IS EQUALITY A DETERMINANT OF WELL-BEING?

A CROSS-NATIONAL ANALYSIS OF INCOME INEQUALITY AND

SELF-REPORTED LIFE SATISFACTION

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ABSTRACT

Research on subjective well-being (SWB)—often referred to as “happiness research”—is gaining momentum in both policy circles and within the academic realm. Global SWB data are increasingly used in both micro- and macro-level economic analyses. However, there are very few cross-country studies relating well-being to income inequality at the macro level. Based on relative deprivation theory, the level of income inequality—as measured by the Estimated Household Income Inequality (EHII)—is conceptualized at the aggregate level to capture the overall scale of social stratification in a society. A regional fixed effects model using data from the World Values Survey and the University of Texas Inequality Project (UTIP-EHII) is employed to empirically test the relationship between income inequality and aggregate levels of life satisfaction in a sample of 51 countries during the period 1981-2002. OLS regression analysis shows that the model explains approximately 73 percent of the variation in reported life satisfaction for the countries in the sample and that, all else equal, people living in egalitarian societies are, on average, more satisfied with their lives.
Many thanks to Robert Bednarzik, Andreas Kern, and Barbara Schone for their comments.

MONICA HANSSEN
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INTRODUCTION

In 2008, President Nicholas Sarkozy of France commissioned economists Joseph Stiglitz, Amartya Sen, and Jean-Paul Fitoussi to re-evaluate conventional measures of economic and social progress in an effort to address what President Sarkozy sees as a “growing gap” between how people assess the conditions of their own lives and the metrics policymakers use to capture those concepts (CMEPSP, 2009, p. 55). In their report released one year later, the Commission on the Measurement of Economic Performance and Social Progress (CMEPSP)\(^1\) recommended that measures of subjective well-being be incorporated more systematically into policymakers’ assessments of quality of life (CMEPSP, 2009). Based on the notion that individuals’ evaluations of their own lives should carry weight as an indicator of national well-being, subjective well-being is defined by self-reported levels of happiness and/or life satisfaction. As the Commission notes, “This approach is closely linked to the utilitarian tradition but has a broader appeal due to the strong presumption in many streams of ancient and modern culture that enabling people to be ‘happy’ and ‘satisfied’ with their life is a universal goal of human existence” (CMEPSP, 2009, p. 42).

Research on subjective well-being (SWB)—commonly referred to as “happiness research”—is gaining momentum in both policy circles and within the academic realm. Despite extraordinary growth in national income among industrialized countries over the last few decades, the trend in happiness has not followed suit. Rising material wealth in Europe and North America has been accompanied by escalating rates of depression, alcoholism, and crime (Layard, 2005; Reich, 2010; Wilkinson & Pickett, 2009). In the United States—by most accounts, the richest nation in the world—levels of happiness and life satisfaction have dropped since the 1970s (Clark, Frijters, & Shields, 2008; Layard, 2005). Public health specialists have observed higher teen pregnancy and homicide rates than would be expected for high-income countries (Pickett, Mookherjee, & Wilkinson, 2005). Nonetheless, research has shown that there is still considerable variation in

\(^1\) CMEPSP is also commonly referred to as “The Stiglitz Commission”. The Commission gathered experts from both the academic and policy communities, releasing their final report in April 2009. More information can be found at their website: http://www.stiglitz-sen-fitoussi.fr/en/index.htm
reported levels of well-being among countries. According to data maintained by the World Database of Happiness, Danes are considerably happier than people living in other parts of the world (Veenhoven, 2006). Indeed, the data on life satisfaction from the World Values Survey mirror this finding, as depicted in Figure 1 below. Countries like Sweden, Denmark, and the Netherlands tend to report greater happiness levels than Italy or Portugal (Blanchflower & Oswald, 2008). In fact, Scandinavian countries consistently score higher on life satisfaction surveys than most other countries (Layard, 2005). While most scholars agree that income matters to a certain point (Layard, 2005; Veenhoven, 1991), the question remains: What else might explain the variation in self-reported well-being among countries with similar income levels?

