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Does Income Class Affect Life Satisfaction? New Evidence from Cross-Country Microdata

Joanne Haddad [1], Jad Chaaban [2,*], Ali Chalak [2] and Hala Ghattas [3]

1 ECARES, Université Libre de Bruxelles, 1050 Brussels, Belgium; joanne.haddad@ulb.be
2 Department of Agriculture, Faculty of Agricultural and Food Sciences, American University of Beirut, Beirut 1107 2020, Lebanon; ac22@aub.edu.lb
3 Center for Research on Population and Health, Faculty of Health Sciences, American University of Beirut, Beirut 1107 2020, Lebanon; hg15@aub.edu.lb
* Correspondence: jc11@aub.edu.lb

Abstract: This paper analyzes the impact of income class on subjective wellbeing. Using rich data from the Gallup World Poll, we investigate whether belonging to locally (both country- and time-specific) defined income classes influences individuals' life satisfaction. We rely on a latent class analysis estimation method, using individual income proxied by household income divided by household size, as an observable characteristic to hypothesize the income classes. We fit a model with one categorical latent variable with three unobserved groupings, here: income classes, which we interpret as lower, middle and upper classes. Our estimates suggest that individuals in the low and middle income classes are, respectively, about 30 and 17 percent of a standard deviation less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class. The effect of income classes remains robust to the inclusion of standard explanatory variables in this literature.

Keywords: income classes; income; life satisfaction; well-being; Gallup World Poll; latent class analysis

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1. Introduction

International trends in income inequality and comparisons across countries have been a key area of investigation in economics. A wide literature, both theoretical and empirical, has focused on measuring how income inequality is related to economic growth. While many papers document a negative linkage (Alesina and Perotti (1994); Alesina and Rodrik (1994); Birdsall et al. (1995); Persson and Tabellini (1994), etc.), the robustness of the relationship remains inconclusive. This is especially true in light of many papers documenting a positive association between income inequality and economic growth (Benabou (1996); Galor and Tsiddon (1997); Saint-Paul and Verdier (1993)).

Although the majority of the research examining inequality has focused on objective measures of wellbeing, such as income, an emerging literature highlights the relevance of using subjective measures as key instruments in the analysis of welfare. The study of subjective wellbeing (SWB) has gained popularity recently and has been made possible given the availability of surveys measuring people's life satisfaction or happiness. Examining the determinants of happiness, Richard Easterlin's (1974) claim, later known as the Easterlin paradox, suggests that increasing average income did not raise average wellbeing when examining a specific country over time. Stated differently, economic growth of nations may not always induce an increase in happiness within them.

Not only is the evidence in support of a longitudinal relationship between income and happiness still mixed (Easterlin paradox) but also a robust relationship between income and subjective wellbeing both within and across nations is still absent. While some papers document a positive association between income and subjective wellbeing across countries and a positive link between absolute income and individuals' reported happiness at the individual or household level (Blanchflower and Oswald (2004); Clark et al. (2008); Deaton (2008); Diener et al. (2010); Easterlin (2001); Frijters et al. (2004); Kahneman and Deaton (2010); Stevenson and Wolfers (2008)), many papers argue that an income satiation point exists beyond which income is no longer associated with subjective wellbeing (Di Tella and MacCulloch (2008); Stevenson and Wolfers (2013)).

The purpose of this paper is to examine whether individuals' income classes influence their subjective wellbeing. Rather than using arbitrary thresholds to define income classes, we rely on individual-level income data (proxied by household income over household size) from the Gallup World Poll (GWP) and a latent class analysis (LCA) method to hypothesize income classes in a given country and year. We fit a latent class model with three classes and one observable variable that is a continuous measure of individual income. We thus hypothesize that there are three income classes, which we refer to as the low, middle and upper income classes, and that they are determined by individuals' observed characteristics in terms of income holdings. We do so for each year–country combination available in our sample. Our final sample is restricted to 1,294,943 respondents in 160 countries between 2009 and 2017. As a robustness check, we test the goodness of the fit using BIC (Bayesian information criterion) in Section 4.

Next, we determine the expected classification for each individual in our dataset based on the predicted posterior class probability. We then rely on an ordered logit response model where we adopt a subjective measure of life satisfaction drawn from the Gallup World Poll as our dependent variable and control for an exhaustive list of explanatory variables, including our main variables of interest: the individuals' class membership indices. Throughout our analysis, we control for country and Gallup World Poll year-wave fixed effects, which allows us to remove the influence of potential unobserved heterogeneity across countries related to life satisfaction and country-defined income classes and capture common general trends in life satisfaction. Furthermore, controlling for unobserved country heterogeneity and time dependence allows us to carry out a within-country analysis of individuals' income inequality effect on subjective wellbeing in a given year.

Given the way we define and compute income classes in a given country–year, our setting allows us to carry out an assessment of a within-country–year-specific impact of relative income of individuals on their subjective well-being. This specification does not, however, account for disparities across countries in income classes and the size of the gaps in individuals' income holding.

Our results confirm that low- and-middle-income-class individuals are less likely to report an overall life evaluation in comparison to the upper income class individuals. The size of our preferred estimates indicates about 30 and 17 percent of standard deviation lower likelihood of reporting higher life satisfaction for individuals in the low and middle income classes in comparison to the upper class.

We thus contribute to the literature on income and its consequences for human welfare with a focus on subjective wellbeing (Alesina et al. (2004); Clark (2003); Graham and Felton (2005); Hagerty (2000); Helliwell (2003); Morawetz et al. (1977); Oishi et al. (2011); Rozer and Kraaykamp (2013); Schwarze and Härpfer (2003); Senik (2004); Verme (2011); Zagorski et al. (2014)). Papers investigating this link have produced controversial results indicating either a positive or a negative effect of income inequality on subjective wellbeing. There is still a lack of consensus on whether individuals residing in highly income-dispersed places have less social wellbeing in comparison to places with more equally distributed income. Alesina et al. (2004), for instance, document lower reported levels of individual happiness in highly unequal places, even after accounting for individual income. Stark differences, however, arise across regions and across groups. Clark (2003) goes beyond examining the link between individuals' wellbeing and others' mean income or consumption levels to further account for the distribution of the income in the reference group. The paper documents that wellbeing significantly positively correlates with reference group income inequality. Verme (2011) explores plausible explanations for the heterogeneity in the impact of income inequality on subjective wellbeing, especially given that some welfare theories predict a positive impact while others support a negative or a non-significant link. The findings from Verme (2011) go in line with a consistent negative impact of income inequality on life satisfaction that is robust to a number of checks and sensitivity analyses.

We first extend this literature using a novel methodological approach in measuring the country–year-specific distribution of individuals across income classes. To our knowledge, we are the first to use a latent class analysis model to hypothesize income classes in a large year–country sample and to rely on income ownership inequality to capture income class membership. The closest methodological analogy to our paper is a work by Anderson et al. (2016), which uses the mixture model technique to identify the size distribution characteristics of each income class in urban China and estimate the probability that an agent belongs to a particular group (i.e., membership shares of each class). Understanding and examining the relationship between income, income inequality and subjective wellbeing using a large year–country sample and a novel methodology is crucial for a number of reasons. First, this allows to cross-check the robustness of previous findings from the literature to the use of a specific approach. Second, it allows to examine the consistency of the findings across different groups, countries and regions. Lastly, it is fundamental to explore the link between income inequality and subjective wellbeing given its importance to social and political policy decisions, particularly for tackling the "how" to improve the SWB question and the "what" other factors affect the relationship between income inequality and subjective wellbeing.

