y_i^f, we use the auxiliary sample to estimate the following equation:

$$y_i^{pf} = \varphi + \gamma z_i^{pf} + \delta_i \quad (2)$$

Where y_i^{pf} is individual income of the pseudo-parents in the auxiliary sample and z_i^{pf} is a vector of time-invariant socioeconomic factors used to predict income, which are included in the regression as categorical dummies. Finally, δ_i is the component of pseudo-parents' income not explained by the control socioeconomic factors. Equation (2) is estimated by OLS and then used to predict fathers' income: $\hat{y}_i^{pf} = \hat{\gamma} z_i^{pf}$.

This method poses an extra problem. The vector of estimated coefficients ($\hat{\gamma}$) is estimated with imperfect and incomplete data, as fathers' occupation and education are the only variables we have to match both samples and to use as regressors in equation (2). Since the exclusion of relevant demographic, socioeconomic or geographical controls makes the imputation highly dependent on data quality, the resulting fitted values are most likely biased.[7]

Bearing all this in mind, and to improve the accuracy of those imputations, we follow Bloise et al, (2020) and apply a Statistical Learning method to increase the precision of our

[6] Due to the late incorporation of women into the labor market and the consequent gender employment gap, the literature generally uses the fathers' earnings, occupation or education to measure intergenerational mobility.

7 For a complete formal explanation see Haider and Solon (2006), Nicoletti and Ermisch (2008), Nybom and Stuhler (2016) or Bloise et al (2020).

intergenerational income mobility estimates. Formally, we want to reduce at a minimum the squared difference between $\hat{y}_i^{pf}$ and y_i^f:

$$min\left\{E\left[\left(y_i^f-\hat{y}_i^{pf}\right)^2\right]\right\}=min\left\{E\left[\left(y_i^f-f\left(z_i^{pf}\right)\right)^2\right]\right\} \tag{3}$$

The expected squared error of equation (3) can be decomposed into three different elements:

$$E\left[\left(y_i^f-\hat{y}_i^{pf}\right)^2\right]=var\left(\hat{f}\left(z_i^{pf}\right)\right)+(bias)^2+var(\delta_i) \tag{4}$$

The first term on the left, $var\left(\hat{f}\left(z_i^{pf}\right)\right)$, is the error coming from the sensibility of equation (2) to the random noise in the auxiliary sample. The second term is the bias of the model, which quantifies the error generated by the selection of the variables in the data generation process. The last term is an irreducible error that captures the smallest possible error we must cope with when predicting y_i^{pf}.

By definition, a trade-off exists in equation (4). Very complex models, such as those including all occupational and educational categories as dummies in vector z_i^{pf}, diminish the bias term but increase the variance, leading to a potential over-fitting. On the contrary, too simple models that use highly aggregated variables as controls diminish the variance component at the expense of increasing the bias term. To solve this tension, Bloise et al (2020) estimated equation (2) using the regularization term first introduced by Zou and Hastie (2005). This statistical learning method consists on adding up an extra term to the classical least-square regression so that the estimated coefficients are obtained by minimizing equation (5):

$$\sum_{i=1}^{n}\left(y_i^{pf}-\sum_{j=1}^{k}\rho_j z_{j,i}^{pf}\right)^2+\lambda\left(\alpha\sum_{j=1}^{k}\left|\rho_j\right|+(1-\alpha)\sum_{j=1}^{k}\rho_j^2\right) \tag{5}$$

The left-hand side term is a canonical OLS element, with all potential k regressors included in the dummy vector $z_{k,i}^{pf}$. The right-hand side element is a regularization term that penalizes over fitting by shrinking some of the estimated coefficients towards zero. The main idea of the algorithm lies on including as much information as possible and, at the same time, eliminating the coefficients that can be omitted because they do not provide meaningful information to minimize equation (3).

This method depends on two parameters: λ and α. The former (λ), controls the importance of the regularization term and can be equal or higher than zero; the latter (α), is the elastic net regulator obtained from a linear combination of two standard Statistical learning techniques. Its possible values range between 0 and 1. Equation (5) is equivalent to the Least Absolute Shrinkage and

Selection Operator (LASSO) when α=1, but it is equal to a ridge regression when α=0 (Varian, 2014; Mullainathan and Spiess, 2017; Athey et al, 2019).

In short, if equation (5) is estimated including a high number of covariates in vector z, in our case all educational and occupational categories, the regularization term will shrink many ρ_j coefficients to zero, optimizing the predictive capacity and avoiding overfitting. Thus, given the available data, estimating the mincerian equation (3) in this way provides the most accurate possible prediction of fathers' income.

Auxiliary database

We use the CIS database as our main sample because it contains the most recent information on the respondents' and their fathers' education and occupation. The data for the auxiliary sample comes from the Household Budget Survey (Encuesta de Presupuestos Familiares, EPF) conducted by the Spanish National Institute of Statistics (Instituto Nacional de Estadística, INE). First implemented in 1973, this survey collects information on incomes, expenses and socioeconomic characteristics of the Spanish Households. The INE carried two other waves in 1980 and 1990 before changing its design to a panel structure in1997. We use the waves surveyed in 1980-81, 1990-91 and 2000. [8]

Even though the literature tends to consider a single wave as the auxiliary sample, we use different waves for two good reasons. First, recall that we restrict the main sample to those who participate in the labor market by keeping individuals aged between 30 and 60 years. The CIS data was collected in 2017, and the respondents are retrospectively asked about the fathers' information when they were 16. If we only used the 1980-81 wave to impute fathers' income, the imputation for the youngest cohorts of the CIS would clearly be biased, as they were not even born in that year. Second, the Spanish economy experienced relevant structural changes during the 80s and 90s, which in turn affected the occupational and wage structures (Anghel et al, 2014). Using a single wave would undoubtedly overlook those changes, so we propose using several waves to partially correct and control those effects.

Following this reasoning, Table 5 presents the correspondence between respondents' age in the main sample (CIS) and the auxiliary waves we employ to impute their respective fathers' income.

[8] The INE has traditionally carried out two types of EPFs: the structural or basic ones every eight or ten years (our 1980-81 and 1990-91 surveys) and, since 1997, the quarterly ones (our 2000 survey). For this last surveys and for each year, the INE also provides a longitudinal database collecting the corresponding four quarter, but relevant variables like education and occupation are too aggregated. Thus, we use the four quarterly databases, which offers more disaggregated classifications, and apply the imputation system proposed by the Bank of Spain (2008) to estimate equation (1). Before doing so, we homogenize the occupational and educational classifications following the documents provided by the INE.

Younger cohorts (those aged between 30 and 35) receive their income imputation from the EPF 2000. Indeed, considering that the data was collected in 2017, those who were aged 32 (the median point between the age range 30-35) were 16 years old when the 2000/01 EPF wave was collected. Following the same reasoning, middle-aged (36-45 years) and older cohorts (45-60 years) receive, respectively, their imputations from the EPF 1990-91 and 1980-81.

Table 5: Relation between the age of the respondent and wave employed to impute fathers' income.

	Group 1	Group 2	Group 3
Age of the respondent in the main sample	30-35	36-45	45-60
EPF wave	2000	1990-91	1980-81
Year when the age-median observation had 16	2000	1992	1980

Imputation.

Once we establish the correspondence between the main sample and the three auxiliary samples, we estimate the pseudo-fathers' income following the above-explained Statistical Learning methodology. Recall that our aim is to minimize the difference between the "true" vector of incomes (y_i^f) and the imputation obtained (y_i^{pf}), as defined in equation (3). In doing so, and following the TSTSLS method's reasoning, we minimize equation (5). However, that equation does not only include the usual parameters affecting the regressors (ρ_j), as it also includes a regularization term with other two undefined extra parameters: λ and α.

The tuning of λ and α should not be arbitrarily selected. Indeed, if their setting was left to the researchers' criteria, they could easily affect the quality of the imputation by implicitly leading to the exclusion of more or less regressors, artificially shrinking their coefficients toward zero. For instance, higher levels of λ would severely increase the weight of the regularization term, and viceversa. Furthermore, for each possible dataset, there is a precise combination of parameters that minimizes the Mean Squared Errors (MSRs) defined in equation (3) and (5).

Avoiding exogenous alterations on the resulting imputation, the algorithms proposed in Zou and Hastie (2005) and Bloise et al (2020) compute all possible tunings and combinations of λ and α to finally select the one that delivers the smallest MSR. To make their selection completely transparent, we plot the relation between the MSRs and several values of λ and α. This way, we check that our tuning provides the smallest possible associated MSRs. Figures 2 to 4 correspond to the imputations performed on the EPF 1980/81, EPF 1990/91 and EPF 2000, respectively.[9]

Figure 2: Mean squared error provoked by the regularization term in an OLS regression, for several values of log (λ) and alphas (Source: EPF 1980/81).