Figure 1: Average life satisfaction from 1981 to 2002

Source: World Values Survey, based on 33 OECD countries and 47 non-OECD countries
Meanwhile, economic inequality in many industrialized nations has been rising since the 1970s and 1980s (Layard, 2005; Reich, 2010). The United States now has the least equitable income distribution, and the lowest level of intergenerational mobility, among industrialized nations—with only Italians and Britons experiencing lower social mobility (Hacker & Pierson, 2010). Among the richest countries in the world, income inequality has been associated with higher homicide rates, adolescent birth rates, and mortality rates (Pickett, Mookherjee, & Wilkinson, 2005). Sarkozy’s CMEPSP reported that, “When there are large changes in inequality (more generally a change in income distribution), gross domestic product (GDP) or any other aggregate computed per capita may not provide an accurate assessment of the situation in which most people find themselves. If inequality increases enough relative to the increase in average per capital GDP, most people can be worse off even though average income is increasing” (CMEPSP, 2009, p. 8). Indeed, among rich countries, life expectancy is unrelated to national differences in per capita GDP but is strongly correlated with the distribution of income in each country (Wilkinson & Pickett, 2009).

In contrast, societies that are more egalitarian tend to be associated with more positive outcomes for population health (Wilkinson & Pickett, 2006). Thus, a proposed explanation for the variation in subjective well-being across countries is that the level of income inequality is a better determinant of SWB than GDP per capita. The research in this area is relatively new and plagued by difficulties in obtaining high-quality income data as well as longitudinal SWB data (Deaton, 2003). Where data have been available, the relationship between relative income and SWB has been explored at the individual level (Blanchflower & Oswald, 2004; Karlsson et al., 2010). However, national correlations between inequality at the societal level and self-reported well-being have not been studied to a similar extent.

This paper will examine the relationship between self-reported life satisfaction and income inequality across countries. By proposing the hypothesis that the societal level of inequality negatively impacts individual well-being, this paper will build on relative deprivation theory, a framework that has been applied mainly to public health outcomes—such as the relationship
between income and life expectancy—but not to self-reported well-being at the country level. This hypothesis is based on the assumption that broad economic processes, such as patterns of inequality, can contribute directly to individual levels of happiness and satisfaction. The following analysis intends to fill this apparent gap in the literature and will contribute to current research by utilizing global data from four waves of the World Values Survey and linking it to a measure of Estimated Household Income Inequality (EHII) created by the University of Texas Inequality Project (UTIP). If a negative link between income inequality and life satisfaction is demonstrated empirically, the role of economic and social equality may gain relevance not only as a contributing factor of national well-being, but also as a policy goal.

THEORETICAL DISCUSSION

Defining the happiness construct

Happiness research is a burgeoning field that has developed at the junction between economics and psychology. Explaining individual well-being—particularly its clinical counterpart, depression—generally falls within the purview of psychologists, but has increasingly gained the attention of economists and policymakers because of the limitations of basing policy on national accounts data, such as Gross Domestic Product (GDP), as indicators of national well-being. As a result, social scientists are trying to capture more direct measures of the “human experience” (Deaton, 2008). As a discipline, economics is founded on the concept of utility—defined as satisfaction or well-being—and is based on the assumption that, all things being equal, human beings strive to maximize satisfaction (Gruber, 2011). Yet, economists have shied away from self-reported feelings of happiness or satisfaction as a measure of utility and focused instead on observed behaviors such as consumption choices. Measures of subjective well-being, however, are increasingly applied as a proxy for experienced utility, based on the notion that individuals’ assessments of their own conditions should supplement income- or consumption-based measures of utility (CMEPSP, 2009; Frey & Stutzer, 2005).
Indeed, for almost three decades social scientists have been asking people to assess their satisfaction levels in household surveys such as the World Values Survey, Gallup World Poll, Eurobarometer survey series, and the U.S. General Social Survey. SWB measures generally strive to capture both an affective and cognitive component (Veenhoven, 1991). Operationally, this is reflected in two types of questions: one that attempts to ascertain the respondent's general feeling of happiness and emotional state (affective component), and one that asks the respondent to reflect thoughtfully about his or her life as a whole (cognitive component). The latter tends to encourage respondents to make an overall evaluation of their lives by asking to what degree they are satisfied with their lives, while the former emphasizes the experiential, and somewhat transient, notion of happiness (Deaton, 2008). Happiness and life satisfaction are terms that are often used interchangeably, and researchers sometimes construct a composite of both components.

