Top Incomes and Human Well-being: Evidence from the Gallup World Poll

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Abstract

The share of income held by the top 1 percent in many countries around the world has been rising persistently over the last 30 years. But we continue to know little about the relationship between the rising top income shares and human wellbeing. Using data from 24 countries and years ranging from 2005 to 2013 in the Gallup World Poll and the World Income Database, this study examines the relationship between top income share and different dimensions of subjective wellbeing. The results are mixed, with the negative relationship between top income shares and average life ladder being driven largely by the European sub-sample. For the European countries, we also document evidence that top income is statistically significantly associated with lower average enjoyment and being well-rested yesterday, and higher average stress and sadness yesterday. Overall, our findings suggest that, at least for individuals in Europe, an economic policy that increases national incomes may have significant crowding-out effect on aggregate evaluative wellbeing if it only increases the share of income at the very top of income distribution. More generally, our results highlight the complex relationships between income inequality and subjective wellbeing across different countries.

JEL: D63; I3

Keywords: top income; life evaluation; wellbeing; income inequality; World Income Database; Gallup World Poll

1. Introduction

There is a growing concern within the social science community over the economic and social implications of the persistent rise in top income shares in the United States and in most other rich countries around the world over the last three decades. Although much of the recent economic research on the topic of income inequality has focused on the identification of the "Top 1 percent"[1] and their dynamics over a long period of time (Atkinson, Piketty, & Saez, 2011; Burkhauser et al., 2012; Piketty & Saez 2014), we continue to know very little about the possible links between the rising share of national income accruing to the top 1 percent and aggregate subjective wellbeing (SWB). Does income inequality at the very top matter to the average life evaluation? What about the average emotional quality of everyday experience, that is, the frequency and intensity of experiences of joy, sadness, anger, and affection that make one's life pleasant or unpleasant? In other words, are different dimensions of SWB correlated with the rising income shares of the richest individuals in their country? Although these are difficult questions, they are important to our understanding of the welfare implications of rising top income shares around the world.

Our paper is the first of its kind to empirically link top income shares data to aggregate SWB across countries and time periods. Using data from the Gallup World Poll and the World Income Database, we first present econometric evidence showing that last year's top income shares have a negative though statistically insignificant correlation with aggregate life evaluation this year, holding personal characteristics and other lagged macroeconomic variables constant. However, a closer examination shows that the partial correlation between top income shares and aggregate life evaluation is negative, sizeable, and statistically significant only for respondents in the European sub-sample. We also show that, at least for individuals residing in Europe, top income shares correlate positively and statistically significantly with stress yesterday, sadness yesterday, and happiness yesterday, and are negatively and

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[1] The top income literature is based on income tax records. Hence it focuses on the share of taxable income held by the top 1 percent of tax unit where a tax unit can be an individual or a family. The survey literature primarily focuses on households. See Burkhauser et al. (2012) for a discussion of this distinction in the context of the top income literature.

statistically significantly correlated with enjoyment yesterday, being well-rested yesterday, and worry yesterday. Overall, our results highlight the complex relationships between top incomes and different measures of SWB across countries in different continents.

2. Income inequality and SWB
2.1. Background literature

There are several channels through which top income shares may affect aggregate wellbeing in a population. One theory is that an increase in income inequality – which is associated with a rise in top income shares – affects aggregate evaluative wellbeing through economic growth. Provided that the marginal propensity to save is higher for the rich than for the poor, a rise in top income shares should lead to an increase in national savings. Higher savings should, in turn, reduce the price of capital and raise investment, which lead to more growth (e.g., Kaldor, 1957) and an increase in income – and aggregate wellbeing – for a large fraction of people from those countries with large redistributive programs (Adelmann & Robinson, 1989).

By contrast, endogenous growth models have indicated that a rising income inequality may instead cause socio-political instability that pressures government to produce policies that allow private individuals to appropriate less of the returns to the promotion of growth activities such as accumulation of human capital and productive knowledge that are most beneficial for people at the bottom of the income distribution (e.g., Alesina & Rodrik, 1993, 1994; Persson & Tabellini, 1994; Saint Paul & Verdier 1996). In addition to this, recent evidence in political science has shown that government tends to prefer policies that maintain the status quo more than redistributive and social transfer policies when the top income share is high (Gilens, 2005; Enns et al., 2014). What this implies is that the net wellbeing losers from countries where the top income share is high are unlikely to be the rich, but the individuals who would have benefited the most from a government's redistributive schemes.

There is also evidence that income inequality changes the nature of the political institutions and the policies that politicians pursue to balance the relative

wellbeing of the rich and the poor. Araujo et al. (2008) and Deaton (2013) suggest that income inequality is associated with the allocation of public goods related to health, such as immunizations and the provision of subsidized medical care. This line of reasoning implies that children, particularly those in households with few resources, will receive fewer health inputs if they grow up during periods of greater income inequality or grow up in countries where income inequality is persistently high (see, e.g., Lillard et al., 2015).

Given that income inequality is often associated with high poverty rates (Ravallion, 2001), it is also possible that observation or perception of income inequality heightens the fear of rising crime rates and the sense of fairness for the rich. Hence, the positive effect of rising top income shares on the wellbeing of the rich may be somewhat "crowded out" by negative externalities that are typically associated with rising income inequality.

Other theories are also possible. For example, Hirschman's (1973) "tunnel effect" hypothesis, which assumes that individuals use information on other people's income progression as a positive signal that their turn will come soon (similar to how individuals who stuck in traffic inside a tunnel interpret movements in the other lane of cars while their lane is still immobile), suggests that an increase in the share of income held by the top 1 percent could potentially have a positive effect on the wellbeing of the other 99 percent. Hence, the tunnel effect hypothesis predicts that the association between income inequality and aggregate wellbeing should be positive (or less negative) in countries where income mobility is high.