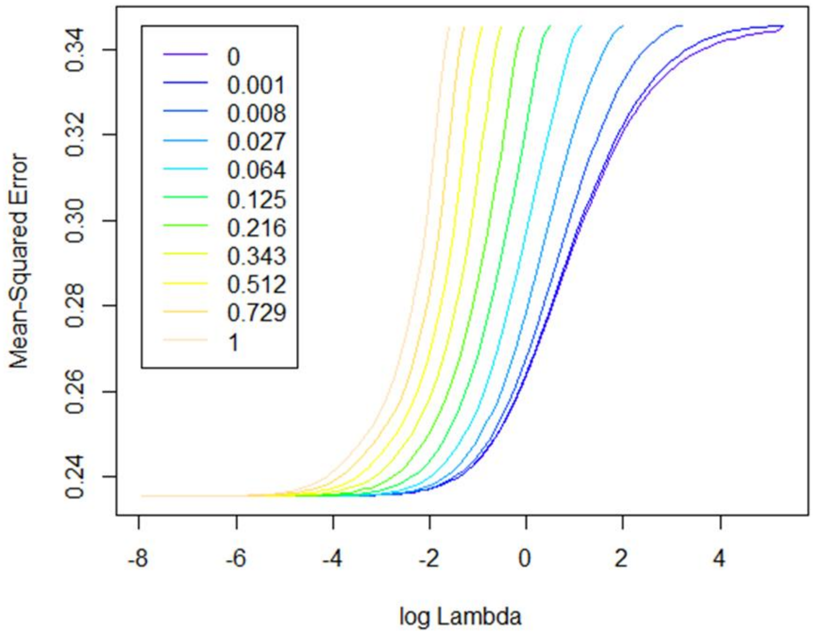
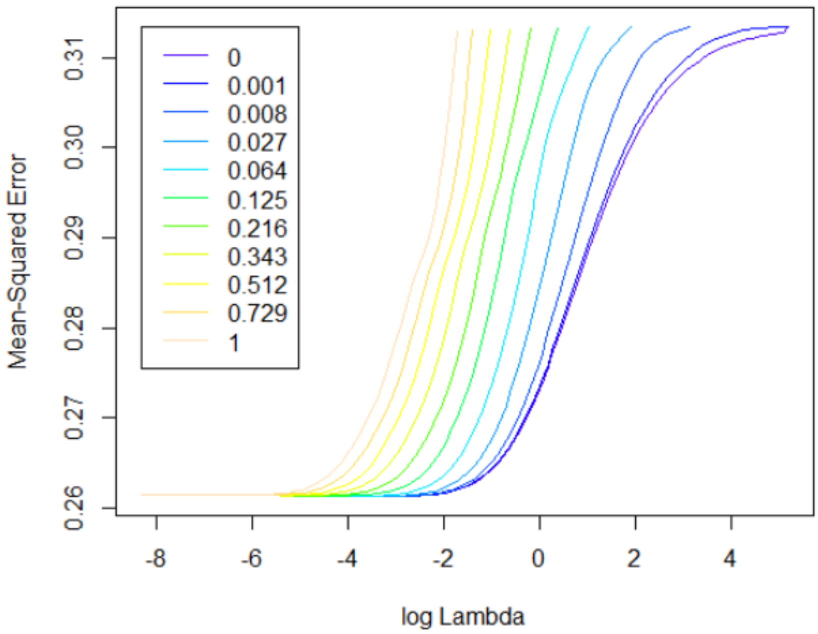


Figure 3: Mean squared error provoked by the regularization term in an OLS regression, for several values of log (λ) and alphas (Source: EPF 1990/91).



[9] In Figures 2 to 4, the different α values have been selected to show the different responses of the MSRs to different tunings and its broadest possible range (0-1), with α=0 being the ridge regression and α=1 the LASSO regression.

Figure 4: Mean squared error provoked by the regularization term in an OLS regression, for several values of log (λ) and alphas (Source: EPF 2000/01).

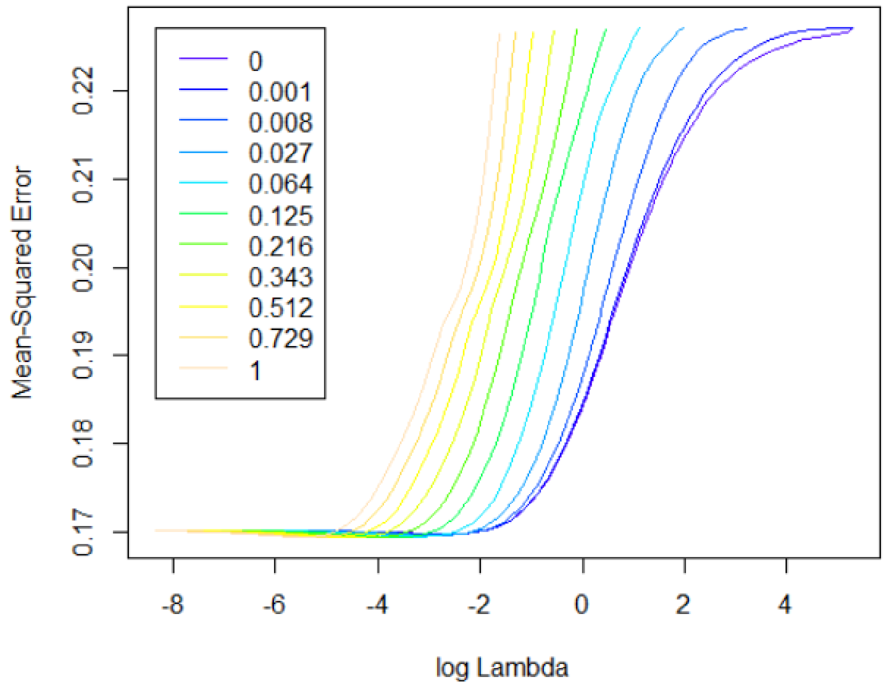


Figure 2 should be interpreted as follows. The MSR produced by equation (5) is stable at around 0.24 for any α value lower than log (λ) ≈ -5. At that point, the MSR associated to α = 1 starts rising, while the MSRs associated to the rest of possible α values remain constant. Indeed, for values of α smaller than 1, the associated MSRs sequentially take off from log (λ) ≈ -5 onwards, until the MSR produced by the ridge regression (α =0) rises at log (λ) ≈ -3. Figures 3 and 4 are interpreted similarly, with diverse MSRs associated to different parameter settings.

Since the algorithm searches for the values of the parameters associated with the lowest stable MSR, it provides the combination of λ and α leading to the most accurate imputation. For instance, in Figure 2, although it cannot be graphically distinguished, this occurs when log(λ) equals -7.2844. At that point, no matter the value of α we select, the MSRs is constant and has the lowest possible value. For any other combination, the associated MSR is higher (for higher λ) or stable (for lower λ).

Table 6 presents the summary statistics of the income imputations performed for each EPF wave. Interestingly, the estimations coming from both the LASSO and ridge regression are similar in any of the three waves. For instance, the means and standard deviations of the income imputations obtained from both regressions only differ by 2€ and 5€, respectively, in the wave 1980-81. Indeed, different alphas do not lead to significant differences in the imputed vectors because the λ value are so small that they barely weights the regularization term. Given the robustness of the imputations, and despite presenting the statistics of both specifications, all our analysis is based on the LASSO imputation.[10]

Table 6: Summary statistics of the imputed fathers' income for the three EPF waves.

Wave	1980-1981	1990-1991	2000-2001
Optimal λ	0.00068613	0.00144062	0.00298784
Log(λ)	-7.28444344	-6.54268170	-5.81320456
Mean income imputed with α=1 (LASSO regression)	1933.82	2027.80	2019.74
Mean income imputed with α=0 (Ridge regression)	1934.86	2029.75	2017.79
Sd of income imputed with α=1 (LASSO regression)	652.46	503.86	455.21
Sd of income imputed with α=0 (Ridge regression)	657.47	516.64	481.00
Number of observations	14987	15567	15567

Intergenerational Income Mobility

Once we estimate the vector of income for each wave, and taking Table 5 as a reference, we impute those values to each cohort in the CIS database by matching the occupation and educational level of the fathers and pseudo-fathers. This last step completes the imputation, as all fathers receive their correspondent imputed income in the main sample.

Intergenerational income mobility

We are ready to analyze intergenerational income mobility, generating an income transition matrix. To do so, we tabulate the quantiles of fathers' imputed income (rows) against the quintiles of household adjusted income (columns), and intuitively relate persistence (observations that remain in the main diagonal), upward mobility (observations situated above the main diagonal) and downward mobility (those below the main diagonal).

[10] All results have also been replicated with the ridge regression imputation, and are available upon request.

Table 8: Intergenerational income transition matrix.

		Household per capita adjusted income					
		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Total
Fathers income	Quintile 1	52	43	29	17	16	157
	Quintile 2	40	41	16	42	17	156
	Quintile 3	28	39	30	35	26	158
	Quintile 4	21	41	22	43	27	154
	Quintile 5	18	25	30	39	46	156
	Total	157	189	127	176	132	781

Table 8 shows the quintile transition matrix for the income imputation based on the LASSO regression imputation. Absolute mobility ratios show that around 35% of our sample experienced upward mobility, while a similar proportion suffered downward mobility. However, when we measure relative mobility, same as Jantti et al (2006) for the United States, Mocetti (2007) for Italy or Cervini-Pla (2015) and Cabrera et al (2020) for Spain, we find a strong persistence at the tails of both distributions. From those fathers belonging to the richest quintile, 29.48% (46/156) have children that stay in the same quintile and only 11.54% (18/156) have descendants in the lowest quintile. On the contrary, while one third of low income fathers (52/157) have low income children, just 10.19% of them have children in the fifth quintile. Overall, even though mobility is relatively even at the center of the distribution, we find higher persistence at the tails, in line with Palomino et al (2018).

Intergenerational occupational mobility

Even though income largely determines consumption or saving capacities and, as a result, is expected to have a major influence on personal welfare, other types of mobility should also be addressed to get a more comprehensive analysis. For instance, sociologists have traditionally used professional occupations as a proxy for social class, since apart from representing a professional status or skill level, it also reflects social recognition (Krieger et al, 1997; Bukodi and Goldthorpe, 2011). In our context, individuals may experience psychological benefits from climbing the social ladder and accessing a profession with more social recognition than that of the father. On the contrary, intergenerational occupational downward mobility could be related to lower levels of life satisfaction as a result of the failure to meet previously-determined expectations.