Recent advances in psychology and neuroscience have made it possible to measure brain activity—specifically, frontal lobe movements—and other physiological responses, such as heart rate and level of salivary cortisol, to provide objective measures of physical and emotional health (Alesina, Di Tella, & MacCulloch, 2004; Blanchflower & Oswald, 2008; Graham, 2010; Layard, 2005; 2010). High levels of salivary cortisol, for instance, indicate stress and are correlated with lower levels of self-reported happiness. The correlations between physiological measures of well-being and self-reports of happiness have generally been consistent across individuals and over time, increasing the validity and reliability of survey data on individual happiness (Alesina et al., 2004; Layard, 2010). Blanchflower and Oswald (2008) found an inverse relationship between reported levels of happiness and high blood pressure, with traditionally happier nations—such as Denmark—reporting fewer problems with hypertension. This indicates that the empirical evidence, based on different measures of health and/or well-being, is producing similar results, with the same countries topping the list of the happiest nations in the world. Although this type of research is still in its infancy, the evidence on the reliability of SWB data is encouraging.
Explaining happiness

Across the social sciences, scholars have looked at a variety of factors that affect happiness, including social capital (Putnam, 2000; Ram, 2010), corruption and crime (Graham, 2010), political freedom and participation (Inglehart, Foa, Peterson, & Welzel, 2008), life expectancy and health systems (Deaton, 2008), as well as aggregate unemployment and the relationship between inflation and unemployment (Di Tella et al., 2001, as cited in Alesina et al., 2004). A number of scholars have also explored the relationship between individual happiness and demographic and socioeconomic factors such as age, gender, marital status, and employment status (Alesina et al., 2004; Blanchflower & Oswald, 2008; Di Tella, MacCulloch, & Oswald, 2003; Melgar & Rossi, 2010).

Over the years, research on the economics of happiness has generated two key findings. First, at any single point in time, wealthier people are generally happier than poor people (Blanchflower & Oswald, 2004; Deaton, 2008; Easterlin, 1995; Graham, 2005; Layard, 2005), implying that higher income increases happiness. Second, the correlation between happiness and income is typically stronger at lower levels of income (Clark, Frijters, & Shields, 2008; Layard, 2005; Veenhoven, 1991). This trend follows the general consensus in the literature that, once basic material needs are met, there are diminishing marginal returns to gains in income (Graham, 2005). Richard Easterlin (1974) famously found that increasing levels of income did not correspond to higher levels of happiness, especially over time and across countries—a phenomenon that has become widely known as the “Easterlin paradox”. Several studies have supported Easterlin's findings. Blanchflower and Oswald (2004) found that happiness did not increase in Britain and the United States despite rising material wealth between the 1970s and 1990s; however, they do not offer an explanation for the stagnation in happiness.

By contrast, Deaton (2008) did not find diminishing returns to income in his study using country data from the Gallup World Poll, challenging the Easterlin Paradox. His results showed a positive, linear correlation between GDP per capita and happiness. The majority of recent findings
suggest that income does indeed matter for happiness, but only up to a certain point—a dynamic that is evident both at the individual and country levels (summarized in Graham, 2005; 2010). Given that research in this area is still developing and individual panel data on happiness are virtually non-existent, this challenges researchers' abilities to draw strong conclusions about changes in happiness over time. Methodological issues have also been blamed for inconsistencies in earlier cross-national studies. Veenhoven (1991), for instance, has criticized Easterlin’s original methods for using different scales in measuring income and happiness. As a result of the data limitations, there are few cross-country studies of self-reported well-being. Moreover, while cross-sectional household data on happiness have been available for a number of countries, there are ongoing methodological debates about how to measure both absolute and relative income (Atkinson, 2003; CMEPSP, 2009; Deaton, 2003).