There is, however, little indication from the existing theories regarding which dimensions of SWB between evaluative and affective wellbeing should be affected by the rising income inequality. According to the study by Kahneman and Deaton (2010), life evaluation – which is an evaluative dimension of SWB that relates more to one's life goals – has been found to be sensitive to an individual's socio-economic status such as income and employment status, whereas measures of emotional wellbeing – which is an affective dimension of SWB that relates to more one's immediate conditions and experiences – have been found to be sensitive to circumstances that evoke emotional responses, such as time spent commuting and caring for others. To the extent that income inequality correlates more with one's

opportunities in life and long-term life goals via its effects on income, education, and health, it is likely that a rise in top income shares will be observed with a significant fall in the aggregate life evaluative score. On the other hand, provided that a rise in top income shares does not have an immediate impact on one's immediate conditions and experiences, we do not expect to observe a strong correlation between top income shares and different emotional experiences.

Turning our attention to the existing empirical findings, there appears to be virtually zero evidence on the relationships between income inequality and measures of daily emotional experiences. On the other hand, there is an accumulation of studies suggesting that aggregate life satisfaction – which is an evaluative measure of SWB – tends to be low when income inequality is high (e.g., Blanchflower & Oswald, 2003; Alesina et al., 2004; Schwarze & Harper, 2007; Verme, 2011; Oishi & Kesebir, 2015; Schröder, 2016)[2]. Yet, a more careful look into the literature suggests that the relationship between income inequality and evaluative wellbeing may be more complex than what it might appear to be on the surface.

For example, a study by Alesina et al. (2004) shows that although European respondents' life satisfaction are substantially lower in countries where income inequality is high, such correlation is not found across states for the American sample in general. Context seems to matter, however, and a closer look at the data reveals that the rich (top half of the income distribution) in America are inequality averse whereas the poor are indifferent to income inequality. The opposite is true for European citizens. The authors argue that these differences are expected because most Americans believe that they live in a highly mobile society where effort is the main determinant of income, which implies that most people who are not at the top of the income distribution can perceive any income inequality as fair. Nevertheless, their finding that most Americans do not dislike income inequality appears to be in contrast with the results obtained by Blanchflower and Oswald (2003) who use the U.S. General Social Survey to show that income inequality, measured by the ratio of the mean of the fifth earnings quintile to the mean of the first, has a negative but small

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[2] For a recent comprehensive review of the literature, see Ferrer-i-Carbonell and Ramos (2014).

relationship with how happy you are these days, which is also more of an evaluative measure than affective measure of SWB.[3]

A study by Senik (2004) finds that the Gini coefficient is positive albeit statistically insignificantly different from zero in life satisfaction regressions for Russia. Jiang et al. (2012) find a positive and statistically significant association between life satisfaction of rural migrants and the Gini coefficient measured at the city-level in urban China. Using Latin American data, Graham and Felton (2006) show that happiness is highest for individuals living in medium inequality countries rather than in low or high inequality countries. In short, it appears that in some countries income inequality might in fact be good for evaluative wellbeing.

There is little empirical attempt in the literature to check the robustness of the results to different ways of measuring income inequality. With very few exceptions, the majority of studies in the literature use Gini as the measure of income inequality in the estimation of life satisfaction regression equations. Although the Gini coefficient is widely accepted as a measure of income inequality, it also has its own fair share of limitations. Since the Gini coefficients are normally derived using survey data, it does a very good job at capturing the income distribution for the bottom 99 percent of the population, but a poor job (relative to tax record data) at measuring the top 1 percent. Additionally, the Gini coefficient gives equal weight to inequality at the top, middle, and bottom of the income distribution, thus making it less sensitive to changes at the tails compared to alternative measures of income inequality that give more weights to the tails of the distribution, e.g., the Theil 0 and 2 measures of income inequality. This would not necessarily pose a problem for researchers who are not concerned about changes in the income distribution at the very top. However, it does pose a problem when changes in the income distribution come mainly from an increase in the share of income held by people at the top 1 percent of the income distribution.

Another drawback of the Gini index is that their measurements obtained from different databases – namely, the World Income Inequality Database (WIID), the United Nations University and the World Institute for Development Economics

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[3] The exact survey question in the US General Social Surveys used in Blanchflower and Oswald (2003) is "*Taken all together, how would you say things are these days? Would you say that you are very happy, pretty happy, or not too happy?*"

Research (UN-WIDER), and the Luxembourg Income Study (LIS) – are often not comparable with one another (for a review, see Atkinson and Brandolini, 2001). While Atkinson and Brandolini (2001) have recommended the LIS as the best source for the Gini coefficients, as it employs a consistent methodology across countries for measuring income and calculating income inequality, its main limitation is that it contains very infrequent observations of income inequality across countries and time. For example, the LIS only contains three observations of the Gini coefficients between 2001-2010 for Australia, the United Kingdom, and the United States, which inevitably limits the scope for careful econometric analysis that allows for country-specific dummy in the regression (Leigh, 2007).

The current study contributes to the literature by introducing the latest data from the World Incomes Database (WID) on the share of incomes held by the top 1 percent as an alternative measure of income inequality. There are pros and cons to using top incomes shares data as a measure of income inequality in a subjective well-being regression equation. First, the tax record data are imperfect. The share of taxable income held by a given percentile varies according to who is taxed, and the data are not adjusted for tax evasion and tax avoidance. Further, because the data measure national income inequality, the data vary only temporally and may reflect trends in other factors that also temporally vary, such as changes in medical technology.