Second, we empirically document the impact of belonging to an income class on individuals' subjective wellbeing, providing evidence in support of the *relative income hypothesis.* We finally show that the effect of income classes remains robust to the inclusion of standard explanatory variables in the literature. Other relevant studies are perhaps two analyses by Kelley and Evans (2017b). The first paper covers the link between national income inequality and individuals' subjective wellbeing by providing exploratory analyses and extending the understanding of the factors that can explain this link, dissecting changes over time as well as expectations for the future. The paper additionally provides a heterogenous analysis of this link based on different categories, including age and political spectrum. Another relevant research study by Kelley and Evans (2017a) examines whether societal income inequality impacts individuals' quality of life and their subjective wellbeing using multilevel models and data from 169 surveys, 68 nations and over 200,000 individuals spanning the period of 1981 to 2008. Brown et al. (2015) overview a comparison of different methods used to examine the *relative income hypothesis*. Other relevant studies that relate to our analysis consider the relationship between income rank and life satisfaction. In this context, Boyce et al. (2010) constitutes the first large-scale study of the link between income rank and overall life satisfaction, documenting the importance of the former in determining the latter. More recent findings are documented in FitzRoy and Nolan (2022) and Acosta-González and Marcenaro-Gutiérrez (2022). This complements the wide and emerging literature that is thoroughly overviewed in the next section.

The remainder of the paper is structured as follows. In Section 2, we present an overview of the previous findings and methodologies. Section 3 details the datasets we use and provides some descriptive statistics. Section 4 presents the methodology and the model specification. In Section 5, we present our results and a discussion of our main findings. The last section briefly concludes.

2. Subjective Wellbeing and Inequality: Theory and Mechanism

This paper revisits income comparisons as a key mechanism in examining the subjective welfare effect of inequality. We provide suggestive evidence in support of the *relative income hypothesis.* The *relative income hypothesis* states that people tend to position their own income with respect to other people's incomes. Thus, other people's income constitutes the reference that individuals would evaluate their position against on the social ladder. People placed at the bottom of the social hierarchy would feel left behind in comparison to those who climbed the social ladder, therefore affecting their subjective wellbeing. As inequality increases, income and status differences become more pronounced, resulting in a definite impact on people's wellbeing. The literature has pointed out the importance of relative income as a key determinant of subjective wellbeing, sometimes outweighing the impact of absolute levels of income (Ball and Chernova (2008); Card et al. (2012); Delhey et al. (2017); Delhey and Dragolov (2014); Easterlin (2001); Layte (2012); Verme (2011); Wolbring et al. (2013)).

In this paper, we revisit *the relative income hypothesis* using a novel methodological approach applied in a comprehensive context. A detailed analysis of our methodology and model specifications can be found in Section 4. Our paper supports predictions of *the relative income hypothesis,* and it provides evidence in line with prior findings from the literature pointing to the impact of income inequality on subjective wellbeing even after accounting for individual income and other standard correlates.

Social comparisons have also been examined as potential means explaining the link between income and health. Thus, the *relative income hypothesis* is narrowly related to the *status anxiety hypothesis* denoting negative health implications as a result of income inequality (Wilkinson and Picket (2009)). This has, furthermore, been investigated within sociology since the theory of the *relative deprivation effect* devised by Runciman (1966). This theory claims that an individual's sensation of deprivation is explained by the relative position that they occupy in comparison to a self-selected reference group. An income application of this theory has been formalized by Yitzhaki (1979), computing relative deprivation as the sum of the distances of an individual's income from all incomes exceeding his. This has been documented to be an equivalent measure to the absolute Gini index. The prediction of this framework is that rising income inequality surges relative deprivation and reduces subjective wellbeing.

The "*tunnel effect theory*" proposed by Hirschman and Rothschild (1973) claims, for instance, a positive association between income inequality and social wellbeing. Rather than being inequality-averse, people may perceive inequality as a positive signal for social mobility. People revise their own expectations about their future social mobility, making them happier as they perceive individuals around them moving upward in the income ladder.

Even though several theories arise in the analysis of the link between income, income inequality and subjective wellbeing, in this paper, we do not seek to provide a comprehensive review of the theoretical literature nor offer an alternative theoretical model. Schneider (2016) presents a good comprehensive overview of this literature. Gasparini and Gluzmann (2012), Graham and Nikolova (2015) and Nikolova (2016) provide a rich discussion on the advantages and caveats of subjective wellbeing measurement and its link with income and income inequalities. In the next subsection, we briefly discuss additional theories and mechanisms linking subjective wellbeing to income and income inequality.

Additional Theories and Mechanisms

The paradox of why a greater income does not always cause higher wellbeing is partly explained by the *income inequality hypothesis* (IIH), which states that inequality in individual incomes has a negative impact on the wellbeing and health over and above the effect of an individual's absolute income (Subramanian and Kawachi (2004); Wilkinson and Picket (2017)). Many explanations as to how income inequality impacts wellbeing were documented in the literature, and these include externalities induced by inequality (i.e., crime and social conflict) and deterioration of social capital (i.e., higher societal divisions) (Delhey and Dragolov (2014); Haller and Hadler (2006)); Berkman and Kawachi (2000); Kawachi and Kennedy (1999); Wilkinson and Picket (2017)). The latter means that a division between social classes or groups, emerging as a result of inequality, increases societal division, including a reduction in generalized trust and social capital. These arguments relate to the *livability hypothesis* (Veenhoven (2005)) and *social capital hypothesis* presented in the literature on income inequality and health. The livability hypothesis claims that social wellbeing is a function of five societal qualities perceived as 'input' indicators (material wealth, freedom, social equality, solidarity and justice). The extent of livability is thus determined by the fit between people's needs and institutional provisions.

Other social–psychological mechanisms include people's perceptions of social mobility and social comparisons and self-worth. These explanations relate to the *status anxiety hypothesis* in the literature on income inequality and health. This is also referred to as the *relative income hypothesis* in economics or *relative deprivation effect* in sociology. The idea is that people position their income with respect to other people's incomes, placing themselves in a social hierarchy. As inequality increases, income and status differences become more pronounced, resulting in a direct impact on people's emotional wellbeing. This argument has been well-documented in the literature as a crucial mechanism through which inequality influences social wellbeing (Ball and Chernova (2008); Card et al. (2012); Delhey et al. (2017); Gardarsdottir et al. (2018); Layte (2012); Wolbring et al. (2013)).

3. Data Sources

The objective of this paper is to revisit the *relative income hypothesis* by analyzing the impact of individual-level relative income class on their subjective wellbeing using data from the Gallup World Poll (GWP). We examine data on a cross-section of respondents nested within countries. The data are drawn from waves of the (GWP) running between 2009 and 2017.

3.1. Subjective Wellbeing

The main source of data for this paper is the Gallup World Poll (GWP). We rely on the following question *(wp16)* to measure the life satisfaction of individuals:

> "Please imagine a ladder/mountain with steps numbered from zero at the bottom to ten at the top. Suppose we say that the top of the ladder/mountain represents the best possible life for you and the bottom of the ladder/mountain represents the worst possible life for you. If the top step is 10 and the bottom step is 0, on which step of the ladder/mountain do you feel you personally stand at the present time?".

For the purpose of our analysis, we focus on a measure of global life evaluation, the Cantril Ladder of Life, which is recorded on a 0–10 scale with end points labelled "Worst possible life for you" and "Best possible life for you".

Some drawbacks and limitations raised concerning the use of this question as a measure of subjective wellbeing include the caveat that respondents might interpret this question differently and, rather than capturing their absolute wellbeing, they might still answer it from a relative-deprivation perspective (i.e., respondents give their answer a positioning meaning with respect to others) (Gasparini and Gluzmann (2012)). However, this type of measure has a significant advantage over other subjective measures of wellbeing as it reflects the person's capabilities, means and long-term opportunities. This is because an evaluation of individuals' life satisfaction requires them to complete a comprehensive evaluation of their circumstances, their past and their present ((Gasparini and Gluzmann (2012); Graham and Nikolova (2015); Nikolova (2016)). Another subjective measure of wellbeing, for instance, that is available from the GWP captures the emotional wellbeing of respondents by registering whether or not they experienced certain feelings a lot in the previous day (dummy variable 1-0 reflecting yes/no response options). The question is formulated as follows: *"Did you experience the following feelings during a lot of the day yesterday? How about _____?"*, and each of several emotions (e.g., enjoyment, stress) is reported separately. Such measures, however, reflect emotions triggered by daily experiences.