**Inequality as a determinant of well-being**

The Gini coefficient is the standard economic measure of inequality and is used frequently for comparative and cross-country analyses. The Gini coefficient is defined as a measure of “the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution” (World Bank Online). A Gini coefficient of 0 indicates perfectly equal income distribution, whereas a coefficient of 1 represents perfect inequality. In 2004, Alberto Alesina and his colleagues used the Gini to compare the effects of income inequality on happiness in Europe and the United States using household-level data from different time periods. Controlling for several micro- and macro-economic factors such as age and unemployment, they found a negative correlation between inequality and happiness for both Europeans and Americans, with a stronger effect for Europeans. Interestingly, they also found that the groups affected most by income inequality were the rich in the United States and the poor in Europe. The authors propose that this may be due to perceptions of social mobility, which are relatively high in the United States, suggesting that Americans in low-income groups
maintained a level of happiness based on their perceptions of being able to climb up the social ladder (Alesina et al., 2004). Testing a similar theory, Di Tella and MacCulloch (2006) used an interaction term between real income and the belief that there is little chance of escaping poverty to explore whether the income effect on happiness is moderated by an individual’s belief in social mobility. Using data from the third wave of the World Values Survey, they found that this belief on its own had a negative impact on happiness—not surprisingly—and that the interaction term was positive, suggesting that the impact of income on happiness may depend on one’s belief in mobility. It is unclear, however, whether the level of income inequality in a society leads to diminished or heightened perceptions of social mobility. Indeed, as Alesina et al. (2004) point out, these perceptions may be culturally determined, as faith in the “American Dream” is alive and well in the United States but does not apply to other societies.

Melgar and Rossi (2010) at the Inter-American Development Bank (IDB) recently published a study where they hypothesized a negative relationship between income inequality and depression. Controlling for various personal characteristics, they found a significantly negative correlation between the Gini coefficient and the probability of depression in 93 countries (Melgar & Rossi, 2010). Because depression can be viewed conceptually as the absence of happiness, this study contributes to happiness research by illuminating the effect on life satisfaction of income inequality at the national level. Their results support the hypothesis that citizens of countries with more equitable income distributions are less likely to be depressed. Compared to the United States, citizens of Denmark, Norway, and Sweden all have lower probabilities of depression, according to the IDB study. Hence, there is growing evidence that income inequality at the macro level may be an important predictor of happiness.

Relative deprivation theory

Richard Wilkinson, a British expert in public health and social epidemiology, has studied the effects of income inequality on a variety of health outcomes and has found national correlations
between inequality and rates of homicide, mortality, and life expectancy (Wilkinson, 1996; Wilkinson & Pickett, 2006). Wilkinson explains the negative impact of inequality using the well-established notion of social comparison, drawn from the social psychology literature. As human beings, he asserts, we tend to attach meaning not only to how we are perceived by others, but also to where we stand in relation to those around us—implying that our well-being is, at least in part, experienced in relative terms. In income terms, it is often predicted that a person whose earnings are comparatively lower than that of a relevant reference group feels relatively deprived and, consequently, less satisfied. Clark and Oswald (1996) found that job satisfaction among British workers was strongly negatively correlated with comparison income levels, and only somewhat correlated with levels of absolute income. Indeed, the most common explanation for this effect is social comparison or, more specifically, the relative deprivation hypothesis, which holds that “when individuals compare themselves to others who are more advantaged, they feel bad, which might result in worse behavior, worse health, and greater mortality” (Evans, Hout & Mayer, 2004, p. 939). The relative deprivation effect operates through externalities, which take the form of psychosocial effects such as shame, anxiety, stress, and lack of trust that manifest across society as inequality increases and social distinctions become more pronounced (Wilkinson & Pickett, 2009).