These shortcomings are, however, more than counterbalanced by four attractive features of tax record data. First, the administrative data measure income for samples that over time are more consistent in whom they include than other data sets—because the data include all taxes paid and all tax-paying units. Second, the data cover information about the top part of the income distribution, which is difficult to capture fully in survey data. Third, the measure correlates well with a country's Gini coefficient (Leigh, 2007). And fourth, the top income shares data are observed much more frequently than the Gini coefficient.

One of the key challenges in the identification and estimation of the coefficient of income inequality is that income inequality is a macroeconomic variable that rarely changes over time (and fixed across country-year units). Since fixed-effects model soaks up most of the explanatory power of slow-moving

variables, using it to estimate the effect of income inequality on SWB will likely result in point estimates that are highly unreliable and sensitive to changes in the specification (e.g., Beck, 2001; Plümper & Troeger, 2007). As a result, previous studies have relied almost exclusively on the between variance when carrying out inference on the effects of income inequality on SWB. However, these cross-section or random effects models, which assume a zero correlation between the income inequality variable and the unobserved unit effects, are likely to produce point estimates that are biased upward. The current study deals with the inefficiency issue of the fixed-effects estimator by introducing the fixed-effects filtered (FEF) estimator (Pesaran & Zhou, 2016) as a way to correct for the unobserved heterogeneity bias in the estimation of the coefficient of top income shares.

2.2. Hypotheses

Based on background literature, we set out to test the following three main hypotheses.

1. Holding other things constant, aggregate life evaluation scores are, on average, lower in countries where the richest 1 percent holds a higher proportion of national income;
2. The estimated conditional correlation between top income shares and aggregate life evaluation is more negative and precisely estimated in countries where individuals believe that they live in less mobile societies, e.g., European countries.

However, we do not have a clear set of predictions for the relationships between top incomes and measures of affective wellbeing. Our general prediction is that the share of top incomes is unlikely to have a significant relationship with daily emotional experiences if it does not have a direct impact on how individuals spend their time on a daily basis.

3. Data

Our primary data come from the Gallup World Poll (GWP). Established in 2005 by the Gallup Organization, the GWP continually surveys citizens in more than 150 countries around the world and interviews approximately 1,000 residents per country. Respondents in the GWP are randomly selected adults 15 years of age and older and are nationally representative. Gallup asks each respondent the survey questions in the respondent's language. The mode of the interview is telephone survey in countries where telephone coverage represents at least 80% of the population. Where telephone penetration is less than 80%, Gallup uses face-to-face interviewing.

The GWP contains a wide range of questions about the respondent's wellbeing. Life evaluation, which is a measure of a person's thoughts about his or her life, is elicited using the Cantril life ladder question. The exact wording of the Cantril life ladder is "*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?*" The corresponding response categories range from 0 (Worst possible life) to 10 (Best possible life).

The GWP also asks a battery of questions on individual's emotional experiences. Questions on respondents' real-time positive experiences include, for example: "*Did you experience the following feelings during a lot of the day yesterday? How about enjoyment?*", "*Did you smile or laugh a lot yesterday?*", "*How about happiness?*", "*Did you feel well-rested yesterday?*" Questions on respondents' real-time positive experiences include, for example: "*Did you experience the following feelings during a lot of the day yesterday? "How about worry?*"; ""*How about stress?*"; "*How about anger?*"; "*How about sadness?*" Each item is recoded so that positive answers are scored as a "1" and "0" if the answer is no.[4] As per advised by Stone and MacKie (2014) and pointed to us by one of the referees, we treat each measure of positive and negative emotional experience separately instead of combining them to form one unified construct.

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[4] The small number of "don't know" and "refused" responses are coded as missing.

To provide household income measurements that are comparable across countries, Gallup asks respondents two questions. The first asks respondents about their monthly income in local currency before taxes. Respondents are instructed to include all income from wages and salaries, remittances from family members living elsewhere, and all other sources. If respondents hesitate to answer or have difficulty answering the first question, they are then presented with a set of income ranges in their local currency and asked which group they fall into. Their estimates are then taken as the midpoint of the range. The income variable in the GWP is expressed in international dollars, creating using the World Bank's individual consumption PPP conversion factor, which makes income estimates comparable across all countries. In order to get household income per capita, we divide the income variable by the household headcount variable in the GWP data set.

Historical time-series data on the share of taxable national income (excluding capital gains) held by the top 1 percent at the country level come from the WID (www.wid.world). To control for movements in other country-year level variables, historical time-series data on standard macroeconomic control variables in SWB equations (Di Tella et al., 2003), i.e., GDP per capita, unemployment rates, and inflation rates) are obtained from the World Bank Database (www.data.worldbank.org).

We use ten waves of the GWP (2005–2014) and restrict the sample from 150 available countries to only those countries featured in the WID. This gives us 25 countries – 135 country-year data points – ready for analysis at the first instance (with some years of data missing – see Appendix 1A), including Australia, Canada, China, Colombia, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Malaysia, Mauritius, Netherlands, New Zealand, Norway, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Great Britain, the U.S.A, and Uruguay. We then further restrict the sample to consisting only individuals that we have data on personal characteristics and other macroeconomic controls, which leaves us with 97 country-year data points (or 147,940 individual observations) in the GWP data. The average income share held by the top 1 percent across the entire sample is 11.92% with a between-country standard deviation of 3.29. However, note that the within-country variation is small (within-country standard deviation = 0.64) because our GWP time series is short. Our final sample restriction consists of observations with non-missing

values on lagged top incomes and other macroeconomic variables. This gives us the final sample that consists of 145,060 individual observations from 94 country-year data points; see Appendix 2A for the overall descriptive statistics of our sample.