Moreover, the survey uses the same questionnaire in all countries, which, for the sake of our analysis, gives us the opportunity to perform a cross-country analysis. Without standardizing the survey questions, this comparison would have been impossible. Finally, the cardinality in the measurement of the global life evaluation given the scale/ladder nature of the question expands our measurement purposes, allowing us to interpret our results in marginal effects.

3.2. Income and Other Explanatory Variables

We proxy for individuals' absolute income level by dividing data on household income by the household size obtained from the GWP. The household income is the annual household income in international dollars. The household size or household headcount is calculated using residents aged 15 and older in the household and children younger than 15.

We control for an exhaustive list of explanatory variables that include individuals' employment status, marital status, age, age squared, gender and residential status. We recategorize employment statuses into the following groupings: employed full-time, employed part-time, unemployed and out of labor force. Original classifications from the GWP include a more profound description of employment statuses. For example, respondents working full-time are asked whether or not they want to be working full-time. We disregard this information and disregard, for example, the division between being employed full-time for self or for an employer. Data on individuals' marital status are obtained from question [*WP1223]* from the GWP. We group separated, widowed and divorced individuals into one category, which we call "ever married". We do not differentiate between domestic partners and married and, thus, we group those into one category. The last category includes individuals who are single or have never been married. We rely on information regarding respondents' residential statuses obtained from question *[WP14]*. We additionally control for gender and household characteristics. For residential status, GWP categorizes respondents' answers into four groupings: rural area or farm, small town or village, suburb of large city and a large city. We also control for some households' characteristics, such as the number of children under 15 years of age and number of adults aged 15 plus that are living in the individuals' household. We do not include education controls in our analysis since this information is missing for about 97% of our sample of respondents. Missing values are not due to respondents opting not to respond but rather due to the fact that the question related to the highest level of education achieved was asked in very few countries' year-wave combinations. Appendix A.5 displays a detailed description of the variables we use in our analysis, in addition to an overview of the type of recoding we apply to the data.

3.3. Sample Construction

Our initial dataset from the Gallup World Poll includes a total of 167 countries. The timespan of our dataset ranges between 2006 and 2017. Given that some year-waves are missing for some countries, we end up with an unbalanced panel of countries. The information is available at the individual level using the same questionnaire for a national sample of adults in each country–year-wave. Gallup World Poll sample sizes are usually of 1000 households per country to ensure national representation. Respondents are adults aged 15 years or older and chosen randomly from within the household. Our initial sample includes a total of 1,863,900 respondents.

We compute a measure of individual-level income as a ratio of the household income "*Annual Household Income in International Dollars*"[1] over the household size "*Total Number Living in Household for Per Capita Income*". Household headcount is calculated using residents aged 15 and older in household and children younger than 15. We disregard individuals with missing information on their household size and/or household income. Doing so, we lose about 21% of our initial sample.[2]

We lose additional observations because of missing values for some of the variables in our list of standard explanatory controls. Our final sample is thus restricted to respondents in 160 countries between 2009 and 2017.[3] About 10% of the entire sample of respondents is interviewed in each of the survey year-waves: 2009, 2010, 2013, 2015, 2016 and 2017. The remaining respondents are interviewed in 2011 and 2014 (about 13% during each survey year-wave), and the rest are interviewed in 2012.

4. Methodology and Model Specifications

Classifying individuals within a country into income classes requires specifying boundaries or frontiers to define inclusion or exclusion conditions. Defining the poor, middle and rich populations, therefore, requires a boundary-based definition of low (or poor), middle and rich (or upper) income classes. However, the partly arbitrary nature of these boundaries leaves them open for criticism. This is especially true in light of the lack of consensus on well-defined universal income class boundaries. Moreover, methodological choices pertaining to the level of aggregation for the analysis, the type of inequality measurement as well as the estimation approach have substantial impacts on findings. For example, if inequality is measured at an aggregated level, then it would highly be a function of the targeted population and the geographic unit of analysis.

We thus carry out an individual-level analysis, and, rather than using arbitrary thresholds (boundaries) to classify individuals within a country into income classes, we rely on a latent class analysis technique that allows us to hypothesize income class categories in a given country in a given year as determined by individuals' observed characteristics.

When fitting a latent class model, finding good starting values might be challenging. In this paper, we fit a latent class model with one categorical latent variable with three classes, referring to the low, middle and upper income classes[4]. We rely on a unique observed variable that is a continuous measure of the individual-level income of respondents. We do so for each year–country combination available in our sample given that observed characteristics could have different impacts on class memberships in different time periods even for the same country.

4.1. Predicted Posterior Class Probabilities

Our analysis of income classes is thus based on individual income, which we perceive as a key factor in determining individuals' class memberships. After fitting the latent class model, we next determine individuals' probability of category membership. Given that this probability is not a 0-1 likelihood, the determination of class membership is said to be probabilistic rather than deterministic. We identify the expected classification for each individual in our dataset based on the predicted posterior class probability.

In this paper, we assume that an individual's predicted class is the one with the highest predicted probability. This class would be allocated a probability of 1 and the remaining classes would take a probability of 0. Of note, high predicted probabilities in our model are very close to 1. By doing so, each individual in our sample is now assigned to one of the hypothesized classes as if deterministically. Obtaining an individual's posterior probability for each class using the most likely class membership defined as the class with the highest or maximum posterior probability is a common practice in the literature (see Nagin (2005), for example). In Appendix A.1, we discuss the goodness of fit and limitations to the predicted posterior class probabilities approach.

4.2. Model Specification: Ordered Logit Response Model

To investigate the impact on individual's life satisfaction, we run the following specification using an ordered logit response model:

$$Y_{icw} = \alpha + \beta \; Income\ Class_1 + \gamma \; Income\ Class_2 + \delta \; Income\ Class_3 + \sigma \; X_{icw} + \sigma_c + \varphi_w + \epsilon_{icw} \quad (1)$$

where Y_{icw} is individual i life satisfaction in country c interviewed in year-wave w. Life satisfaction is recorded on a 0–10 scale with end points labelled "Worst possible life for you" and "Best possible life for you". $Income\ Class_1$, $Income\ Class_2$ and the omitted category $Income\ Class_3$ are individuals' membership indices described thoroughly in Section 4.1. Thus, β, γ and δ are our key parameters of interest. Given that these three income classes are mutually exclusive, one category of individuals will thus be excluded. This is because each individual might belong to only one of these three income classes; i.e., every individual has an estimated probability of 1 of belonging to one of the hypothesized income classes and zero otherwise. The sum of individuals belonging to these different income classes add up to the entire respondents' population. The omitted category includes individuals in the upper hypothesized income class; i.e., the excluded group is $Income\ Class_3$ and our interpretations of the sign and magnitude of β and γ are in comparison to the omitted category. X_{icw} is a list of exhaustive individual controls, including employment and marital status, age, age squared, residential status, gender and household characteristics (number of children aged below 15 years and adults aged above 15 years residing in the household).

As previously mentioned, we control throughout our analysis for country and year-wave fixed effects, which allows us to remove the influence of potential unobserved heterogeneity across countries related to life satisfaction and country-defined income classes and capture common general trends in life satisfaction. Thus, we include the following parameters in Equation (1): σ_c for country fixed effects and φ_w for year-wave fixed effects. Finally, ϵ_{icw} is our error term. We cluster our standard errors at the country level and apply respondent-level weights from the Gallup World Poll data.

5. Main Results

5.1. Descriptive Statistics of Hypothesized Income Classes

We present an overview of the demographic and socio-economic characteristics of individuals by hypothesized income class[5]. In Table 1, we show the characteristics of individuals belonging to hypothesized income class 1 in column (1), income class 2 in column (2) and income class 3 in column (3), respectively. Given that the individual income is the highest among the individuals belonging to hypothesized income class 3, followed by those in class 2 and last class 1, it is fair to refer to these classes as upper, middle and lower income classes, respectively.[6]

The average age is close to 40 irrespective of the income class. The individuals belonging to income class 1 (or the lower income class) are more likely to be single (about 40%), whereas the individuals belonging to the middle and upper income classes are almost as likely to be single. The upper income class individuals are more likely to be residing in large cities and are as likely to have full-time employment as middle class individuals. In Appendix A.3, we check for the validity of our sample-based income cut points.