Table 9 presents the occupational transition matrix we estimate tabulating the professional status of the fathers (rows) against that of the children (columns).[11] Around 50% of our sample has a job with a qualification requirement similar to that of their fathers, while 25.86% experience upward mobility and 24.34% downward mobility. Nevertheless, when we analyze relative mobility, we find that fathers' position is also quite likely to condition the occupation of the descendent. From fathers who participated in the highest occupational level, 36.89% (38/103) have descendants in that same category, but only 7.76% (8/103) have children in the less qualified jobs. By contrast, while just 12.24% (6/49) of low qualified fathers have descendants that reach the highest occupational level, around one third (16/49) of their children remain in the lowest category. Table A4 in the Appendix repeats the table for the unrestricted sample.

Table 9. Transition matrix of occupation.

		Respondents occupation				
		ISCO-08=9, Unqualified workers	ISCO-08=4-8, Semi-qualified and qualified workers	ISCO-08=3, Technicians and support professionals	ISCO-08=1-2, Managers and professionals	TOTAL
Fathers occupation	ISCO-08=9, Unqualified workers	16	23	4	6	49
	ISCO-08=4-8, Semi-qualified and qualified workers	83	318	64	88	553
	ISCO-08=3, Technicians and support professionals	6	36	17	17	76
	ISCO-08=1-2, Managers and professionals	8	39	18	38	103
	TOTAL	113	416	103	149	781

Intergenerational educational mobility

Finally, we study educational mobility. The literature has shown that higher levels of education affect happiness and life satisfaction by indirect channels not necessarily collected in higher income possibilities. Particularly, among the benefits of upward educational mobility, having

[11] Table A7 in the Appendix confirms that the results remain unchanged when we use the restricted sample.

access to a wider variety of forms of cultural consumption and leisure has been related to higher personal welfare (Goldthorpe, 1980; Clark and Oswald, 1996; Bjornskov et al, 2013; Torche, 2015; Schuck and Steiber, 2017).

Table 10 presents the transition matrix of education, while Table A5 in the Appendix repeats it for the unrestricted sample. Around half of the sample (49.93%) experienced upward mobility, while only 7.04% have less education than their fathers. Indeed, absolute mobility ratios are somehow encouraging but, once again, the relative mobility analysis highlights the strong persistence of the educational levels between generations and the unequal opportunities that hide behind these results. While 70.41% (69/98) of highly educated fathers have kids with the same educational level, this ratio descends to a mere 17.94% (94/524) when we consider fathers with primary or lower studies and highly educated children. Clearly, upward mobility has not been homogeneously distributed among the Spanish population.

Table 10. Transition matrix of education.

		Education of the respondents				
		ISCED=0-1, Primary education	ISCED=2, Low secondary education	ISCED=3-4, Upper secondary education	ISCED=5-8, Post secondary	TOTAL
Education of the fathers	ISCED=0-1, Primary education	217	68	145	94	524
	ISCED=2, Low secondary education	12	16	30	24	82
	ISCED=3-4, Upper secondary education	4	10	34	29	77
	ISCED=5-8, Post secondary	1	6	22	69	98
	TOTAL	234	100	231	216	781

4. Results

This section delves deeper into the relation between personal wellbeing and intergenerational mobility. We start by applying the new graphical tools presented in Jenkins (2019, 2020) to analyze the bivariate connection between the dependent (life satisfaction) and the independent variables (intergenerational income, occupational or educational mobility). After that, we get a deeper understanding by running several regressions and robustness checks that account for several sociodemographic controls.

As shown in Jenkins (2019), distributional comparisons for ordinal variables cannot be undertaken with the same methods commonly applied to cardinal variables, so analogous techniques are required. The analytical tools presented by the author adapt the dominance checks routinely used for comparisons of income distributions to ordinal variables such as life satisfaction or personal happiness. Being based on Cumulative Distribution Functions (CDFs), these techniques allow ranking two distributions without strong assumptions about the nature of the social welfare function.

On the one hand, the F-dominance tell us that distribution A has higher well-being levels than B if A F-dominates B. Formally, following the First-Order Stochastic Dominance criteria, distribution A F-dominates B if and only if the CDF_A lies nowhere above the CDF_B. On the other hand, the S-dominance shows which distribution is more unequal, understanding inequality in this context as having greater spread away from the median. Formally, distribution A S-dominates B (A is more evenly distributed) if two conditions are fulfilled. First, both distributions share the same median value m. Second, for all categories $k<m$, the CDF_B is nowhere bellow CDF_A, while for all categories $k \geq m$, the CDF_B is nowhere above the CDF_A. Note that, by definition, F-dominance and S-dominance are incompatible: the CDFs cannot cross for F-dominance, but the CDFs for A and B must cross each other once for S-dominance. Finally, the Generalized Lorenz Curves (GLC) also show which distribution is more or less equally distributed. In particular, distribution A is more equally distributed than distribution B if GLC_B lies everywhere below GLC_A.

In our case, we are interested in checking whether personal wellbeing is higher or more unequally distributed for those individuals who experience a given type of intergenerational mobility. In doing so, we compute the CDFs of life satisfaction for each of the three different groups we created in the previous section: immobile, upward and downward moving individuals. Note that these Figures are separately computed for income, occupational and educational mobility to detect whether further differences exist between the three mobility types.

First, we focus on the F-dominance and study if wellbeing is higher for certain group. Figure A1 in the Appendix shows the CDFs of life satisfaction for each of the three categories of intergenerational income mobility. We find that upward mobility F-dominates immobility, meaning that the former present higher levels of life satisfaction than the latter. Interestingly, no F-dominance is found between upward and downward income mobility, as their curves cross at the right tail of the distribution. Figure A7 repeats the analysis using personal happiness as the dependent variable. Now, upward mobility F-Dominates the other two distributions.

Similarly, Figures A2 and A3 display the CDFs of life satisfaction conditioned on the different categories of intergenerational occupational and educational mobility. No F-dominance is found and, in general, the relation between the CDFs is not as clear as for income mobility. Up to the median, those who experience upward mobility are more satisfied with their lives, but the CDFs cross and mislead the analysis from that point onwards. Again, Figures A8 and A9 use personal happiness as the dependent variable and confirm the lack of dominances.

Now we move to the S-dominance and check whether some groups have more equal or unequal wellbeing distributions. Coming back to Figures A1 and A3, the CDFs of both the different income and educational mobility groups cross at different parts of the distributions, but they do not fulfill the necessary conditions to confirm S-dominance. We just see that the spread around the median life satisfaction is quite homogeneous across intergenerational income and educational mobility categories. According to Figure A2, upward occupational mobility S-dominates downward and immobility, meaning that individuals who climb the occupational ladder are more clustered around the median ($m = 8$) and have a more equal distribution than those belonging to the other two mobility categories. However, this result is not robust to the dependent variable, as the S-dominance disappears when we consider personal happiness (Figure A8). Moreover, we have checked that the GLCs show similar findings.

The absence of clear dominances calls for a more precise econometric analysis. We run several OLS regressions to disentangle the effects of intergeneration mobility and control for other factors that might also affect personal wellbeing.[12] We are aware of the limitations inherent to the data and the models, which prevent us from making strong causal assessments on the relation between our dependent and the explanatory variables. Consequently, our results only explain the plain correlations between the variables considered, leaving the causal analysis and discussion of possible channels for further research benefited from more complete data.

All Tables hereby presented include four different models accounting for different possible effects of intergenerational mobility on personal wellbeing. In doing so, each model uses one of the mobility variables we derive from the transition matrices presented in section 3. In particular, Model 1 includes mobility as a discrete variable to measure its direct impact, where -1 represents downward mobility, 0 immobility and 1 upward mobility. Model 2 considers the intensity of the mobility experienced, this is, the magnitude of the movement. Indeed, this measure is constructed with the number of ladders ascended or descended between generations. For instance, education

[12] Despite ordered probit regressions being the most accurate model, the large number of categories that are included in the dependent variable (defined from 0 to 10) make the interpretation of the results quite cumbersome. Thus, our analysis is based on traditional OLS regression, but we have checked that the results are robust to using ordered probit regressions. All results are available upon request.

is classified in four levels, so respondents who achieve the highest educational level and have a low educated father are assigned a value of 3 (they ascend three steps in the educational ladder), while those whose fathers attended upper secondary education but are low educated receive a -2 (they descend two steps). Model 2 assumes that the effect of intensity is linear in mobility, this is, homogeneous and independent from the number of steps climbed or descended. Model 3 broadens the analysis and accounts for potential non-linearities by squaring the previous "intensity" variable.[13] Finally, Model 4 includes two dummies, one for upward and the other for downward mobility, the immobility status being the omitted category. This final model is used to disentangle whether the effects found in Models 1, 2 or 3, if significant, are caused by those who improve or worsen their situation.

Table 11 relates life satisfaction and income mobility. Despite the parameters associated to mobility are positively correlated with life satisfaction, the relation is never significant. The four different specifications maintain and confirm these results, which are in line with Zhang and de Graaf (2016) and Iveson and Deary (2017). Indeed, despite the signs in Model 4 are in line with the common reasoning, this is, upward mobility is related to higher life satisfaction and vice versa, they are far from being significant. Table A6 in the Appendix confirms the robustness of this finding by employing personal happiness as the dependent variable.