4. Empirical strategy

Consider the following wellbeing regression equation:

$$W_{i,ct} = \alpha + X'_{i,ct}\gamma + Z'_{ct}\beta + \pi_{ct} + u_{i,ct}, \tag{1}$$

where $n = 1, 2, \ldots, N$; $c = 1, 2, \ldots, C$; $t = 1, 2, \ldots, T$; W_{ct} is aggregate self-rated wellbeing score (e.g., life ladder) of all individuals from country c in year t, X_{ct} is a vector of individual characteristics that vary by country and year; Z_{ct} is a vector of country variables that only vary over the cross-section, ct; π_{ct} is country-year fixed effects. It is clear from equation (1) that, without further restrictions on π_{ct}, β cannot be identified even if γ is known.

To estimate β, we apply the FEF estimator to equation (1)[5], which can be computed using the following two-step procedure:

Step 1: Using equation (1), compute the country-year fixed-effects estimator of γ, denoted by $\hat{\gamma}$, and the associated residuals $\hat{u}_{i,ct}$, which is defined by

$$\hat{u}_{i,ct} = W_{i,ct} - \hat{\gamma}X_{i,ct}, \tag{2}$$

Step 2: Compute the country-year averages of these residuals, $\bar{\hat{u}}_{ct} = N^{-1}\sum_{i=1}^{N}\bar{\hat{u}}_{ct}$. Regress $\bar{\hat{u}}_{ct}$ on Z_{ct} with an intercept to obtain $\hat{\beta}_{FEF}$, where

$$\hat{\beta}_{FEF} = \left[\sum_{c=1}^{C}\sum_{t=1}^{T}(Z_{ct} - \bar{Z})(Z_{ct} - \bar{Z})'\right]^{-1}\sum_{c=1}^{C}\sum_{t=1}^{T}(Z_{ct} - \bar{Z})(\bar{\hat{u}}_{ct} - \bar{\hat{u}})'$$

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[5] Alternative models to FEF estimator include Fixed Effects Vector Decomposition (FEVD) (Plumper & Troeger, 2007) and, in the case where one or more of the time-invariant regressors are endogenous and there are valid instrumental variables (IVs), the Hausman-Taylor random coefficient panel data model (Hausman & Taylor, 1981). Given that we do not have valid IVs for our time-invariant variables and that the variance estimator proposed for FEVD estimator is inconsistent (Green, 2011; Breusch et al., 2011), our preference is to use FEF model, which has been shown to be consistent under fairly general conditions. In addition to this, the FEF model has been shown to produce estimates with extremely small bias even with N=100 (Note that N=94 in most cases in our paper).

$$\text{(3)}$$

and

$$\hat{\alpha}_{FEF} = \bar{\bar{u}} - \hat{\beta}'_{FEF}\bar{Z}, \tag{4}$$

where $\bar{\bar{u}} = \sum_{c=1}^{C}\sum_{t=1}^{T}\bar{\bar{u}}_{ct}$. Since π_{ct} is removed from the equation in Step 1, $\hat{\beta}_{FEF}$ is free from the usual unobserved heterogeneity bias.

Pooled OLS can then be used to estimate $\hat{\beta}_{FEF}$. However, the current study uses the STATA code "*xtfef*", which was created by Qiankun Zhou, to run our country-year level model.[6] Finally, following a referee's suggestion, the country-year variables used in the second-stage of FEF regression will be lagged by one year in order to avoid (or minimise) the problem of reversed causality. In addition to this, for ease of interpretation, all of our dependent variables are standardised to have zero mean and a standard deviation of 1.

5. Results

Figure 1 presents a first pass to the research question by plotting unconditional weighted country-year averages between the share of national income held by the top 1 percent in year *t*-1 and the average standardised life evaluation in year *t*. It shows that there is a small but pronounced negative correlation between country-year averages of life evaluation in year *t* and taxable income share held by people in the top 1 percent in year *t*-1. Fitting the best line of fit produces a coefficient on the top income shares of -0.024 ($p < 0.001$). This indicates that a 1-percentage point increase in the top 1 percent is associated with an average drop of 0.024 standard deviation in the life evaluation scale.

To explore the issue more carefully, we estimate life evaluation regression equations that adjust for possible confounding influences that also include controlling for (or rather, filtering out) country-year fixed effects. We do this by estimating the FEF model with country-year fixed effects, and report the second-stage estimation

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[6] The user-generated STATA code *xtfef* can be downloaded from Qiankun Zhou's website at: http://qiankunzhou.weebly.com/research.html

results in Table 1.[7] In the first-stage of the FEF model, we control for a set of standard variables that include gender, age, age-squared, age-cubed, log of real household income per capita, employment status, education level, marital status, number of children, and physical health index. In the second-stage of the FEF model, we include, as country-year specific variables, one-year lags of the share of national income held by the top 1%, log of real GDP per capita, unemployment rate, and inflation rate. See Appendix 3A for the first-stage life evaluation estimates.

We begin in Column 1 of Table 1 with only the lagged top 1 percent as the only independent variable. Here, we can see that an increase in the share of taxable income held by the top 1 percent in year t-1 is negatively and statistically significantly associated with aggregate life evaluation in year t; a 1 percent increase in the top income shares is associated with a decrease in the life evaluation score of around 0.02 standard deviation.

However, adding other lagged macroeconomic variables seems to have reduced this estimated coefficient by almost a half; see Column 2. What this implies is that much of the conditional correlation in Column 1 between top incomes at t-1 and aggregate life evaluation at t is confounded by the omitted lagged real GDP per capita variable, which has a high partial correlation with aggregate life evaluation.

Column 3 goes on to control for different continent dummies in the second-stage of the FEF model. One rationale behind this is that there may be important clustering effects by continents, which may have confounded the estimates of macroeconomic effect on aggregate wellbeing. However, including continent dummies does very little to change the size and the statistical insignificance of the lagged top income shares coefficient, although it reduces the size of the lagged real GDP per capita coefficient and significantly increases the size of the negative coefficient of lagged unemployment rate. It is also worth noting that aggregate life evaluation is lowest in Asia, and highest in North America.