Table 1. Characteristics of individuals belonging to lower, middle and upper hypothesized income classes.

Variables	Lower Class (1) (N = 29,106)	Middle Class (2) (N = 723,000)	Upper Class (3) (N = 686,507)	*p*-Value: Difference in Means (1)–(2)	*p*-Value: Difference in Means (1)–(3)	*p*-Value: Difference in Means (2)–(3)
Individual income	14.92 (107.96)	10,223 (594,599)	9303 (106,798)	(0.0000) *	(0.0000) *	(0.2066)
Natural logarithm of one plus individual income	0.25 (1.08)	7.75 (1.90)	8.21 (1.35)	(0.0000) *	(0.0000) *	(0.0000) *
Age	41 (19)	40 (17)	42 (18)	(0.0000) *	(0.0000) *	(0.0000) *
Female	0.54 (0.49)	0.52 (0.49)	0.54 (0.49)	(0.0000) *	(0.5658)	(0.0000) *
Marital status: Single	0.34 (0.47)	0.28 (0.44)	0.27 (0.44)	(0.0000) *	(0.0000) *	(0.0000) *
Separated	0.03 (0.17)	0.01 (0.13)	0.02 (0.15)	(0.0000) *	(0.0000) *	(0.0000) *
Widowed	0.08 (0.28)	0.06 (0.24)	0.07 (0.26)	(0.0000) *	(0.0000) *	(0.0000) *
Divorced	0.03 (0.18)	0.03 (0.18)	0.03 (0.19)	(0.3839)	(0.0000) *	(0.0000) *
Married	0.44 (0.49)	0.56 (0.49)	0.52 (0.49)	(0.0000) *	(0.0000) *	(0.0000) *
Domestic partner	0.05 (0.21)	0.03 (0.19)	0.05 (0.22)	(0.0000) *	(0.0021) *	(0.0000) *

Table 1. *Cont.*

Variables	Lower Class (1) (N = 29,106)	Middle Class (2) (N = 723,000)	Upper Class (3) (N = 686,507)	p-Value: Difference in Means (1)–(2)	p-Value: Difference in Means (1)–(3)	p-Value: Difference in Means (2)–(3)
Residence: Large city	0.23 (0.42)	0.29 (0.45)	0.35 (0.47)	(0.0000) *	(0.0000) *	(0.0000) *
Rural area or farm	0.37 (0.48)	0.27 (0.44)	0.24 (0.42)	(0.0000) *	(0.0000) *	(0.0000) *
Small town or village	0.32 (0.46)	0.31 (0.46)	0.31 (0.46)	(0.0006) *	(0.0072) *	(0.0082) *
Suburb of a large city	0.07 (0.25)	0.10 (0.31)	0.08 (0.28)	(0.0000) *	(0.0000) *	(0.0000) *
Employment: full-time	0.19 (0.39)	0.40 (0.49)	0.40 (0.49)	(0.0000) *	(0.0000) *	(0.4383)
Employment: part-time	0.16 (0.36)	0.14 (0.34)	0.14 (0.35)	(0.0000) *	(0.04) *	(0.04) *
Unemployed	0.13 (0.33)	0.06 (0.24)	0.05 (0.23)	(0.0000) *	(0.04) *	(0.04) *
Out of labor force	0.51 (0.49)	0.38 (0.48)	0.38 (0.48)	(0.0000) *	(0.04) *	(0.5045)

Mean estimates are reported in the first row, followed by standard deviations reported between parentheses. The sample size for the marital status, residential and employment status variables is slightly smaller. In the last 3 columns, we test the equality of means by income class. We report the statistical significance of the difference in means tests between parentheses. Stars indicate a statistically significant difference in means.

5.2. Impact on Life Satisfaction

Table 2 presents the results from ordered logit models. In column 1, we control for an exhaustive list of standard explanatory variables from the literature. In column 2, we additionally control for our key variables of interest, dummies for individuals' class membership indices of belonging to one of the hypothesized income classes. The structure of column 3 is similar to column 1 but further includes country and year-wave fixed effects. Finally, column 4 repeats the same specifications as in column 2 but accounting for country and year-wave fixed effects.

Table 2. Main results: income classes and life satisfaction (ordered response models . . .).

Life Satisfaction	(1)	(2)	(3)	(4)
$Income\ Class_1$		−0.813 *** (0.087)		−0.687 *** (0.061)
$Income\ Class_2$		−0.162 (0.115)		−0.358 *** (0.082)
$Income\ Class_3$	Omitted	Omitted	Omitted	Omitted
Individual income	8.51×10^{-8} (0.000)	8.52×10^{-8} (1.90×10^{-7})	8.15×10^{-8} (2.34×10^{-7})	8.16×10^{-8} (2.27×10^{-7})
Age	−0.020 *** (0.003)	−0.001 (0.001)	−0.010 *** (0.000)	−0.037 *** (0.002)
Age squared	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)
Female	0.139 *** (0.015)	0.128 *** (0.140)	0.101 *** (0.010)	0.111 *** (0.011)
Single	0.068 * (0.015)	0.128 *** (0.031)	0.036 ** (0.015)	−0.059 *** (0.018)
Ever married	−0.420 *** (0.028)	−0.392 *** (0.028)	−0.314 *** (0.028)	−0.346 *** (0.015)
Married	Omitted	Omitted	Omitted	Omitted

Table 2. *Cont.*

Life Satisfaction	(1)	(2)	(3)	(4)
Residing rural areas	−0.653 *** (0.028)	−0.634 *** (0.065)	−0.329 *** (0.028)	−0.322 *** (0.027)
Residing small towns	−0.254 *** (0.060)	−0.243 *** (0.061)	−0.193 *** (0.019)	−0.192 *** (0.019)
Residing suburban areas	0.109 (0.077)	0.125 (0.077)	−0.079 *** (0.019)	−0.080 *** (0.019)
Residing large city	Omitted	Omitted	Omitted	Omitted
Employed full-time	0.254 *** (0.030)	0.192 *** (0.029)	0.086 *** (0.014)	0.144 *** (0.015)
Employed part-time	0.079 ** (0.039)	0.039 (0.037)	0.015 (0.014)	0.054 *** (0.014)
Unemployed	−0.422 *** (0.031)	−0.447 *** (0.031)	−0.480 *** (0.027)	−0.435 *** (0.024)
Out of labor force	Omitted	Omitted	Omitted	Omitted
Number of Adultsresiding in the HH	−0.056 *** (0.011)	−0.054 *** (0.012)	0.031 *** (0.004)	0.032 *** (0.004)
Number of childrenresiding in the HH	−0.157 *** (0.010)	-.0152 *** (0.010)	−0.043 *** (0.004)	−0.038 *** (0.004)
Year-wave fixed effects	No	No	Yes	Yes
Country fixed effects	No	No	Yes	Yes
Observations	1,294,943	1,294,943	1,294,943	1,294,943

Standard errors in parentheses are clustered at the country level. Respondent-level weights are applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We test for the statistical significance of the difference between the point estimates for low and middle income classes and find a p-value of 0.000.

Our preferred specification is the one reported in column 4. It includes all the standard explanatory controls from the literature, the fixed effect indicators and our variables of interest for individuals' class memberships. We find negative and statistically significant estimates for individuals belonging to $Income\ Class_1$ and $Income\ Class_2$ in comparison to the omitted category, here: $Income\ Class_3$. Our findings suggest that individuals in the low and middle income classes are, respectively, about 30 and 17 percent of a standard deviation less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class (Daraei and Mohajery (2013); Gardarsdottir et al. (2018); Roth et al. (2016)).