Table 11: Life Satisfaction and Income Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	0.111			
	(0.081)			
Mob. Intensity		0.059		
		(0.042)		
Mob. Intensity (squared)			-0.000	
			(0.014)	
Up Mob.				0.095
				(0.149)
Down Mob.				-0.126
				(0.154)
Sex	0.009	0.046	0.050	0.008
	(0.116)	(0.116)	(0.116)	(0.116)
Age	-0.014	-0.014	-0.016	-0.013
	(0.077)	(0.077)	(0.077)	(0.077)
Age squared	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.516***	0.505***	0.506***	0.516***

[13] This transformation assumes a convex relation between mobility and personal wellbeing. We have also checked for a concave relation by specifying a squared root transformation, finding no changes in the results.

	(0.083)	(0.085)	(0.085)	(0.083)
Married	0.439***	0.455***	0.470***	0.439***
	(0.146)	(0.146)	(0.144)	(0.146)
Kids	-0.092	-0.097	-0.098	-0.091
	(0.148)	(0.149)	(0.149)	(0.149)
Poverty	-0.154***	-0.153***	-0.151***	-0.155***
	(0.051)	(0.051)	(0.051)	(0.051)
Income quantile 2	0.341*	0.357*	0.398*	0.342*
	(0.206)	(0.211)	(0.212)	(0.208)
Income quantile 3	0.516**	0.516**	0.597***	0.517**
	(0.209)	(0.217)	(0.213)	(0.210)
Income quantile 4	0.398*	0.388*	0.524**	0.399*
	(0.211)	(0.223)	(0.206)	(0.211)
Income quantile 5	0.238	0.222	0.400*	0.237
	(0.249)	(0.268)	(0.228)	(0.248)
Constant	6.649***	6.690***	6.602***	6.660***
	(1.724)	(1.736)	(1.745)	(1.730)
Observations	789	781	781	789
R-squared	0.163	0.164	0.162	0.163

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The coefficients, signs and significance of the control variables are remarkably robust among the different specifications and present no surprising results. Gender, age and having kids are not relevant for life satisfaction. On the contrary, and in line with the literature, enjoying good health is one of the variables that contribute the most to personal wellbeing (Deaton and Arora, 2009; Iveson and Deary, 2017). In general, healthy people are less likely to report sadness, physical pain, stress and anger, which are emotions related to lower levels of life satisfaction. Same as Clark and D'Angelo (2009), we find a consistent and positive effect of being married on life satisfaction, while the self-assessed poverty is negatively related.

Tables 12 and 13 analyze the effect of educational and occupational mobility on life satisfaction, respectively. All these models confirm the robustness of our previous results: none of the mobility measures have a significant relation with life satisfaction and the controls tell a similar story. Moreover, Tables A7 and A8 in the Appendix also confirm that neither occupational nor educational mobility are significantly related to personal happiness, and that the control variables overall provide the same ideas. Finally, Tables A9 to A12 repeat this regression analysis for the unrestricted sample (observations with missing incomes are included) to convince the reader that the results are not driven by a reduced sample bias. Clearly, neither the significance nor the signs of the coefficients vary, while their size remains quite similar.

Table 12: Life Satisfaction and Occupational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	-0.076			
	(0.109)			
Mob. Intensity		-0.046		
		(0.070)		
Mob. Intensity (squared)			-0.039	
			(0.035)	
Up Mob.				-0.073
				(0.157)
Down Mob.				0.078
				(0.186)
Sex	0.021	0.021	0.023	0.021
	(0.115)	(0.115)	(0.115)	(0.115)
Age	-0.008	-0.008	0.001	-0.008
	(0.078)	(0.078)	(0.078)	(0.078)
Age squared	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.536***	0.535***	0.538***	0.536***
	(0.083)	(0.083)	(0.083)	(0.084)
Married	0.520***	0.518***	0.506***	0.520***
	(0.146)	(0.146)	(0.144)	(0.147)
Kids	-0.049	-0.049	-0.045	-0.049
	(0.147)	(0.147)	(0.147)	(0.147)
Poverty	-0.197***	-0.196***	-0.200***	-0.197***
	(0.049)	(0.049)	(0.048)	(0.049)
Qualified occup.	-0.077	-0.093	-0.174	-0.076
	(0.224)	(0.215)	(0.209)	(0.250)
Technicians	-0.240	-0.268	-0.368	-0.241
	(0.278)	(0.260)	(0.231)	(0.275)
Directives and professionals	0.164	0.158	0.089	0.164
	(0.285)	(0.281)	(0.217)	(0.285)
Constant	6.905***	6.917***	6.830***	6.905***
	(1.778)	(1.775)	(1.771)	(1.779)
Observations	789	789	789	789
R-squared	0.155	0.155	0.156	0.155

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Life Satisfaction and Educational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	0.105			
	(0.103)			
Mob. Intensity		0.040		
		(0.051)		
Mob. Intensity (squared)			0.005	
			(0.020)	
Up Mob.				0.008
				(0.150)
Down Mob.				-0.279
				(0.235)
Sex	0.028	0.027	0.027	0.032
	(0.116)	(0.116)	(0.116)	(0.116)
Age	-0.023	-0.022	-0.022	-0.024
	(0.079)	(0.079)	(0.079)	(0.079)
Age squared	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.535***	0.537***	0.535***	0.535***
	(0.083)	(0.083)	(0.083)	(0.084)
Married	0.496***	0.496***	0.498***	0.500***
	(0.144)	(0.144)	(0.144)	(0.144)
Kids	-0.064	-0.058	-0.052	-0.061
	(0.148)	(0.148)	(0.147)	(0.148)
Poverty	-0.203***	-0.204***	-0.204***	-0.203***
	(0.049)	(0.049)	(0.049)	(0.049)
Compulsory Secondary	-0.395	-0.355	-0.335	-0.313
	(0.241)	(0.229)	(0.227)	(0.258)
Post-compulsory Secondary	-0.260	-0.239	-0.195	-0.182
	(0.178)	(0.178)	(0.172)	(0.196)
Tertiary	-0.170	-0.163	-0.112	-0.115
	(0.179)	(0.186)	(0.185)	(0.187)
Constant	7.457***	7.420***	7.390***	7.465***
	(1.798)	(1.801)	(1.806)	(1.800)
Observations	789	789	789	789
R-squared	0.155	0.155	0.154	0.156

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The lack of significant relation between life satisfaction and intergenerational mobility should not lead us to claim that both variables are by no means connected. Rather, we propose another explanation. The wellbeing literature does not agree on whether the effects of mobility on life satisfaction are permanent or transitory. In particular, the hedonic adaptation hypothesis claims that as the individuals climb or descend the socioeconomic ladder, they rapidly adjust to their new acquired status. As a consequence, the positive or negative effects associated to intergenerational mobility would be transitory, finding no significant effects between both variables. For instance, in the case of upward mobility, it has been found that despite higher levels of consumption capabilities increase marginal utility, its positive psychological effects dissipate relatively soon (Di Tella et al, 2006). On the contrary, the comparison theory suggests that the wellbeing effects arising from upward or downward mobility are permanent (Clark and Oswald, 1996; Miles and Rossi, 2007). According to them, individuals have a certain reference group during their lives, which in many cases is composed by the elder relatives. Achievements and events in life are put in perspective, balancing them with the permanent status of the comparison group. Interestingly, it has been shown that the psychological self-punishment derived from downward mobility is stronger than the reward obtained from upward mobility (Guilbert and Paul, 2009)

Our results demonstrate that intergenerational mobility does not have a permanent impact on personal wellbeing, and thus reject the prevalence of the comparison theory in Spain. If the effect was permanent, we would have found a significant relation, most probably positive for upward and negative for downward mobility. Given these results, we suggest that if income, educational or occupational improvements ever affect wellbeing in Spain, their effect disappear with time and, on average, end up not affecting life satisfaction or personal happiness. Besides, even though we have find that enjoying good health or being married have long-lasting positive effects on personal welfare, testing the hedonic adaptive hypothesis requires a different data structure. We would need a panel to properly account for the evolution of life satisfaction and personal happiness throughout life. Being our data purely cross sectional, we leave the confirmation of the hedonic adaptation theory open for further research once the appropriate data is available.

5. Conclusions

This paper explores the relation between personal wellbeing and intergenerational mobility in Spain (2017). First, we apply innovative Statistical Learning techniques to overcome data limitations and estimate intergenerational income mobility, opening up the avenue for future research with incomplete databases. Second, we broaden the analysis by also estimating intergenerational educational and occupational mobility. Third, we employ the analytic tools recently proposed by Jenkins (2019) to make distributional comparisons of ordinal welfare variables (life satisfaction and personal happiness) between different mobility group (immobility, upward and downward mobility). Finally, we run several OLS regressions to control for the traditional socio demographic factors affecting wellbeing.

The dominance checks performed using Jenkins' (2019) graphical tools show that personal wellbeing is neither higher nor more unequally distributed for a given type of intergenerational mobility. In general, experiencing upward or downward mobility is unrelated to higher or lower levels of life satisfaction or personal happiness. Moreover, these results are robust to the three forms of mobility considered: that of income, education and occupation. The econometric analysis confirms these ideas. Different specifications show that mobility does not have a permanent impact on wellbeing. However, and in line with previous literature, other sociodemographic variables have a significant impact on personal wellbeing. According to our results, enjoying good health and being married are positively connected to wellbeing, whereas the association is negative for being poor.