Empirically, a distinction must be made between individual- and aggregate-level measures of relative income. The “relative income hypothesis” (Layard, 2005) generally refers to the idea that relative income matters more to individuals than absolute income, once basic needs are met. Thus, at the country level, these effects are usually studied only in OECD countries. In the literature this is closely associated with social comparison theory and several studies have explored these effects at the individual level (Blanchflower & Oswald, 2004; Clark & Oswald, 1996). However, the evidence on the effect of relative income on happiness is mixed. Relative gains and losses across individuals may cancel each other out resulting in no net effect on happiness at the macro level (Deaton, 2008; Inglehart, 2010). Moreover, identifying a relevant reference group with which to compare incomes
at the individual level is not straightforward and is often imposed by the researchers themselves in these studies (Clark, Frijters, & Shields, 2008; Wilkinson & Pickett, 2007).

Wilkinson (1996) uses national measures of income inequality to gauge the societal level of relative deprivation, reflecting an overall measure of “the scale of social stratification” (Wilkinson & Pickett, 2006, p. 1768). Wilkinson and Pickett (2007) challenge the tendency among researchers to focus on social comparison effects as largely locally situated—“within and between smaller constituent areas”—and instead concentrate on what they call “the role of nationally constituted social differentiation” (p. 1967). Thus, the relative deprivation effect is conceptualized at the aggregate level and, as such, represents an “alternative manifestation of social comparison” (Diener, Diener, & Diener, 1995). Although individuals’ feelings of deprivation are, by definition, relative to each individual, it is hypothesized that the total sense of deprivation in society can be captured, empirically, by the overall level of income inequality in that society. Indeed, Yitzhaki (1979) has shown that average relative deprivation is equivalent to the Gini coefficient multiplied by mean income (as cited in Eibner & Evans, 2005; Evans, Hout & Mayer, 2004). Other scholars have noted that, “Income inequality can be seen as a proxy for deprivation, in that as inequality increases, the gap between the ‘haves’ and the ‘have-nots’ grows, and the overall deprivation in society increases” (Eibner & Evans, 2005, p. 592).

Relative deprivation theory applies to advanced and developing nations alike because it describes the negative impact of greater social distances between individuals within a country. The level of income inequality in a society therefore tells us something about the scale of relative distances across society as a whole. While Wilkinson and Pickett (2009) discuss inequality and its accompanying social problems primarily in advanced industrial nations, the problem of inequality is global and its impact on well-being may operate through a similar mechanism—overall feelings of deprivation—in both rich and poor countries, even if inequality likely affects people in poor countries in multiple ways. Relative deprivation in a poor society may translate into differences in
access to basic needs such as water and shelter. Over time, as income levels increase in these
countries, inequality may lead to further differences in health and social outcomes. As Wilkinson
and Pickett (2009) write, “We should perhaps regard the scale of material inequalities in a society as
providing the skeleton, or framework, round which class and cultural differences are formed. Over
time, crude differences in wealth gradually become overlaid by differences in… education, sense of
self and all the other markers of class identity” (p. 28). This paper attempts to isolate the effect of
income inequality on well-being across both rich and poor countries.

DATA & METHODOLOGY

Description of data

Data on self-reported well-being have been collected through household surveys created by
the World Values Survey, partially modeled after the European Values Survey and the
Eurobarometer survey series. Since 1981, the World Values Survey (WVS) has posed questions on
social and political issues to heads of households in over 80 countries worldwide. The survey
includes questions on key social and political issues such as perceptions of trust and freedom of
choice. It also includes two familiar questions commonly used to capture the concept of happiness:
one focusing on the respondent’s feelings of happiness on a scale from one to four, and the other
asking the respondent to evaluate his or her level of general life satisfaction on a scale from one to
ten. Data from the WVS questionnaire are collected through face-to-face interviews with all
residents in the sampling frame between the ages of 18 and 85 years. All questionnaires are
translated into the local language and the same questions were asked of respondents over time,
through different waves of the survey.