Marginal effects are not reported in Table 2. We interpret the size of our estimates after standardizing our dependent variable to have a mean of zero and a standard deviation of one. One way to gauge the size of our estimates is to standardize the dependent variable for all respondents (within each year, within each country) to have a mean of zero and a standard deviation of one. We then run an ordinary-least-squares (OLS) regression using equation[7] (1). As stated, our findings reveal that individuals in the low and middle income classes are, respectively, about 30 and 17 percent of a standard deviation less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class. Our results showing negative and statistically significant estimates for income classes indicate a negative association with life satisfaction.

Alternatively, we interpret marginal effects obtained for our preferred specification following the structure of Table 2, column 4. These reveal positive and statistically significant likelihoods associated with lower levels of life satisfaction for individuals belonging to $Income\ Class_1$ and $Income\ Class_2$ in comparison to the omitted category, here: $Income\ Class_3$. Average predicted probabilities of reported life satisfaction of 1 to 6 ranges between 0.01 and 0.03 for $Income\ Class_1$ and about 0.01 for $Income\ Class_2$. The likelihood for higher reported life satisfaction (beyond 7) predicts negative and statistically significant marginal effects ranging between 0.01 and 0.04 in absolute terms and between 0.006 and 0.02 for individuals belonging to $Income\ Class_1$ and $Income\ Class_2$, respectively.

Furthermore, the positive relationship between absolute income and life satisfaction is in line with previous findings (Blanchflower and Oswald (2004); Clark et al. (2008); Deaton (2008); Diener et al. (2010); Easterlin (2001); Frijters et al. (2004); Kahneman and Deaton (2010); Stevenson and Wolfers (2008)).

Because our context is different from prior literature, in terms of the pool of country–year-waves we investigate, as well as the methodological approach we use, this makes our findings not directly comparable to the prior studies that examined the impact of income inequality on life satisfaction. However, the direction and interpretation of our results do converge (Alesina et al. (2004); Clark (2003); Graham and Felton (2005); Hagerty (2000)). Most of our covariates' coefficients are in line with the literature (Wu and Li (2017)). To check whether our exhaustive list of covariates is robust to the inclusion of income class indicators, we initially report the point estimates for these controls alone in column (1), then introduce income classes indicators in column (2). Although the magnitude of our estimates for the list of covariates slightly decreases between column (1) and (2), the estimates remain statistically significant and in the same direction. This is also robust to the inclusion of country and year-wave fixed effects in column (3). Thus, our covariates seem to have an explanatory power for life satisfaction independent from income status. Our preferred specification in column 4 shows that single individuals report a lower life satisfaction in comparison to married people. We find a positive link between being a female (in comparison to male) and life satisfaction. This means that men report a lower life satisfaction than women. Our findings also indicate that life satisfaction decreases with age. Finally, residents in non-large cities are less likely to report a better overall life evaluation in comparison to individuals residing in large cities.

In order to confirm the validity of our main analysis with ordered probit response modelling, we repeat our analysis using the predicted posterior probabilities of class memberships as the main explanatory variables carrying out an ordinary-least-squares (OLS) estimation technique. Our dependent variable of interest is the Cantril Ladder of Life variable from the Gallup World Poll, which is recorded on a 0–10 scale with end points labelled "Worst possible life for you" and "Best possible life for you". We thus refrain from standardizing the dependent variable of interest in this analysis. We report the results from completing this analysis in Table 3[8]. The structure of the table is similar to the one in Table 2. These results confirm the validity of our main results.

Table 3. OLS results: income classes and life satisfaction.

Life Satisfaction	**(1)**	**(2)**	**(3)**	**(4)**
$Income\ Class_1$		−0.938 *** (0.104)		−0.727 *** (0.069)
$Income\ Class_2$		−0.213 (0.144)		−0.415 *** (0.094)
$Income\ Class_3$	Omitted	Omitted	Omitted	Omitted
Individual income	8.87×10^{-8} (0.000)	8.84×10^{-8} (0.000)	2.76×10^{-8} (0.000)	2.58×10^{-8} (0.000)
Age	−0.0281 *** (0.005)	−0.0284 *** (0.005)	−0.0437 *** (0.003)	−0.0436 *** (0.003)
Age squared	0.000281 *** (0.000)	0.000282 *** (0.000)	0.000345 *** (0.000)	0.000345 *** (0.000)
Female	0.181 *** (0.020)	0.177 *** (0.021)	0.132 *** (0.014)	0.132 *** (0.014)
Single	0.0855 * (0.047)	0.0874 ** (0.044)	−0.0574 *** (0.022)	−0.0560 *** (0.021)

Table 3. *Cont.*

Life Satisfaction	(1)	(2)	(3)	(4)
Ever married	−0.513 *** (0.038)	−0.510 *** (0.038)	−0.379 *** (0.018)	−0.376 *** (0.018)
Married	Omitted	Omitted	Omitted	Omitted
Residing rural areas	−0.806 *** (0.082)	0.786 *** (0.084)	−0.383 *** (0.033)	−0.367 *** (0.032)
Residing small towns	0.321 *** (0.075)	0.310 *** (0.077)	−0.227 *** (0.023)	−0.220 *** (0.023)
Residing suburban areas	0.113 (0.097)	0.133 (0.097)	−0.0960 *** (0.023)	0.0953 *** (0.023)
Residing large city	Omitted	Omitted	Omitted	Omitted
Employed full-time	0.321 *** (0.041)	0.305 *** (0.043)	0.173 *** (0.019)	0.161 *** (0.019)
Employed part-time	0.0993 ** (0.048)	0.0890 * (0.048)	0.0649 *** (0.018)	0.0589 *** (0.018)
Unemployed	−0.533 *** (0.040)	−0.525 *** (0.038)	−0.502 *** (0.030)	−0.494 *** (0.029)
Out of labor force	Omitted	Omitted	Omitted	Omitted
Number of Adultsresiding in the HH	−0.0660 *** (0.015)	−0.0648 *** (0.015)	0.0323 *** (0.005)	0.0341 *** (0.005)
Number of childrenresiding in the HH	−0.186 *** (0.013)	0.178 *** (0.013)	−0.0447 *** (0.005)	−0.0406 *** (0.005)
Year-wave fixed effects	No	No	Yes	Yes
Country fixed effects	No	No	Yes	Yes
Observations	1,294,943	1,294,943	1,294,943	1,294,943

Standard errors in parentheses are clustered at the country level. Respondent-level weights are applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3. Robustness Analysis: One-Way Fixed Effects Model

As a robustness check, we estimate equation (1) and account for country and year-wave fixed effects separately. Table 4 shows the results from completing this analysis. We report the estimates from carrying out an OLS regression with a standardized dependent variable for all the respondents (within each year, within each country). Our results remain robust, thus supporting the validity of our preferred specification from column (4) of Table 2 with a two-way fixed effects model. Our findings across columns (1) and (2), where we omit both country and year fixed effects and with the one-way year fixed effects model, respectively, go in the same direction, although with a smaller magnitude than our estimates with country and year-wave fixed effects simultaneously (column (4) of Table 2). The estimates with country one-way fixed effects modelling are of the same magnitude as our main results. These indicate that individuals in the low and middle income classes are, respectively, about 30 and 17 percent of a standard deviation less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class.

Table 4. Robustness analysis: one-way fixed effects models.