We find clear evidence rejecting a long-lasting positive or negative psychological effect derived from intergenerational mobility. However, the cross-sectional nature of the data does not allow us to test the short-term impact of intergenerational mobility on wellbeing. Checking the hedonic adaptation theory requires having a panel data that allows accounting for the evolution of life satisfaction and personal happiness throughout life. Future surveys in Spain should have a panel structure so that researches are capable of studying the evolution and the short-term effects of intergenerational mobility on welfare.

Appendix

Table A1: Summary Statistics of the occupation of the respondents and their fathers in the unrestricted sample (N=1190).

	Respondents	Fathers
ISCO-08=9 (Unqualified workers)	12.44%	6.55%
ISCO-08=4-8 (Semi-qualified and qualified workers)	53.70%	71.09%
ISCO-08=3 (Technicians and support professionals)	13.87%	8.91%
ISCO-08=1-2 (Managers and professionals)	20.00%	13.45%
Mean	2.41	2.29
Standard Deviation	0.94	0.78

Table A2: Summary Statistics of the education of the respondents and their fathers in the unrestricted sample (N=1190).

	Respondents	Fathers
ISCED=0-1, Primary education (1)	30.50%	67.56%
ISCED=2, Low secondary education (2)	13.11%	10.92%
ISCED=3-4, Upper secondary education (3)	29.58%	9.58%
ISCED=5-8, Post secondary (4)	26.81%	11.93%
Mean	2.53	1.66
Standard Deviation	1.18	1.06

Table A3: Summary Statistics of the control variables in the unrestricted sample (N=1190).

	Mean	Standard Deviation
Age	45.10	8.32
Gender (Men=1)	0.50	0.50
Civil Status (Married=1)	0.60	0.49
Kids (Have kids=1)	0.73	0.46
Poverty (0=poorest, 10=richest)	4.89	1.41

Table A4. Transition matrix of occupation for the unrestricted sample (N=1190).

		Occupation of the respondents				
		ISCO-08=9, Unqualified workers	ISCO-08=4-8, Semi-qualified and qualified workers	ISCO-08=3, Technicians and support professionals	ISCO-08=1-2, Managers and professionals	TOTAL
Occupation of the fathers	ISCO-08=9, Unqualified workers	25	36	7	10	78
	ISCO-08=4-8, Semi-qualified and qualified workers	108	494	104	140	846
	ISCO-08=3, Technicians and support professionals	7	49	23	27	106
	ISCO-08=1-2, Managers and professionals	8	60	31	61	160
	TOTAL	148	639	165	238	1190

Table A5. Transition matrix of education in the unrestricted sample (N=1190).

		Education of the fathers				
		ISCED=0-1, Primary education	ISCED=2, Low secondary education	ISCED=3-4, Upper secondary education	ISCED=5-8, Post secondary	TOTAL
Education of the fathers	ISCED=0-1, Primary education	335	108	220	141	804
	ISCED=2, Low secondary education	17	22	48	43	130
	ISCED=3-4, Upper secondary education	8	17	50	39	114
	ISCED=5-8, Post secondary	3	9	34	96	142
	TOTAL	363	156	352	319	1190

Table A6: Personal Happiness and Income Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	0.115			
	(0.081)			
Mob. Intensity		0.052		
		(0.044)		
Mob. Intensity (squared)			0.005	
			(0.015)	
Up Mob.				0.070
				(0.147)
Down Mob.				-0.160
				(0.156)
Sex	0.182	0.216*	0.220*	0.180
	(0.118)	(0.118)	(0.118)	(0.119)
Age	-0.037	-0.035	-0.037	-0.036
	(0.078)	(0.078)	(0.078)	(0.078)
Age squared	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.434***	0.419***	0.420***	0.433***
	(0.088)	(0.089)	(0.089)	(0.088)
Married	0.404***	0.415***	0.426***	0.406***
	(0.146)	(0.146)	(0.146)	(0.146)
Kids	-0.064	-0.084	-0.085	-0.060
	(0.152)	(0.152)	(0.152)	(0.152)
Poverty	-0.128**	-0.124**	-0.122**	-0.129**
	(0.052)	(0.052)	(0.052)	(0.052)
Income quantile 2	0.160	0.194	0.238	0.163
	(0.216)	(0.220)	(0.222)	(0.217)
Income quantile 3	0.339	0.365	0.446**	0.342
	(0.219)	(0.226)	(0.223)	(0.220)
Income quantile 4	0.222	0.247	0.375*	0.223
	(0.225)	(0.236)	(0.224)	(0.225)
Income quantile 5	0.043	0.071	0.229	0.040
	(0.253)	(0.271)	(0.237)	(0.252)
Constant	7.746***	7.740***	7.633***	7.776***
	(1.762)	(1.770)	(1.772)	(1.762)
Observations	789	781	781	789
R-squared	0.129	0.129	0.127	0.129

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A7: Personal Happiness and Occupational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	-0.104			
	(0.110)			
Mob. Intensity		-0.047		
		(0.070)		
Mob. Intensity (squared)			-0.029	
			(0.035)	
Up Mob.				-0.098
				(0.166)
Down Mob.				0.109
				(0.184)
Sex	0.195*	0.195*	0.196*	0.195*
	(0.118)	(0.118)	(0.118)	(0.118)
Age	-0.033	-0.033	-0.025	-0.033
	(0.078)	(0.078)	(0.078)	(0.079)
Age squared	0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.443***	0.444***	0.446***	0.443***
	(0.087)	(0.087)	(0.086)	(0.087)
Married	0.484***	0.478***	0.467***	0.484***
	(0.146)	(0.146)	(0.145)	(0.146)
Kids	-0.020	-0.020	-0.018	-0.020
	(0.151)	(0.151)	(0.151)	(0.151)
Poverty	-0.160***	-0.160***	-0.163***	-0.160***
	(0.049)	(0.049)	(0.048)	(0.048)
Qualified occup.	-0.081	-0.117	-0.187	-0.078
	(0.219)	(0.210)	(0.205)	(0.243)
Technicians	-0.258	-0.323	-0.416*	-0.259
	(0.269)	(0.252)	(0.230)	(0.267)
Directives and professionals	0.077	0.027	-0.056	0.077
	(0.274)	(0.271)	(0.211)	(0.274)
Constant	7.887***	7.918***	7.864***	7.888***
	(1.795)	(1.796)	(1.802)	(1.797)
Observations	789	789	789	789
R-squared	0.127	0.126	0.126	0.127

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Personal Happiness and Educational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	0.135			
	(0.112)			
Mob. Intensity		0.055		
		(0.053)		
Mob. Intensity (squared)			0.007	
			(0.020)	
Up Mob.				-0.005
				(0.158)
Down Mob.				-0.386
				(0.297)
Sex	0.190	0.189	0.189	0.197*
	(0.118)	(0.117)	(0.118)	(0.118)
Age	-0.038	-0.037	-0.036	-0.039
	(0.079)	(0.079)	(0.079)	(0.078)
Age squared	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.444***	0.447***	0.445***	0.444***
	(0.086)	(0.086)	(0.087)	(0.086)
Married	0.451***	0.450***	0.454***	0.457***
	(0.144)	(0.144)	(0.144)	(0.144)
Kids	-0.041	-0.034	-0.026	-0.036
	(0.152)	(0.152)	(0.152)	(0.152)
Poverty	-0.163***	-0.163***	-0.163***	-0.162***
	(0.050)	(0.050)	(0.050)	(0.049)
Compulsory Secondary	-0.214	-0.165	-0.138	-0.095
	(0.243)	(0.231)	(0.229)	(0.273)
Post-compulsory Secondary	-0.207	-0.186	-0.127	-0.095
	(0.179)	(0.179)	(0.177)	(0.208)
Tertiary	-0.213	-0.212	-0.145	-0.135
	(0.180)	(0.187)	(0.193)	(0.196)
Constant	8.135***	8.090***	8.050***	8.146***
	(1.799)	(1.800)	(1.804)	(1.794)
Observations	789	789	789	789
R-squared	0.124	0.124	0.123	0.126

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Life Satisfaction and Occupational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	-0.013			
	(0.088)			
Mob. Intensity		-0.001		
		(0.057)		
Mob. Intensity (squared)			-0.011	
			(0.029)	
Up Mob.				0.084
				(0.138)
Down Mob.				0.097
				(0.143)
Sex	0.022	0.022	0.023	0.023
	(0.092)	(0.092)	(0.092)	(0.092)
Age	-0.083	-0.082	-0.081	-0.086
	(0.060)	(0.060)	(0.060)	(0.060)
Age squared	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.484***	0.485***	0.485***	0.485***
	(0.067)	(0.067)	(0.067)	(0.067)
Married	0.520***	0.519***	0.518***	0.520***
	(0.116)	(0.116)	(0.114)	(0.115)
Kids	-0.039	-0.039	-0.039	-0.040
	(0.118)	(0.118)	(0.118)	(0.118)
Poverty	-0.216***	-0.217***	-0.217***	-0.215***
	(0.040)	(0.040)	(0.040)	(0.040)
Qualified occup.	-0.094	-0.102	-0.113	-0.043
	(0.184)	(0.177)	(0.172)	(0.201)
Technicians	-0.233	-0.248	-0.255	-0.242
	(0.228)	(0.214)	(0.193)	(0.226)
Directives and professionals	-0.025	-0.042	-0.030	-0.025
	(0.237)	(0.236)	(0.187)	(0.237)
Constant	8.927***	8.933***	8.914***	8.922***
	(1.382)	(1.381)	(1.378)	(1.382)
Observations	1,191	1,191	1,191	1,191
R-squared	0.154	0.154	0.154	0.154