Our FEF estimates have so far indicated that an increase in the size of the income pie for the top 1 percent that came not as an expense to the respondent's own income has a negative, albeit statistically insignificant, relationship with aggregate

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[7] First-stage FEF estimates on individual characteristics can be found in Table 3A in the Appendix.

life evaluation. This is inconsistent with our first hypothesis, which states that aggregate evaluative wellbeing is likely to be sensitive to an increase in the share of top incomes.

The second hypothesis states that the estimated conditional correlation between top income shares and aggregate life evaluation is more negative and precisely estimated in countries where individuals believe that they live in less mobile societies, e.g., European countries. To test this, we introduce in Column 4 a set of interaction terms between lagged top income shares variable and continent dummy variables in the second-stage of the FEF regression.

Looking at Column 4, we can see that the main effect of the lagged top 1 percent is now negative and statistically significant; a 1 percent increase in the top income shares is associated with a decrease in the life evaluation score of around 0.034 standard deviation. All three interaction terms are positive, two of which (Asia and Others) are statistically significantly different from zero at conventional levels. In particular, the positive interaction coefficient between lagged top incomes and "Others" dummy – which includes respondents in South Africa, Australia, New Zealand, Colombia, Mauritius, and Uruguay – is relatively sizeable when compared to the negative coefficient of the lagged top income shares. Hence, what these estimated coefficients are implying is that, while a rise in top income shares in year t-1 is associated with a significant drop in the aggregate life evaluation for individuals residing in Europe, the same cannot be said for residents in other countries in our data, especially those living in Asia and Latin America. This is consistent with the findings by Alesina et al. (2004), who find aggregate life satisfaction to be significantly correlated with lower aggregate life satisfaction for the Europeans but not for the Americans.

For the Europeans, the differences in average life evaluation across different degrees of income inequality are not small. The estimated coefficient of -0.034 is roughly twice the size of the estimated unemployment effect on average life evaluation faced by the Europeans, which is estimated to be -0.017 (not shown in the table).

What is the association between the top income shares and daily emotional experience? Table 2 reports the second-stage FEF estimates for different measures of emotional experiences – namely enjoyment, happiness, being well-rested, smile, worry, stress, anger, and sadness. Only the estimates obtained from the full interaction model, i.e., the specification used in Column 4 of Table 1, are reported. Note also that, like the life evaluation variable, the dependent indicator (0,1) variables are standardised to have zero mean and a standard deviation of 1.

Looking across Table 2's columns, we can see that the estimated main effects of the top income shares are statistically significant in three (out of four) positive emotional wellbeing regressions and three (out of four) negative emotional wellbeing regressions. This suggests that, for the European sample in our data, an increase in top income shares in year t-1 is associated with a significant decrease in enjoyment yesterday and being well-rested yesterday. An increase in top income shares in year t-1 is also associated with a significant increase in stress and sadness yesterday. Perhaps harder to interpret, we find lagged top income shares to be associated with higher levels of happiness yesterday, as well as lower levels of worry yesterday, among the Europeans. More generally, we can conclude that rising top income shares have a strong partial correlation with how people in Europe report their daily emotional wellbeing, both positive and negative. One the other hand, given that the majority of the interaction terms between lagged top incomes and continent dummies have opposite signs to the estimated lagged top income coefficients, rising top income shares seem to explain very little variation in the measures of emotional wellbeing for countries outside Europe.

As a robustness check, Appendix 4A tests whether the estimated relationship between top income shares and life evaluation are different between males and females, young and old, people with high education and those with low education, and between the top 40% and the bottom 40% income people within each country. First, although it can be seen that the coefficient of top income shares is more negative for men than for women, for the older cohorts than the younger cohorts, for the low educated than for the high educated, and for the relatively poor than the relatively rich in the country, we cannot reject the null hypothesis that the paired

coefficients are statistically significantly different from each other across all subgroups.

5. Conclusions

The share of income held by the top 1 percent in many countries around the world has been rising persistently over the last 30 years. However, little is known about how the rise in top income shares may affect different dimensions of human subjective wellbeing. In this paper, we make one of the first empirical attempts to establish this link.

Using the latest combined data from the WID and the GWP, we explored the relationship between the share of taxable income held by the top 1 percent and aggregate evaluative and affective wellbeing. By implementing Pesaran and Zhou's (2016) FEF model on the slow-moving top income shares variable, we initially show top income shares in year t-1 to have a negative but statistically insignificant conditional correlation with aggregate life evaluation in year t. We later document evidence that only people in Europe are significantly less tolerable of rising top income shares than those from other countries, which is consistent with the findings by Alesina et al. (2004). In addition to this, we find some statistical evidence to suggest that rising top income shares may have had a negative impact on how people in Europe spend their days, although we must admit that the results on emotional wellbeing are much harder to explain than those conditional correlations between top income shares and aggregate life evaluation.

We believe our findings have several important implications. First, evidence on the relationship between top income shares and aggregate life evaluation appears to corroborate well with previous studies that found a negative relationship between Gini index and life satisfaction (e.g., Blanchflower & Oswald, 2003; Alesina et al., 2004; Oishi & Kesebir, 2015). This implies that top income shares can potentially offer a good substitute for other measures of income inequality in cases where alternative income inequality measures are of low quality or missing, which is consistent with Leigh (2007).

Second, our estimates provide a rough idea of how big the negative net effect of rising top income shares on the aggregate evaluative wellbeing of a society might

be in Europe. Our ability to quantify the possible effect of top income shares on aggregate SWB of a population helps fuel further debate on whether income inequality is good or bad for society in general; as some of our estimates suggest, not all countries are averse to rising top income shares, e.g., countries in Asia and Latin America. For example, provided that we can take our estimates at their face value, one policy implication – at least for the government in the European countries – is that economic policies that raise national income may also face a significant crowding-out effect on aggregate wellbeing if it only raises incomes for the very rich in the society.