Life Satisfaction	(1)	(2)	(3)
$Income\ Class_1$	−0.233 *** (0.019)	−0.240 *** (0.020)	−0.305 *** (0.030)
$Income\ Class_2$	−0.0502 *** (0.011)	−0.0510 *** (0.011)	−0.177 *** (0.043)
$Income\ Class_3$	Omitted	Omitted	Omitted

Table 4. *Cont.*

Life Satisfaction	(1)	(2)	(3)
Individual income	1.35×10^{-8} (0.000)	1.35×10^{-8} (0.000)	1.34×10^{-8} (0.000)
Age	−0.0208 *** (0.002)	−0.0208 *** (0.002)	−0.0205 *** (0.002)
Age squared	0.000166 *** (0.000)	0.000166 *** (0.000)	0.000161 *** (0.000)
Female	0.0662 ** (0.007)	0.0661 *** (0.007)	0.0639 *** (0.007)
Single	−0.0297 *** (0.011)	−0.0307 *** (0.011)	−0.0326 *** (0.011)
Ever married	−0.189 *** (0.010)	−0.189 *** (0.010)	−0.196 *** (0.010)
Married	Omitted	Omitted	Omitted
Residing rural areas	−0.148 *** (0.014)	−0.148 *** (0.014)	−0.171 *** (0.015)
Residing small towns	−0.0879 *** (0.011)	−0.0885 *** (0.011)	−0.102 *** (0.010)
Residing suburban areas	−0.0441 *** (0.011)	−0.0450 *** (0.011)	−0.0421 *** (0.011)
Residing large city	Omitted	Omitted	Omitted
Employed full-time	0.0855 *** (0.010)	0.0842 *** (0.010)	0.0806 *** (0.010)
Employed part-time	0.0341 *** (0.008)	0.0330 *** (0.009)	0.0286 *** (0.009)
Unemployed	−0.229 *** (0.014)	−0.231 *** (0.014)	−0.237 *** (0.014)
Out of labor force	Omitted	Omitted	Omitted
Number of Adultsresiding in the HH	0.0132 *** (0.002)	0.0139 *** (0.002)	0.0181 *** (0.002)
Number of childrenresiding in the HH	−0.0220 *** (0.002)	−0.0222 *** (0.002)	−0.0197 *** (0.002)
Year-wave fixed effects	No	Yes	No
Country fixed effects	No	No	Yes
Observations	1,294,943	1,294,943	1,294,943

Standard errors in parentheses are clustered at the country level. Respondent-level weights are applied. ** $p < 0.05$, *** $p < 0.01$.

5.4. Robustness Analysis: Heterogeneity by Income Country Group

We test for the heterogeneity of the effect of income classes on life satisfaction by income group level. We rely on the distribution of countries based on their gross national income per capita (GNI per capita) level into four groups: high income group (HIG), upper middle-income group (UMIG), lower middle-income group (LMIG) and low-income group (LIG). We report the estimates from carrying out an OLS regression with a standardized dependent variable for all the respondents (within each year, within each country) by income group in Table 5. We document a negative and statistically significant effect of belonging to the low and middle income classes on individuals' life satisfaction. This provides insights on the uniformity and robustness of the results across different groups of countries as categorized based on their GNI per capita distribution.

Table 5. Heterogeneity analysis: by income country group.

Life Satisfaction	**HIG Countries (1)**	**UMIG Countries (2)**	**LMIG Countries (3)**	**LIG Countries (4)**
$Income\ Class_1$	−0.196 *** (0.056)	−0.333 *** (0.054)	−0.266 *** (0.054)	−0.288 *** (0.045)
$Income\ Class_2$	−0.102 (0.097)	−0.246 ** (0.093)	−0.112 * (0.064)	−0.112 * (0.041)
$Income\ Class_3$	Omitted	Omitted	Omitted	Omitted
Individual income	1.03×10^{-8} (0.000)	0.000000409 (0.000)	0.0000287 *** (0.000)	0.00000497 ** (0.000)
Age	−0.0326 *** (0.002)	−0.0258 *** (0.002)	−0.0114 *** (0.003)	−0.00314 * (0.002)
Age squared	0.000274 *** (0.000)	0.000195 *** (0.000)	0.0000820 ** (0.000)	0.0000133 (0.000)
Female	0.0843 *** (0.010)	0.0714 *** (0.011)	0.0566 *** (0.013)	0.0147 (0.023)
Single	−0.148 *** (0.017)	−0.0133 (0.011)	0.0316 *** (0.011)	0.0474 *** (0.012)
Ever married	−0.285 *** (0.012)	−0.162 *** (0.016)	−0.135 *** (0.012)	−0.125 *** (0.019)
Married	Omitted	Omitted	Omitted	Omitted
Residing rural areas	−0.0480 ** (0.021)	−0.206 *** (0.023)	−0.182 *** (0.024)	−0.256 *** (0.029)
Residing small towns	−0.0535 *** (0.013)	−0.110 *** (0.018)	−0.101 *** (0.022)	−0.222 *** (0.031)
Residing suburban areas	−0.0293 ** (0.013)	−0.0429 * (0.023)	−0.0111 (0.021)	−0.103 ** (0.037)
Residing large city	Omitted	Omitted	Omitted	Omitted
Employed full-time	0.151 *** (0.015)	0.0590 *** (0.017)	0.00864 (0.014)	0.0571 ** (0.025)
Employed part-time	0.0740 *** (0.013)	0.0162 (0.013)	−0.0325 * (0.017)	0.0549 ** (0.022)
Unemployed	−0.354 *** (0.024)	−0.257 *** (0.016)	−0.181 *** (0.026)	−0.105 ** (0.038)
Out of labor force	Omitted	Omitted	Omitted	Omitted
Number of Adultsresiding in the HH	0.0138 ** (0.005)	0.0115 *** (0.004)	0.0239 *** (0.003)	0.0219 *** (0.004)
Number of childrenresiding in the HH	−0.0110 ** (0.005)	−0.0275 *** (0.004)	−0.0191 *** (0.004)	−0.0127 *** (0.003)
Year-wave fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	432,025	366,617	341,483	144,291

Standard errors in parentheses are clustered at the country level. Respondent-level weights are applied. High income group (HIG), upper middle-income group (UMIG), lower middle-income group (LMIG) and low-income group (LIG). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions

This paper revisited income comparisons as a fundamental mechanism in examining individuals' income class effect on life satisfaction. We analyzed the impact of income classes using a novel methodological approach, a latent class model, allowing us to hypothesize country–year-specific income classes. Using predicted exterior probabilities, we investigated whether individuals' classifications into these hypothesized income classes impact their subjective wellbeing. Our methodology relies on individual-level income data that are proxied by the household income over the household size from the Gallup World Poll (GWP). The latent class analysis (LCA) fits a latent class model with three classes and one observable variable that is a continuous measure of individual income. This allowed us to hypothesize income classes in a given country and year based on individuals' observed characteristics in terms of income holdings. Our methodology and the large sample of year–country combinations ensure the representation of one of the novelties of this study.

We did so for each year–country combination available in our sample. Our final sample is restricted to 1,294,943 respondents in 160 countries between 2009 and 2017. As a robustness check, we tested the goodness of the fit using BIC (Bayesian information criterion) in Section 4.

Next, we determined the expected classification for each individual in our dataset based on the predicted posterior class probability. We then relied on an ordered logit response model where we adopted a subjective measure of life satisfaction drawn from the Gallup World Poll and accounted for the influence of potential unobserved heterogeneity across countries related to life satisfaction and country-defined income classes and captured common general trends in life satisfaction. Our setting allowed us to carry out an assessment of a within-country–year-specific impact of the relative income of individuals on their subjective well-being.

Our estimates suggest that individuals in the low and middle income classes are, respectively, about 30 and 17 percent of a standard deviation less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class. These results are robust to alternative specifications and estimation strategies.

While the link between income, income inequality and subjective wellbeing has been a subject of interest for many emerging studies, the results and intakes remain controversial. This is particularly true given the various theories and mechanisms that exist and that predict a positive, negative or a non-significant impact. Thus, this manuscript serves as additional evidence in the context of consistent evidence of a significant impact of income inequality on subjective wellbeing.

A potential drawback of our analysis is that it relies on a measure of global life evaluation, the Cantril Ladder of Life, from the Gallup World Poll data, which might be problematic for our analysis if respondents interpret this question differently. Thus, rather than capturing their absolute wellbeing, respondents might still answer this question from a relative-deprivation perspective (i.e., respondents give their answer a positioning meaning with respect to others). This is, however, a common limitation to all studies that use these types of questions to capture individuals' subjective wellbeing.