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A10: Life Satisfaction and Educational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	0.093			
	(0.081)			
Mob. Intensity		0.034		
		(0.042)		
Mob. Intensity (squared)			0.009	
			(0.016)	
Up Mob.				0.049
				(0.124)
Down Mob.				-0.167
				(0.185)
Sex	0.018	0.018	0.018	0.020
	(0.092)	(0.092)	(0.092)	(0.092)
Age	-0.089	-0.088	-0.088	-0.089
	(0.061)	(0.061)	(0.061)	(0.061)
Age squared	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.486***	0.486***	0.485***	0.486***
	(0.067)	(0.067)	(0.067)	(0.067)
Married	0.505***	0.507***	0.509***	0.506***
	(0.115)	(0.115)	(0.115)	(0.115)
Kids	-0.043	-0.037	-0.034	-0.042
	(0.118)	(0.118)	(0.118)	(0.118)
Poverty	-0.221***	-0.222***	-0.222***	-0.221***
	(0.041)	(0.041)	(0.041)	(0.041)
Compulsory Secondary	-0.144	-0.108	-0.094	-0.107
	(0.190)	(0.181)	(0.178)	(0.209)
Post-compulsory Secondary	-0.170	-0.149	-0.124	-0.135
	(0.142)	(0.141)	(0.135)	(0.157)
Tertiary	-0.182	-0.172	-0.149	-0.157
	(0.147)	(0.155)	(0.151)	(0.156)
Constant	9.130***	9.092***	9.078***	9.126***
	(1.396)	(1.397)	(1.398)	(1.396)
Observations	1,191	1,191	1,191	1,191
R-squared	0.154	0.153	0.153	0.154

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A11: Personal Happiness and Occupational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	-0.062			
	(0.086)			
Mob. Intensity		-0.020		
		(0.057)		
Mob. Intensity (squared)			0.004	
			(0.029)	
Up Mob.				0.063
				(0.140)
Down Mob.				0.171
				(0.142)
Sex	0.113	0.112	0.111	0.114
	(0.093)	(0.093)	(0.093)	(0.093)
Age	-0.110*	-0.110*	-0.110*	-0.114*
	(0.060)	(0.060)	(0.061)	(0.061)
Age squared	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.409***	0.410***	0.411***	0.410***
	(0.069)	(0.069)	(0.069)	(0.069)
Married	0.515***	0.511***	0.507***	0.515***
	(0.118)	(0.118)	(0.117)	(0.117)
Kids	-0.040	-0.041	-0.042	-0.043
	(0.121)	(0.121)	(0.121)	(0.121)
Poverty	-0.170***	-0.170***	-0.171***	-0.168***
	(0.040)	(0.040)	(0.040)	(0.040)
Qualified occup.	-0.070	-0.099	-0.111	-0.004
	(0.179)	(0.172)	(0.169)	(0.194)
Technicians	-0.142	-0.194	-0.223	-0.154
	(0.217)	(0.207)	(0.192)	(0.216)
Directives and professionals	0.093	0.043	-0.011	0.093
	(0.224)	(0.225)	(0.180)	(0.224)
Constant	9.767***	9.786***	9.805***	9.760***
	(1.388)	(1.389)	(1.391)	(1.389)
Observations	1,191	1,191	1,191	1,191
R-squared	0.127	0.127	0.127	0.128

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A12: Personal Happiness and Educational Mobility

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Mobility	0.063			
	(0.087)			
Mob. Intensity		0.036		
		(0.042)		
Mob. Intensity (squared)			0.014	
			(0.016)	
Up Mob.				0.018
				(0.129)
Down Mob.				-0.139
				(0.219)
Sex	0.106	0.105	0.104	0.108
	(0.092)	(0.093)	(0.093)	(0.093)
Age	-0.108*	-0.108*	-0.108*	-0.108*
	(0.061)	(0.061)	(0.061)	(0.061)
Age squared	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Health	0.412***	0.413***	0.413***	0.412***
	(0.069)	(0.069)	(0.069)	(0.069)
Married	0.496***	0.496***	0.498***	0.497***
	(0.117)	(0.117)	(0.117)	(0.117)
Kids	-0.043	-0.040	-0.037	-0.042
	(0.122)	(0.122)	(0.122)	(0.122)
Poverty	-0.175***	-0.175***	-0.176***	-0.175***
	(0.041)	(0.041)	(0.041)	(0.041)
Compulsory Secondary	0.014	0.030	0.040	0.053
	(0.189)	(0.179)	(0.177)	(0.215)
Post-compulsory Secondary	-0.108	-0.113	-0.097	-0.072
	(0.144)	(0.144)	(0.140)	(0.166)
Tertiary	-0.089	-0.108	-0.103	-0.063
	(0.146)	(0.153)	(0.153)	(0.159)
Constant	9.752***	9.739***	9.732***	9.749***
	(1.394)	(1.394)	(1.396)	(1.394)
Observations	1,191	1,191	1,191	1,191
R-squared	0.126	0.126	0.126	0.126

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure Appendix

Figure A1: Cumulative Density Function of Life Satisfaction by Income Mobility

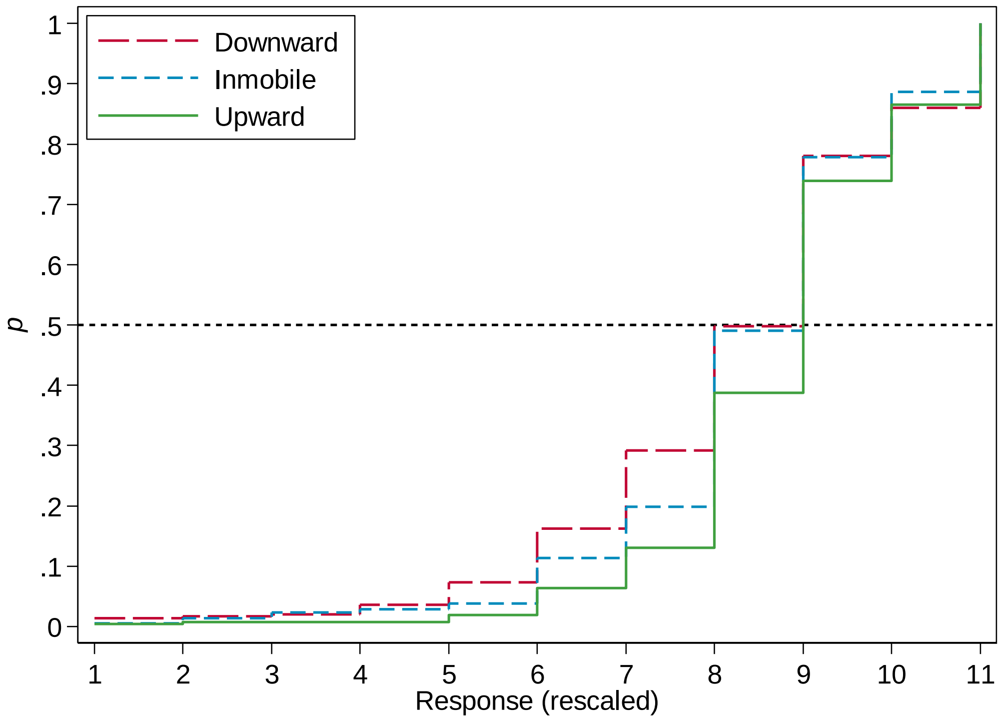


Figure A2: Cumulative Density Function of Life Satisfaction by Occupation Mobility

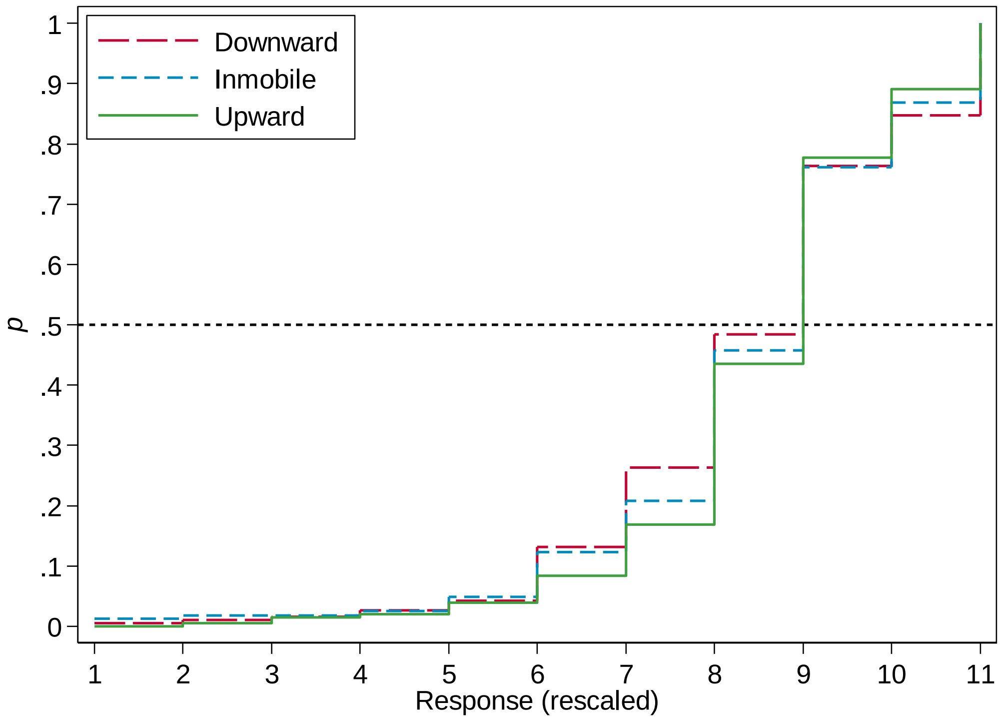


Figure A3: Cumulative Density Function of Life Satisfaction by Education Mobility