And finally, our successful implementation of the FEF model to the top income shares data means that future researchers wanting to estimate the effects of other slow-moving macroeconomic variables on SWB can also apply the same estimation method provided in the outline of this paper, as well as those provided in Pesaran and Zhou (2016).

However, our study is not without some notable limitations. First, our aim was primarily to document correlations in the data rather than to identify the cause and effect of rising top income shares on SWB. This is mainly because it is unclear what type of variables could serve as a valid instrumental variable for lagged top income shares in a SWB equation. Secondly, because the WTID and the GWP are still relatively new ventures, we are inevitably limited by the number of countries that could be matched and studied in our analysis. Third, since top income shares rarely change over time in our relatively short time-series, we were unable to estimate a model that identify whether adaptation to rising income inequality is possible (and if so, whether adaptation was partial or complete across countries). As both data sets continue to expand and include more variables and events, future research may need to return to these issues.

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Figure 1: Top Income Shares and Standardised Life Evaluation
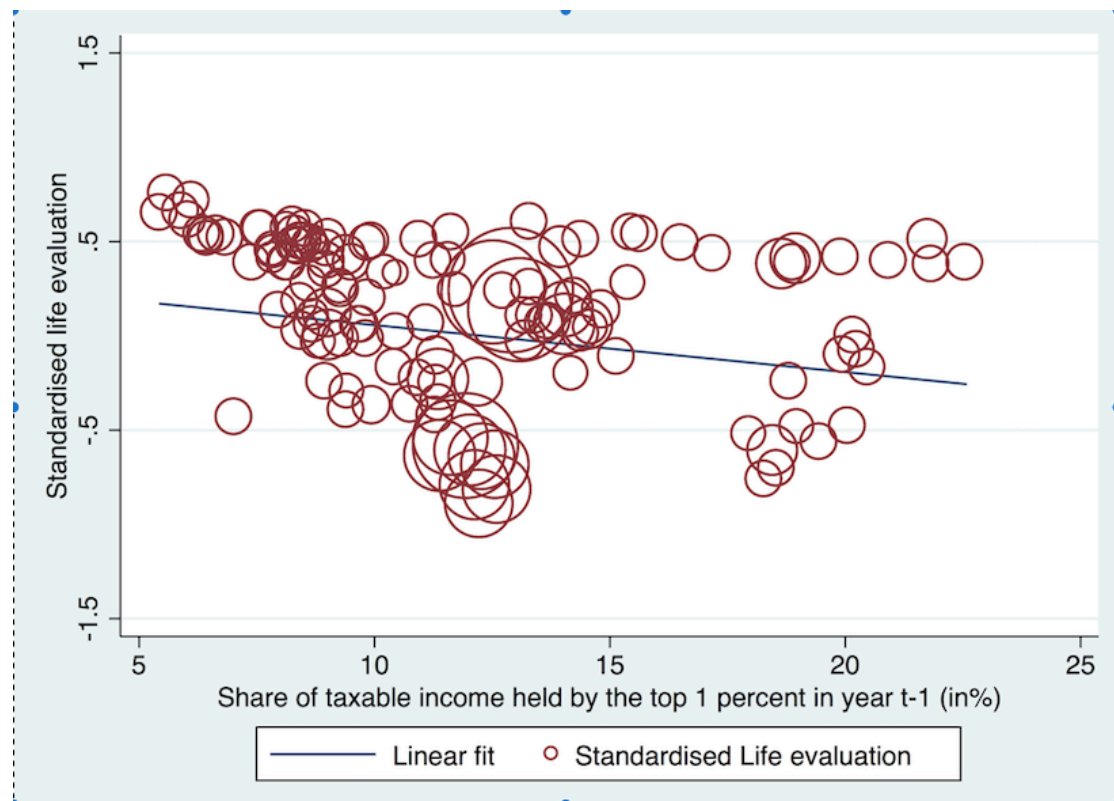
Note: Each circle represents (unconditional) raw country-year averages. Data represent 94 country-year local averages. The size of the circles reflects the number of observations used in calculating the average. Subjective well-being measures are standardized to have zero mean and a standard deviation of 1.

Table 1: Estimates from the Fixed Effects Filtered Life Evaluation Model: The Gallup World Poll, 2005-2014

Dependent variable: **Standardized mean residual life ladder in year** t	**(1)**	**(2)**	**(3)**	**(4)**
Share of taxable income held by the top 1 percent in year t-1	-.018***	-.010	-.008	-.034***
	[.007]	[.007]	[.007]	[.007]
Ln (real GDP per capita in t-1)		.345***	.145***	.201***
		[.067]	[.044]	[.039]
Unemployment rate (% of total labor force) in t-1		.008	-.021***	-.025***
		[.005]	[.004]	[.005]
Inflation - consumer prices (annual %) in t-1		.021	.001	-.005
		[.017]	[.008]	[.007]
North America dummy			.130*	.205*
			[.065]	[.121]
Asia dummy			-.569***	-.959***
			[.055]	[.267]
Others dummy			.087**	-.432***
			[.036]	[.085]
Top incomes in t-1 × North America dummy				.006
				[.009]
Top incomes in t-1 × Asia dummy				.039*
				[.022]
Top incomes in t-1 × Others dummy				.050***
				[.009]
Number of groups	94	94	94	94
Individual observations	145,060	145,060	145,060	145,060

Note: ***<1%, **<5%, *<10%. The first-stage regression is reported in Table 3A in the Appendix.