Another caveat of our study is that it relies on a latent class analysis estimation method to hypothesize income classes and determine individuals' posterior expected probabilities of belonging to one of these classes. Such methodologies are critically affected by the starting values. We fit a latent class model with one categorical latent variable with three classes, referring to the low, middle and upper income classes. Even though we carried out robustness checks to validate our choice of one categorical latent variable with three classes, this remains subject to criticism. Moreover, the choice of observed variables is crucial for fitting purposes. We relied on a unique observed variable that is a continuous measure of the individual-level income of respondents, and, as a robustness check, we used a combination of four observed variables, including a continuous measure of individual income and a binary measure of asset ownerships (see Appendix A.4), which might be criticized as well.

Our empirical findings have interesting policy implications. First, we provide evidence that disaggregated levels of income classes matter above and beyond the overall previously well-documented country level inequality effects for subjective wellbeing. We also show that the effect of income classes remains robust to the inclusion of standard explanatory variables in this literature. Second, our results confirm and go in line with previous papers that investigated the relationship between income classes, standard explanatory variables in the literature, such as age, age squared, gender, marital status, etc., and life satisfaction. This provides further evidence in support of the validity of using individual income in examining income classes and individuals' life satisfaction. Finally, these findings suggest that economic policies or shocks targeting individuals may shape their overall life satisfaction.

Future research could potentially focus on other subjective measures of wellbeing, especially those that capture the emotional wellbeing of respondents. This can be completed using feelings-related questions. For instance, questions from the Gallup World Poll, such as *"Did you experience the following feelings during a lot of the day yesterday? How about _____?"*, including several emotions (e.g., enjoyment, stress), could serve as a way to develop studies using broader subjective measures of the wellbeing of individuals.

Furthermore, the health wellbeing of individuals is a natural crucial outcome of interest. A future potential study can examine whether individuals' income classes have implications on their health wellbeing using similar methodologies as the one proposed in this work. Finally, future research can expand further the list of observed variables that potentially determine individuals' income classes and test for the validity of doing so.

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Appendix A

Appendix A.1. Goodness of Fit and Limitation: Predicted Posterior Class Probabilities

As a robustness check, and in order to assess the number of components (latent category classes), we modify our command to specify one through five latent classes and then store our results. Using the Bayesian information criterion (BIC), we compare the model with three classes to the one with four and five latent classes. We find that the model with three latent classes has the smallest value of BIC and, thus, is considered as the best based on this information criterion[9]. The other possible values of components (one and two) were never selected. The optimal number of latent classes was thus selected as three, which we interpret as low, middle and upper income class.

One criticism of relying on predicted posterior class probabilities is that the classification might be highly dependent on the specification of observed variables. One way to get around this is by altering the model specifications and assessing its robustness. Our focus in this paper is to classify individuals based on their income and then assess the validity of this approach by comparing our findings to prior literature using other techniques (non-latent class model specifications). As a robustness check, we include additional observable characteristics, including individuals' asset ownership, and we find that the direction of our results remains robust to the inclusion of asset ownership dummies. We, however, deny the need of entering and/or altering additional observed variables to our main model specification. Other authors (Alkire and Foster (2011); Anderson (2010); Anderson et al. (2011)) present a good review of the caveats regarding adding more characteristics to the list of observables that determine classes. This is because adding more characteristics to the list of observables that determine class membership makes it much more difficult and arbitrary to set boundaries for the determination of classes.

Appendix A.2. Distribution by Hypothesized Income Classes by Region

We provide a descriptive analysis of the distribution of respondents in our final dataset by hypothesized income classes by region. Each individual is assigned to one of the hypothesized classes based on the predicted posterior probability of belonging to each class. We attribute individuals to the most probable class membership, defined as the class with the highest or maximum posterior probability. We present the descriptive statistics broken down by region. Countries in our final sample are grouped into seven regions. Table A1 shows that the highest proportion of respondents belong to the middle class across almost all regions. Individuals are almost equally distributed between the middle and upper class for the Arab states. The highest proportion of individuals belonging to the upper class belongs to respondents in the South/Latin America region.

Table A1. Descriptive statistics: distribution by hypothesized income class by region.

	Lower Class (1)	Middle Class (2)	Upper Class (3)
Africa	0.051 (0.21)	0.594 (0.49)	0.353 (0.47)
Arab States	0.014 (0.11)	0.465 (0.49)	0.519 (0.49)
Asia and Pacific	0.010 (0.10)	0.595 (0.48)	0.393 (0.48)
Europe	0.010 (0.10)	0.387 (0.48)	0.602 (0.49)
Middle East	0.011 (0.10)	0.724 (0.44)	0.264 (0.44)
North America	0.021 (0.14)	0.970 (0.17)	0.008 (0.09)
South/Latin America	0.027 (0.16)	0.220 (0.41)	0.751 (0.43)

Appendix A.3. Validity of Sample-Based Income Cut Points

We now test for the validity of our sample-based income cut points. Given that our methodology defines within-country–year-wave-specific income classes, we opt to check the validity of these cuts at the country–year-wave level. Our sample of 10 balanced countries is divided between high- and low-income countries using data on countries' gross national income per capita (GNI per capita). We randomly selected 10 countries, which are reported in Table A2. These were extracted from the high- and low-income groups. Given that the vast majority of respondents belong in a given country–year-wave context to the middle income class (i.e., $Income\ Class_2$ dummy is equal to 1), leaving us with few observations for the lower and upper income class, we focus on examining the validity of income cut points for the middle income class. We computed the average country–year-wave (in 2017)-specific sample-based annual household income in international dollars for our sample of selected countries. We compare this to thresholds in column (2) of Table A2, where we report the dollar value for the "middle 40% share" national income threshold (by country in $ in 2018) and the "top 10% share" national income threshold (by country in $ in 2018). [10] These are non-sample-based cut points for countries in 2018 extracted from the World Inequality Database. The top 10% share indicator captures the upper income class, and the middle 40% share indicator captures the income cut points for the middle income class.

We computed the average sample-based incomes of selected countries using 2017 GWP data for the middle income class, i.e., for respondents with $Income\ Class_2$ dummy is equal to 1. We find that these are very close to thresholds from the middle 40% share indicator. Moreover, these fall below the top 10% share indicator (threshold defining the upper income class individuals). This confirms the validity of our sample-based income cut points.

Table A2. Validity of income cut points.

Country	Sample-Based Income $Income\ Class_2$ (1)	Non-Sample-Based Income (2)
Switzerland	*57,143$*	$Income\ Class_1$: $Income\ Class_2$: *57,863$* $Income\ Class_3$: *125,569$*
Norway	*72,800$*	$Income\ Class_1$: $Income\ Class_2$: *63,713$* $Income\ Class_3$: *126,827$*
Sweden	*62,206.58$*	$Income\ Class_1$: $Income\ Class_2$: *51,737$* $Income\ Class_3$: *98,287$*
Iceland	*73,504.11$*	$Income\ Class_1$: $Income\ Class_2$: *61,298$* $Income\ Class_3$: *120,583$*
United States	*88,754.38$*	$Income\ Class_1$: $Income\ Class_2$: *42,956$* $Income\ Class_3$: *137,944$*
Afghanistan	*5533.179$*	$Income\ Class_1$: $Income\ Class_2$: *2470$* $Income\ Class_3$: *7316$*
Nepal	*7638.33$*	$Income\ Class_1$: $Income\ Class_2$: *3293$* $Income\ Class_3$: *9734$*
Morocco	*6347$*	$Income\ Class_1$: $Income\ Class_2$: *6733$* $Income\ Class_3$: *24,383$*
Bolivia	*11,367.44$*	$Income\ Class_1$: $Income\ Class_2$: *6833$* $Income\ Class_3$: *23,360$*
Philippines	*7647.99$*	$Income\ Class_1$: $Income\ Class_2$: *7323$* $Income\ Class_3$: *26,653$*

Appendix A.4. Income and Asset Inequality

In this subsection, we change our main specification and rely on a latent class analysis estimation method using individual income proxied by household income divided by household size and asset holdings as observable characteristics to hypothesize income classes. Individual-level asset ownership is measured using information on ownership of a business, of a landline telephone at home and of a mobile phone from the Gallup World Poll (GWP). We thus fit a latent class model with three classes and a combination of four observable variables, including a continuous measure of individual income and a binary measure of asset ownership. We do acknowledge that more direct asset measures, such as home ownership, which are missing from the Gallup World Poll, would serve as better measures to capture inequalities in asset ownership across individuals.