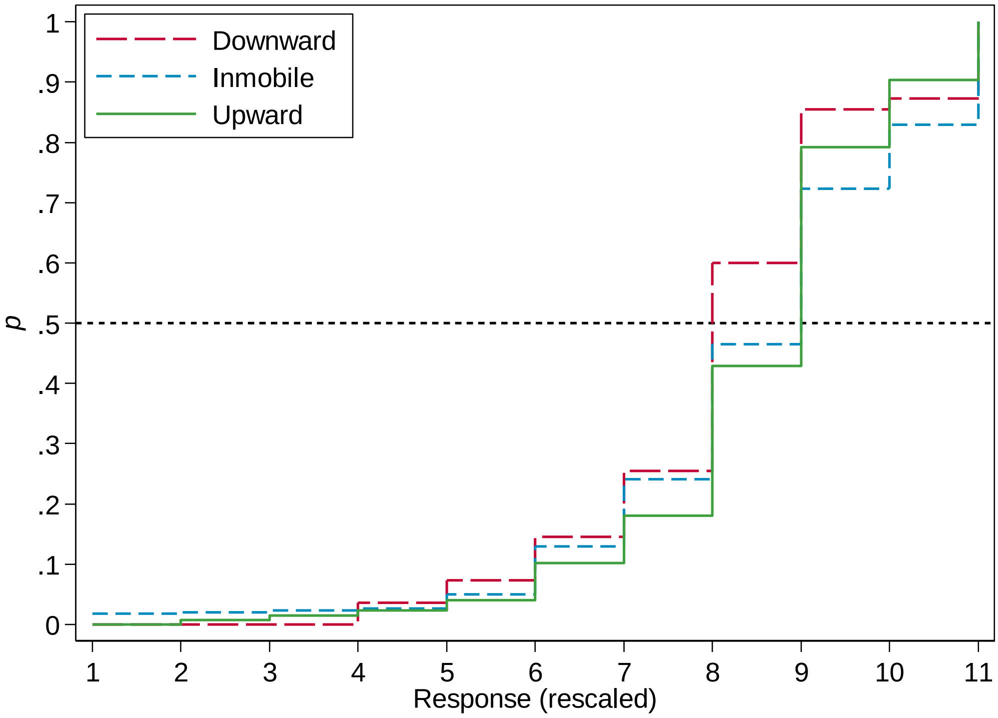


Figure A4: Generalized Lorenz Curves of Life Satisfaction by Income Mobility

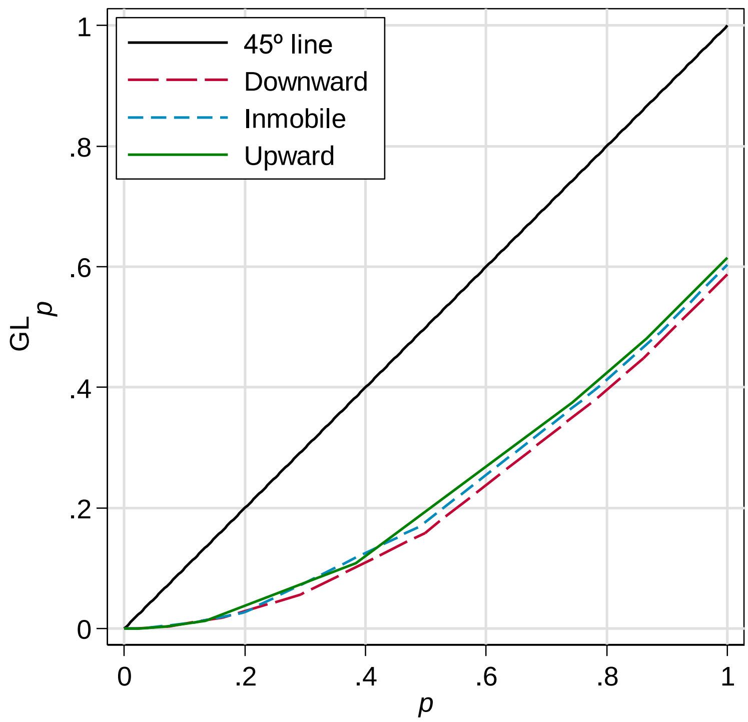


Figure A5: Generalized Lorenz Curves of Life Satisfaction by Occupation Mobility

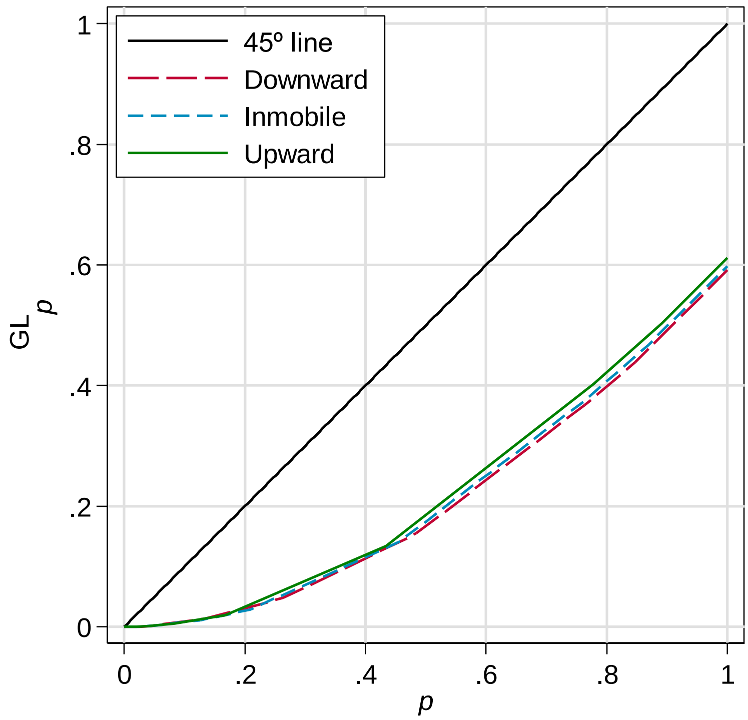


Figure A6: Generalized Lorenz Curves of Life Satisfaction by Education Mobility

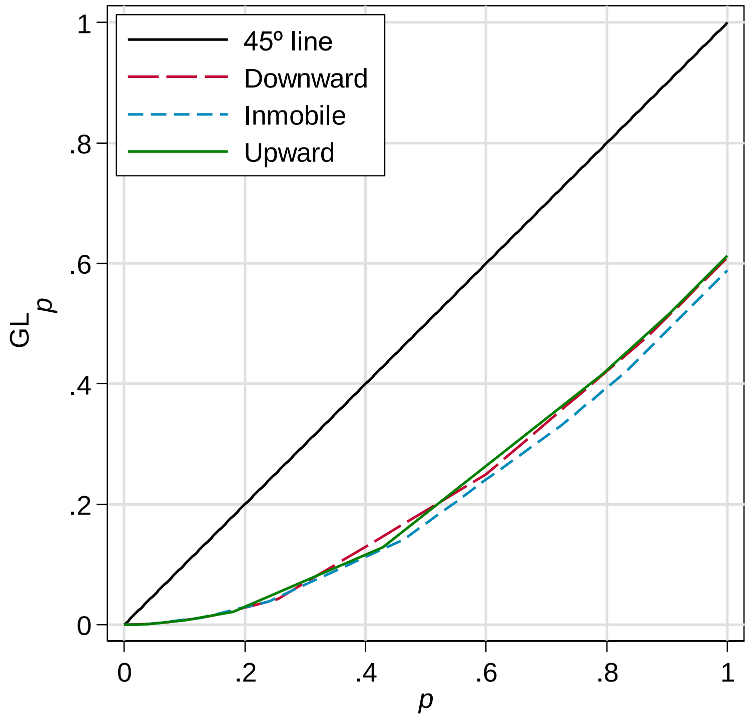


Figure A7: Cumulative Density Function of Happiness by Income Mobility

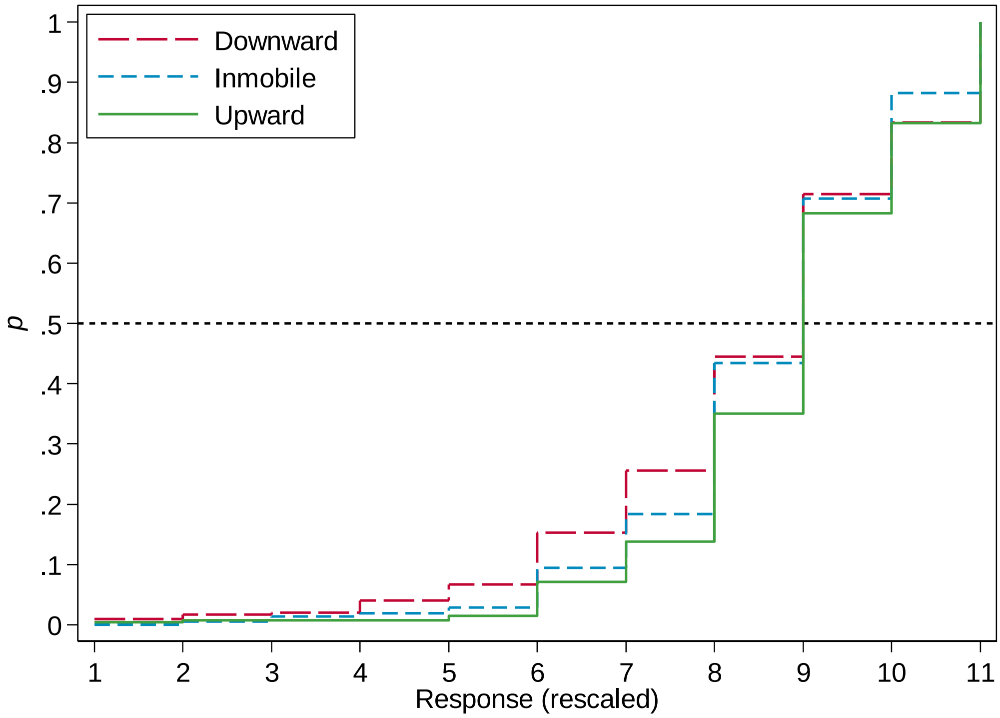