The analysis presented in this paper is based on life satisfaction as a measure of well-being.
While both happiness and life satisfaction data exist in the WVS data set, there is far more variation
in life satisfaction than happiness (see Appendix for details). This is a pattern that is relatively
common with data on subjective well-being and is largely a result of the nature of the two concepts:
happiness is an emotional state that can vary in intensity throughout any given day, whereas life satisfaction refers to an assessment of one’s life as a whole, which encourages the respondent to take a more long-term, evaluative view of their lives (Deaton, 2008). Indeed, people’s life circumstances differ greatly across countries, but emotions tend to be fairly universal. As Ed Diener, Daniel Kahneman, and John Helliwell note in the introduction to their recent edited volume *International Differences in Well-being* (2010): “The emotions that are averaged in the affect balance—enjoyment, laughter, worry, sadness, depression, and anger during the preceding day—are largely universal in their incidence, with relatively little difference from country to country. By contrast, there is much more international variation in average life assessments” (Diener, Helliwell & Kahneman, 2010, p. xii). To obtain the level of life satisfaction, the interviewer asks the following question to respondents: “All things considered, how satisfied are you with your life as a whole these days?” The interviewer also shows the respondent a card depicting a horizontal scale from one to ten to visually denote a continuum of satisfaction. The life satisfaction data utilized in the current analysis were obtained from the first four waves of the World Values Survey, covering the time period 1981-2002.

The relationship of primary interest in this paper is that between life satisfaction and income inequality. Indeed, as other scholars have noted, the distribution of income in a country may be a stronger predictor of well-being than absolute income (Alesina et al., 2004; Melgar & Rossi, 2010; Wilkinson & Pickett, 2009). Income inequality is usually measured using the Gini coefficient, where zero indicates perfectly equal income distribution and one represents perfect inequality. Given the ongoing methodological debates surrounding the measurement of poverty and economic inequality, however, methodologically consistent data on inequality across countries and over time are difficult to come by (Atkinson, 2003; Deaton, 2003; Jaumotte, Lall & Papageorgiou, 2008). For that reason, many researchers have had to rely on different sources of data for between-country inequality measures. For their study of the distributional consequences of economic growth, for instance, David Dollar and Aart Kraay (2002) gathered data from four separate sources, including the World
Income Inequality Database (WIID), which is based on the Deininger and Squire data set developed at the World Bank—one of the first comprehensive data sets for global inequality (Deininger & Squire, 1996).² Other researchers in the field (Alesina et al., 2004; Blanchflower & Oswald, 2004) have chosen to focus solely on advanced industrial nations, often obtaining inequality data from national statistical agencies. Dollar and Kraay (2002) explain: “As is well known there are substantial difficulties in comparing income distribution data across countries. Countries differ in the coverage of the survey (national versus subnational), in the welfare measure (income versus consumption), the measure of income (gross versus net), and the unit of observation (individuals versus households)” (p. 201).

In an attempt to address some of these issues, James K. Galbraith and his research team (Galbraith & Kum, 2004) at the University of Texas Inequality Project (UTIP) have constructed a measure of household income inequality by effectively combining the Gini coefficient and another measure of inequality known as Theil’s t statistic, which is based on between-group changes in industrial pay as compiled by the United Nations Industrial Development Organization (UNIDO). They found a significant relationship between these industry pay dispersion measures and income inequality as measured by the Gini coefficient, and because UNIDO gathers the most up-to-date time series data on industry pay, this new measure (with a few additional adjustments) covers more countries and years than any other existing data set for global inequality (for technical details, see Galbraith & Kum, 2004). Thus, the UTIP Estimated Household Income Inequality (EHII) is used as the measure of inequality for the model employed in this paper, with higher numbers reflecting greater inequality. Table 1 depicts the EHII averaged over the period from 1981 to 2002 for the countries included in the current sample, ranked from low to high inequality. As expected, all the Scandinavian countries are represented among the top ten countries with lowest inequality.