Table 2: Estimates from the Fixed Effects Filtered Positive and Negative Emotional Experience Model: The Gallup World Poll, 2005-2014

Dependent variable: Standardized mean residual life ladder in year *t*	Positive Emotional Experience				Negative Emotional Experience			
	Enjoyment	Happiness	Well-rested	Smile	Worry	Stress	Anger	Sadness
Share of taxable income held by the top 1 percent in year *t*-1	-.024***	.050***	-.009**	-.005	-.014**	.033***	.006	.012***
	[.008]	[.010]	[.004]	[.006]	[.005]	[.006]	[.006]	[.003]
Ln (real GDP per capita in *t*-1)	-.237***	-.078*	-.005	-.073	-.017	-.099***	-.032	.026
	[.060]	[.043]	[.032]	[.043]	[.029]	[.030]	[.027]	[.016]
Unemployment rate (% of total labor force) in *t*-1	-.023***	.002	.004	.001	.001	-.002	.005	.001
	[.003]	[.004]	[.003]	[.002]	[.005]	[.002]	[.003]	[.002]
Inflation - consumer prices (annual %) in *t*-1	-.002	-.006	.001	-.004	.002	-.010	-.019***	-.003
	[.009]	[.008]	[.005]	[.006]	[.006]	[.007]	[.006]	[.004]
North America dummy	-.082	.744***	-.182	.070	.013	.113	-.204	.040
	[.115]	[.155]	[.140]	[.119]	[.084]	[.080]	[.127]	[.052]
Asia dummy	.314	1.715***	.237	.744***	-.249	-.029	-.216	-.197
	[.370]	[.277]	[.176]	[.273]	[.174]	[.284]	[.187]	[.141]
Others dummy	-.160	.923***	-.221***	-.045	-.180**	.522***	.018	.068
	[.090]	[.155]	[.060]	[.071]	[.073]	[.082]	[.096]	[.043]
Top incomes in t-1 × North America dummy	.027**	-.049***	.020**	.004	.008	-.006	.007	-.008**
	[.009]	[.012]	[.008]	[.008]	[.006]	[.007]	[.008]	[.003]
Top incomes in t-1 × Asia dummy	-.058*	-.179***	-.005	-.080***	.025	-.008	.019	.012
	[.035]	[.023]	[.016]	[.024]	[.014]	[.022]	[.015]	[.012]
Top incomes in t-1 × Others dummy	.017*	-.079***	.025***	.004	.017**	-.050***	-.007	-.005
	[.010]	[.014]	[.005]	[.007]	[.007]	[.008]	[.008]	[.004]
Number of groups	94	80	94	94	94	90	94	94
Individual observations	144,492	124,130	145,323	143,825	145,363	140,978	145,410	145,278

Note: ***<1%, **<5%, *<10%.

Appendix

Table 1A: Average Top Income Shares and Subjective Well-Being by Country

Countries	Top percentile's income share	Life evaluation	Years used in the analysis with a full set of controls
United States	19.11	7.29	2009-2013
	(1.54)	(1.99)	
United Kingdom	12.89	6.91	2009-2012
	(0.58)	(1.85)	
France	8.53	6.69	2008-2013
	(0.39)	(1.77)	
Germany	13.21	6.64	2007-2011
	(0.45)	(1.82)	
Netherlands	6.47	7.54	2008-2012
	(0.18)	(1.26)	
Spain	9.00	6.58	2008-2012
	(0.45)	(1.93)	
Italy	9.52	6.71	2008-2009
	(0.14)	(1.92)	
Sweden	8.80	7.43	2008-2013
	(0.22)	(1.61)	
Denmark	6.01	7.81	2007-2010
	(0.35)	(1.53)	
China	11.69	5.07	2009-2014
	(0.31)	1.99	
Singapore	14.15	6.56	2008-2011
	(0.73)	(1.54)	
Japan	10.82	6.07	2007-2010
	(0.34)	(1.94)	
South Africa	18.74	5.11	2009-2012
	(0.39)	(2.09)	
Canada	14.07	7.52	2005-2010
	(0.58)	(1.61)	
Australia	8.39	7.39	2008, 2010
	(0.35)	(1.74)	
New Zealand	8.11	7.29	2008-2013
	(0.49)	(1.70)	
South Korea	11.77	5.96	2007-2012
	(0.42)	(2.14)	
Colombia	20.26	6.21	2006-2010
	(0.20)	(2.46)	

Finland	8.50	7.67	2008
	(0.00)	(1.41)	
Ireland	10.48	7.42	2008-2009
	(0.09)	(1.64)	
Malaysia	9.22	5.72	2009-2012
	(0.20)	(1.53)	
Norway	7.78	7.61	2008
	(0.00)	(1.53)	
Switzerland	10.54	7.49	2009
	(0.00)	(1.67)	
Uruguay	14.33	6.34	2010-2012
	(0.25)	(2.25)	

Note: Standard deviations are reported in parentheses.

Source: Estimated by authors using country-based data on top incomes from the World Top Income Database and individual-based data life satisfaction from the Gallup World Poll.