Figure 8: Cumulative Density Function of Happiness by Occupation Mobility

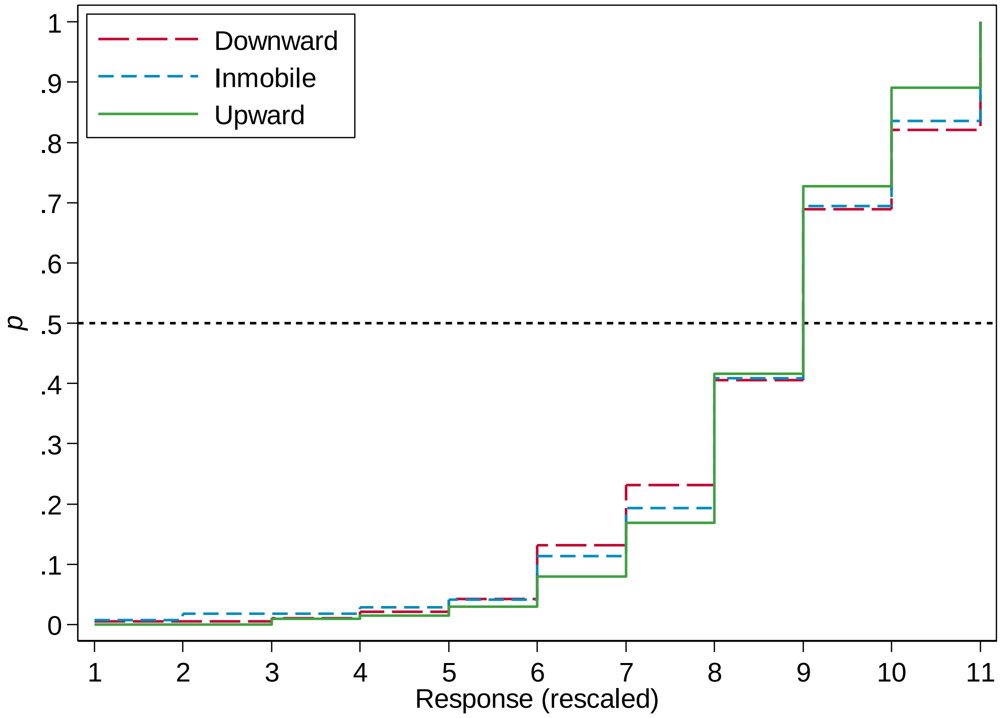


Figure 9: Cumulative Density Function of Happiness by Education Mobility

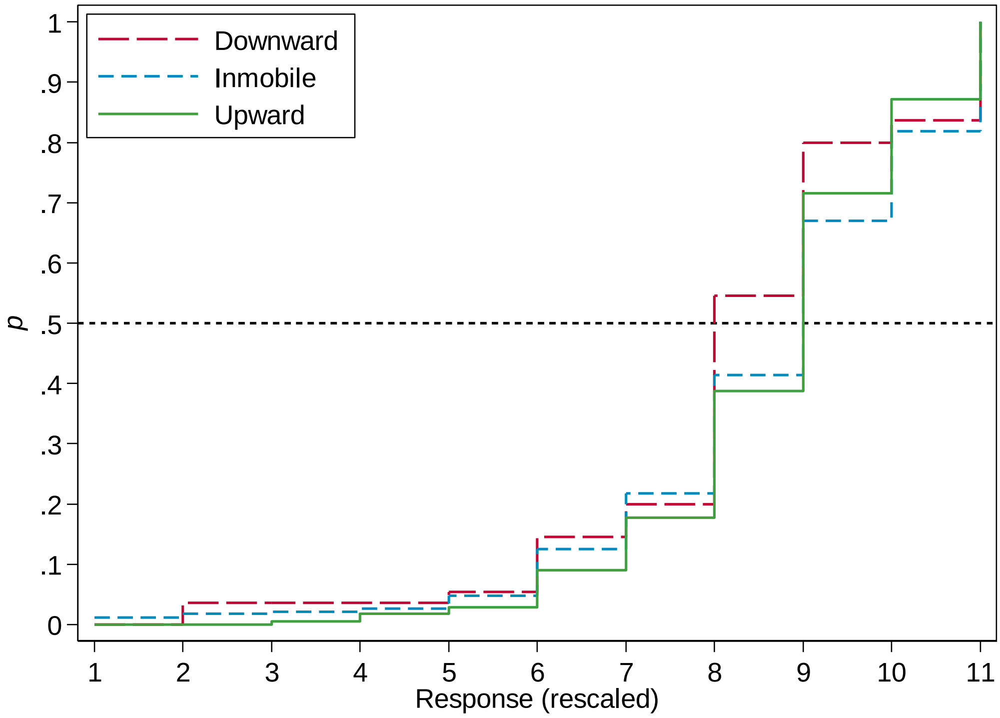


Figure 10: Generalized Lorenz Curves of Happiness by Income Mobility

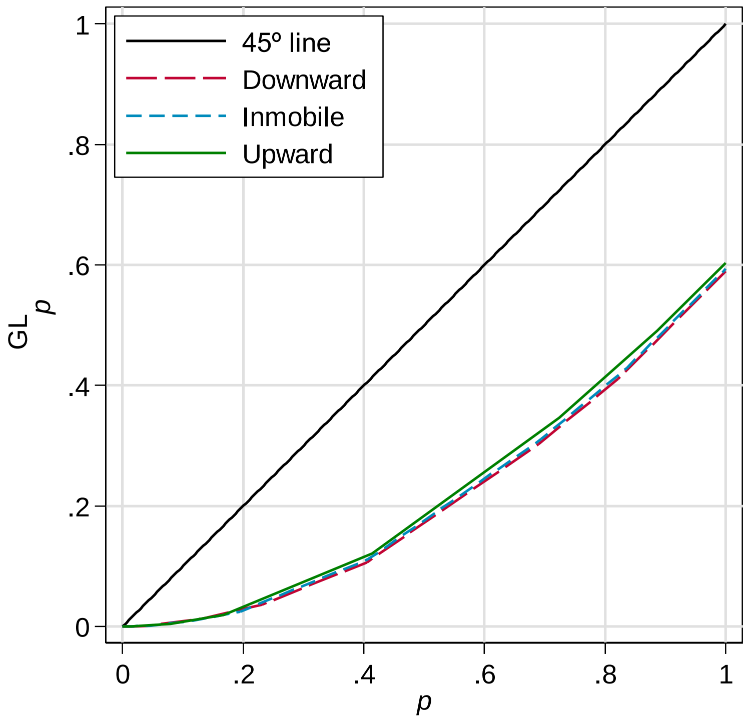


Figure 11: Generalized Lorenz Curves of Happiness by Occupation Mobility

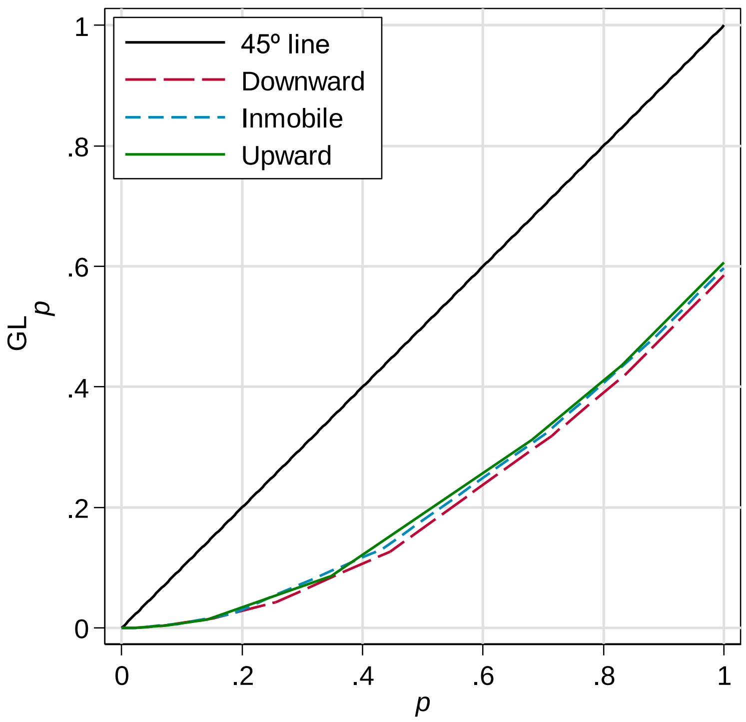


Figure 12: Generalized Lorenz Curves of Happiness by Education Mobility