² Dollar & Kraay made substantial improvements to the WIID data for their analysis and therefore this was a natural place to start when gathering inequality data for this paper. However, the total number of observations was significantly reduced when these data were applied to the WVS survey data and was not suitable for robust econometric analysis. The World Development Indicators (WDI) database also lacks sufficient time series data for the Gini coefficient.
worldwide—as is the Czech Republic, which evidently has the lowest level of household income inequality over this time period. The United States ranks 22nd among 31 OECD countries in average level of inequality over this period and, while these figures only provide a snapshot at the aggregate level, this is very much in line with what other scholars have found at the micro level (Hacker & Pierson, 2010). Non-OECD countries have higher inequality than OECD countries: the average level of inequality in OECD countries is 36.16, compared to 44.39 in non-OECD countries.

Table 1: Average Estimated Household Income Inequality (EHII) 1981-2002

<table>
<thead>
<tr>
<th>OECD Countries</th>
<th>EHII</th>
<th>Non-OECD Countries</th>
<th>EHII</th>
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<tbody>
<tr>
<td>Czech Republic</td>
<td>26.83</td>
<td>Malta</td>
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<tr>
<td>Sweden</td>
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<td>45.46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chile</td>
<td>46.02</td>
<td></td>
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</tr>
</tbody>
</table>

Source: UTIP-EHII, based on 31 OECD countries and 25 non-OECD countries
Hypothesis & empirical strategy

Based on prior research on the link between inequality and well-being (Alesina et al., 2004; Blanchflower & Oswald, 2004; Melgar & Rossi, 2010; Wilkinson & Pickett, 2009), income inequality is expected to be negatively associated with life satisfaction, holding constant other macroeconomic factors such as GDP per capita, inflation, and total unemployment. Thus, the hypothesis tests whether higher income inequality is associated with lower life satisfaction. The model below will be tested using Ordinary Least Squares (OLS) regression analysis, with countries as the unit of analysis.

Life satisfaction$_{it} = a + b \cdot \text{Inequality}_it + c \cdot \text{Macro}_it + d \cdot \text{Region}_it + \varepsilon_{it}$, over $i$ countries and $t$ years

The hypothesis tested in this paper is concerned primarily with the influence of macroeconomic factors on life satisfaction. As such, the model does not include microeconomic control variables.\(^3\) Because of the positive correlation between national income and well-being (Deaton, 2008; Di Tella, MacCulloch, & Oswald, 2003), GDP per capita is an important control variable in the model and is obtained per country and year from the World Development Indicators (WDI) database. Also included as macroeconomic controls are annual inflation and unemployment rates, also obtained from the WDI database, as described in Exhibit 1.

---

\(^3\) Based on these same data, a model was initially tested for heads of households, which controlled for personal characteristics like age, gender, and marital status. However, there was substantial correlation between life satisfaction and the error term, suggesting that there was some other factor accounting for variation in life satisfaction at the individual level that was not captured in the model. This problem highlights the difficulty inherent in explaining individual life satisfaction, especially across countries. Even with multiple controls at the micro and macro levels, this model was insufficient to explain life satisfaction at the individual level. Because the focus of this paper is on inequality at the societal level, isolating the impact of this macroeconomic variable may be more difficult using household level data because there is more noise at that level. As discussed elsewhere in this paper, other scholars using household or individual level data on life satisfaction and/or happiness have tended to focus only on a small number of advanced industrialized nations.
Any characteristics associated with a particular region of the world that may be systematically related to self-reported life satisfaction are controlled for using regional fixed effects. This should control for broad cultural traits within a particular region—such as cultural views of happiness—as well as geographical characteristics such as climate, both of which may impact reported levels of well-being (Di Tella & MacCulloch, 2006). The countries available for this analysis have therefore been divided into the following six regions: Europe, North America, Latin America and the Caribbean, East Asia and the Pacific (including South Asia), Africa, and Eastern Europe and Central Asia (including the Middle East).

The sample of countries consists of 51 countries and 103 total observations, representing the years and countries for which all variables used in the regression were available. Notably, Switzerland, Iceland, and Greece are missing from the group of OECD countries. There are also very few African countries represented in the sample, with data only available for Morocco and South Africa. By contrast, the sample contains 14 countries in Eastern Europe and Central Asia.
Any cultural disparities in reporting well-being between these regions, however, should be captured by including regional fixed effects in the model.