Table 2A: Descriptive Statistics, the Gallup World Poll 2006-2012

Variables	M	SD	Range	Description
Life evaluation	6.41	2.07	0-10	"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?" The corresponding response categories range from 0 (Worst possible life) to 10 (Best possible life).
Enjoy	.79	.40	0-1	Did you experience enjoyment yesterday?
Happiness	.79	.40	0-1	Did you experience happiness yesterday?
Well-rested	.73	.44	0-1	Did you feel well-rested yesterday?
Smile	.78	.41	0-1	Did you smile or laugh a lot yesterday?
Worry	.28	.45	0-1	Did you experience a lot of worry yesterday?
Stress	.30	.46	0-1	Did you experience a lot of stress yesterday?
Anger	.14	.35	0-1	Did you experience a lot of anger yesterday?
Sadness	.15	.36	0-1	Did you experience a lot of sadness yesterday?
Share of taxable income held by the top 1 percent	11.92	3.29	5.44-21.83	Share of taxable income held by the top 1 percent at the country-year level (in %)
Log of household income per capita - 2010 PPP	9.00	1.32	1.75-14.98	Log of household income per capita, PPP-corrected at 2010 price
Age	47.47	17.65	15-99	Age
Male	.44	.49	0-1	Male
Employed full time for self	.09	.29	0-1	Employed full time for self
Employed PT but do not want FT job	.06	.24	0-1	Employed part time but do not want full time job
Unemployed	.03	.18	0-1	Unemployed
Employed part time but want full time job	.04	.20	0-1	Employed part time but want full time job

Out of workforce	.30	.45	0-1	Out of workforce
Completed secondary - 3 year Tertiary School	.53	.49	0-1	Completed secondary - 3 years Tertiary School
Completed high school/college degree	.23	.42	0-1	Completed high school/college degree
Married	.56	.49	0-1	Married
Separated	.01	.13	0-1	Separated
Divorced	.05	.22	0-1	Divorced
Widowed	.07	.26	0-1	Widowed
Domestic partner	.001	.03	0-1	Domestic partner
Number of children under aged 15	.58	1.00	0-32	Number of children under aged 15
Physical health index	76.91	25.46	0-100	Perception of one's own health
Country-year variables				
Country GDP per capita - current international price/$10,000	3.11	1.45	.83-7.49	Country's sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of products divided by midyear population divided by 10,000
Unemployment rate (% of total labor force)	7.20	4.87	2.5-24.8	Share of the total labor force that is without work but available for and seeking employment
Inflation - consumer prices (annual %)	2.67	1.82	-4.47-8.09	Annual percentage change in the cost to the average consumer of acquiring a basket of goods and services

Table 3A: First-stage FEF estimates

Dependent variable: Standardized life ladder in year t	β
Male	-.136***
	[.012]
Age	-.093***
	[.008]
Age-squared	.001***
	[.000]
Age-cubed	-.000***
	[.000]
Log(real household income per capita)	.117***
	[.013]
Employed full time for self	-.005
	[.025]
Employed PT but do not want FT job	.067***
	[.017]
Unemployed	-.311***
	[.034]
Employed PT but want FT job	-.077***
	[.032]
Out of workforce	-.063***
	[.015]
Completed secondary - tertiary School	.135***
	[.014]
Completed high school/college degree	.286***
	[.021]
Married	.165***
	[.015]
Separated	-.086***
	[.031]
Divorced	-.053**
	[.024]
Widowed	-.021
	[.019]
Domestic partner	.082
	[.122]
Number of children under aged 15	.035***
	[.004]
Physical health index	.010***
	[.000]
Country × Year fixed effects	Yes
Number of groups	94
Individual observations	145,060

Note: ***<1%, **<5%, *<10%. The employment status variable is standardized in the GWP since 2010. A missing dummy variable for the missing values of this variable is included for all respondents prior to 2010.

Table 4A: Estimates from the Fixed Effects Filtered Life Evaluation Model by Subsamples

Dependent variable: Standardized mean residual life ladder in year *t*	Male	Female	Age<40	Age>=40	High education	Low education	Top 40% income share in the country	Bottom 40% income share in the country
Share of taxable income held by the top 1 percent in year *t*-1	-.036***	-.033***	-.027***	-.037***	-.030***	-.036***	-.026***	-.043***
	[.007]	[.008]	[.006]	[.008]	[.006]	[.008]	[.006]	[.011]
Ln (real GDP per capita in *t*-1)	.169***	.226***	.196***	.195***	.189***	.198***	.212***	.285***
	[.046]	[.037]	[.045]	[.039]	[.031]	[.040]	[.050]	[.036]
Unemployment rate (% of total labor force) in *t*-1	-.021***	-.028***	-.023***	-.025***	-.019***	-.026***	-.027***	-.024***
	[.004]	[.005]	[.006]	[.004]	[.006]	[.005]	[.006]	[.004]
Inflation - consumer prices (annual %) in *t*-1	-.006	-.005	-.009	-.002	.005	-.005	-.008	-.004
	[.008]	[.007]	[.008]	[.007]	[.006]	[.008]	[.008]	[.008]
North America dummy	.027	.334***	.028	.288**	.211**	.216	.305***	.172
	[.147]	[.128]	[.153]	[.116]	[.100]	[.154]	[.114]	[.215]
Asia dummy	-1.180***	-.767***	-.938***	-.888***	-.958***	-.996***	-.735***	-.992***
	[.377]	[.225]	[.263]	[.321]	[.248]	[.290]	[.262]	[.312]
Others dummy	-.420***	-.447***	-.493***	-.377***	-.510***	-.407***	-.449***	-.358***
	[.088]	[.093]	[.082]	[.090]	[.073]	[.089]	[.092]	[.116]
Top incomes in t-1 × North America dummy	.016	-.000	.010	.004	.004	.007	-.005	.015
	[.010]	[.010]	[.009]	[.009]	[.007]	[.011]	[.007]	[.015]
Top incomes in t-1 × Asia dummy	.056	.023	.036	.034	.043**	.040*	.019	.040
	[.030]	[.019]	[.020]	[.027]	[.021]	[.024]	[.022]	[.025]
Top incomes in t-1 × Others dummy	.048***	.053***	.048***	.049***	.056***	.049***	.048***	.048***

	[.009]	[.009]	[.008]	[.009]	[.007]	[.009]	[.009]	[.012]
Number of groups	94	94	94	94	94	94	93	93
Individual observations	64,412	80,648	53,512	91,548	33,839	110,007	59,054	51,420

Note: ***<1%, **<5%, *<10%. See Table 1's notes.