We lose a large number of observations from our sample due to missing values for asset ownership variables. These are due to the fact that questions regarding business, landline telephone and mobile phone ownership were not included throughout the 2006 to 2017 year-waves. We report the results from completing this analysis in Table A3 using ordered response logit models. The structure of the table is similar to the one in Table 2. Our findings suggest that individuals in the low and middle income classes are less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class. We also document that the effect of income class remains robust to the inclusion of standard explanatory variables in this literature.[11]

Table A3. Robustness analysis: income and asset inequality.

Life Satisfaction	(1)	(2)	(3)	(4)
$Income\ Class_1$		−0.517 *** (0.193)		−1.178 *** (0.088)
$Income\ Class_2$		−0.282 ** (0.144)		−0.656 *** (0.034)
$Income\ Class_3$	Omitted	Omitted	Omitted	Omitted
Individual income	6.32×10^{-6} (0.000)	6.29×10^{-6} (0.000)	6.17×10^{-6} (0.000)	1.82×10^{-6} (0.000)
Age	0.000 (0.002)	0.000 (0.002)	−0.007 *** (0.001)	−0.007 *** (0.001)
Female	0.060 ** (0.025)	0.063 *** (0.024)	0.064 *** (0.015)	0.063 *** (0.015)
Single	0.096 * (0.058)	0.115 ** (0.050)	0.090 *** (0.020)	0.087 *** (0.019)
Ever married	−0.155 ** (0.064)	−0.147 ** (0.063)	−0.227 *** (0.030)	−0.194 *** (0.027)
Married	Omitted	Omitted	Omitted	Omitted
Residing rural areas	−0.397 * (0.130)	−0.327 *** (0.119)	−0.365 *** (0.05)	−0.219 *** (0.043)
Residing small towns	−0.177 (0.110)	−0.123 (0.105)	−0.194 *** (0.040)	−0.099 *** (0.034)
Residing suburban areas	−0.072 (0.156)	−0.046 (0.153)	−0.068 ** (0.039)	−0.046 (0.036)
Residing large city	Omitted	Omitted	Omitted	Omitted
Employed full-time	0.109 ** (0.049)	0.077 (0.054)	0.047 ** (0.028)	−0.033 (0.028)
Employed part-time	0.024 (0.070)	0.009 (0.066)	−0.038 (0.033)	−0.080 ** (0.032)
Unemployed	−0.153 ** (0.067)	−0.132 ** (0.062)	−0.363 *** (0.047)	−0.348 *** (0.047)
Out of labor force	Omitted	Omitted	Omitted	Omitted
Number of Adultsresiding in the HH	−0.019 (0.027)	−0.017 (0.027)	0.039 *** (0.007)	0.0457 *** (0.007)
Number of childrenresiding in the HH	−0.064 *** (0.018)	−0.055 *** (0.019)	−0.043 *** (0.007)	−0.022 *** (0.006)
Year-wave fixed effects	No	No	Yes	Yes
Country fixed effects	No	No	Yes	Yes
Observations	149,388	149,388	149,388	149,388

Standard errors in parentheses are clustered at the country level. Respondent-level weights are applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A.5. Gallup World Poll Survey Variables

In Table A4, we provide a detailed description of the variables we use in our analysis from Gallup World Poll as well as a description of the type of grouping/recoding we apply to the data.

Table A4. Description of survey variables: Gallup World Poll.

Variable Name	Question	Response Options	Recoding
WP5	Country		NA
YEAR_WAVE	Wave Year	2006–2017	NA
WP16	Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you	00 Worst Possible 01 02 03 04 05 06 07 08 08 10 Best possible 98 (DK) 99 (Refused)	NA
Income_2	Annual Household Income in International Dollars	Continuous variable	NA
HHsize	Total Number Living in Household for PerCapita Income	Continuous variable	NA
WP1220	Please tell me your age.	99 99+ 100 (Refused)	NA
WP1219	Gender	1 Male 2 Female	Generate dummy: -Female
WP1223	What is your current marital status?	1 Single/Never been married 2 Married 3 Separated 4 Divorced 5 Widowed 8 Domestic partner 6 (DK) 7 (Refused)	Generate dummies: - Single - Ever married (combines separated, divorced and widowed - Married
WP14	Residential status: Urban/Rural	1 A rural area or on a farm 2 A small town or village 3 A large city 6 A suburb of a large city	Generate dummies: - Residing rural areas - Residing small towns - Residing suburban areas - Residing large city
WP12	Residents 15+ in Household	Continuous variable	NA
WP1230	Children under 15 in Household	Continuous variable	NA
EMP_2010	Employment status	1 Employed full-time for an Employer 2 Employed full-time for self 3 Employed part-time do not want full-time 4 Unemployed 5 Employed part-time want full Time 6 Out of workforce	Generate dummies: - Employed full-time (combines employed full-time for an employer or for self) - Employed part-time (combines employed part-time do not want full-time and want full-time) - Unemployed - Out of labor force

Notes

1 *"Annual Household Income in International Dollars" is constructed by Gallup World Poll using another variable, which is the "Annual Household Income in Local Currency". Conversion from local currency to international dollars (ID) for all ID estimates is completed using purchasing power parity (PPP) ratios based on the 2011 International Comparison Program (ICP). The annual household income in international dollars (ID) is thus calculated using the latest World Bank's PPP private consumption conversion factor available, making income estimates comparable across all respondents, communities, local regions, countries and global regions.*

2 Information on the "Annual Household Income in International Dollars" is not available from the Gallup World Poll prior to 2009. We thus restrict our sample to country–year-waves 2009–2017. Doing so, our sample decreases by 396,751 respondents (21% of the initial sample of 1,863,900 respondents between 2006 and 2017).

3 We checked the country–year-wave rate of missingness and found that the average number of observations across 1297 country–year-wave combinations is 1200 respondents. The lowest number of respondents in a given country–year is 500 respondents.

4 We rely on the "GSEM" STATA command to fit the latent class analysis model.

5 See Appendix A.2 for an overview of the distribution of respondents across hypothesized income classes by region.

6 Individual income in its original scale is a highly skewed variable, as shown by standard deviations from the means, especially for the middle and upper income classes. We, therefore, adjust for this by transforming the variable to natural log form, which we perform in the analysis. Of note, the difference in means between the middle and upper income classes is not statistically significant, with a p-value of 0.2.

7 We refrain from displaying the results obtained using an OLS estimation with standardized dependent variable and solely interpret the size of the effects in-text.

8 The mean response for the life satisfaction question from the GWP for our final sample of 1,294,943 respondents is 5.483 with a standard deviation of 2.321. This means that lower- and middle-income-class individuals report about 30 and 18 percent lower life satisfaction in comparison to the upper-income-class individuals.

9 Details on this are available upon request. An alternative way to compare models is based on Akaike's information criterion (AIC). In this paper, we strictly rely on Schwarz's Bayesian information criterion (BIC).

10 An additional reason to focus on middle-income-class individuals is the missing information on the dollar value by country for the bottom national income threshold. We do, however, report in column (4) the threshold for the "top 10% share" indicator and use this value as an upper bound, below which individuals would belong to the middle income class, bounded by a lower bound, the "middle 40% share" indicator.

11 For space consideration, we do not report the results that allow us to gauge the size of our estimates by standardizing the dependent variable for all respondents (within each year, within each country) to have a mean of zero and a standard deviation of one and then running an OLS regressions using equation (1). We find that individuals in the low and middle income classes are, respectively, about 37 and 62 percent of a standard deviation less likely to report a higher life satisfaction in comparison to individuals belonging to the upper income class.

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