The relationship between self-reported life satisfaction and inequality is depicted for OECD and non-OECD countries in Figures 1 and 2, respectively. The values for life satisfaction and income inequality (EHII) have been aggregated over the time period for which data were available for both variables. The figure shows average life satisfaction for each country in order from more to less satisfied (from left to right), with Denmark as the most satisfied nation on the far left among OECD countries and Moldova as the least satisfied on the bottom right among non-OECD countries. The line depicts average income inequality and shows that the lowest points of inequality tend to coincide with higher levels of life satisfaction relative to other countries. There appears to be a slight negative relationship between inequality and life satisfaction among both OECD and non-OECD countries.

Figure 1: Patterns of inequality and life satisfaction, aggregate levels from 1981 to 2002

Figure 2: Patterns of inequality and life satisfaction, aggregate levels from 1981 to 2002

The estimation of the regional fixed effects model for the sample of 51 countries shows that income inequality has a significant negative impact on reported levels of life satisfaction, supporting the hypothesis proposed in this paper. Indeed, the regression coefficient on inequality is statistically significant at the five percent level. This implies that, at the aggregate level, an increase in income inequality results in a reduction in life satisfaction. Indeed, moving from the minimum to the maximum level of inequality in the sample decreases life satisfaction by -0.95 points (on a 10-point scale). The model explains approximately 73 percent of the variation in reported life satisfaction in these countries. Moreover, these results proved robust in terms of meeting the standard assumptions of OLS regression analysis (see Appendix). The effects of GDP per capita and inflation are also statistically significant in the expected direction. However, the inequality effect is larger than both GDP per capita and inflation. The coefficient on total unemployment is negative as expected, but it
is not statistically significant. This may be due to the nature of the data, which represent an unbalanced panel. In their paper on the macroeconomics of happiness, Di Tella, MacCulloch, and Oswald (2003) run separate regressions for 12 European nations and the United States, using household data, and find a significant negative effect for the unemployment rate on life satisfaction.

At the societal level, income inequality and life satisfaction move in opposite directions. Alesina, Di Tella, and MacCulloch (2004) reported similar findings at the individual level using happiness as the dependent variable for the United States for the period 1981-1996, and life satisfaction as the dependent variable for Europe over the time period 1975-1992. Using more sophisticated econometric techniques, they found a significant negative relationship (at the ten percent level) between the life satisfaction measures and the Gini coefficient, controlling for both micro- and macro-economic factors. The results presented in the current analysis thus confirm the direction of the inequality effect on well-being at the aggregate level. This supports Melgar and Rossi’s (2010) recent cross-country study of the impact of inequality on incidence of depression, which can be conceptualized as the absence of happiness or satisfaction. Moreover, this analysis presents similar results using a different inequality data set, covering more recent years, that has not previously been employed in this way.

Limitations

There are important limitations that should be noted when analyzing cross-national data on self-reported well-being because of the inherent difficulties in comparing happiness and life satisfaction levels across countries. Clearly, there is a great deal of individual variation in natural disposition and comparing subjective perceptions of happiness thus introduces some bias because of unobserved personality differences such as intrinsic pessimism or optimism. These effects should be minimized to some degree when aggregated across an entire country to obtain an average level of life satisfaction per country. Across cultures, however, there may be potential biases in responses to questions about satisfaction or happiness depending on the underlying norms that determine how well-being is defined in a particular culture and whether or not expressing extreme satisfaction—or
dissatisfaction—is socially accepted. Including region dummies in the model should account for some of these differences—to the extent that the regions represent culturally similar groups of people—but there are clearly additional factors that affect life satisfaction that cannot be accounted for in a simple econometric model (for a methodological discussion of cross-cultural comparisons in happiness research, see Oishi, 2010).

Historical circumstances can also play a role in determining life satisfaction. For instance, people living in nations previously under Soviet rule tend to be extremely dissatisfied with their lives even though these countries are not among the poorest—or least egalitarian—in the world, which is why they have been described as “underachievers” by Inglehart et al. (2008). Because of the extreme economic fluctuations endured by people living in these nations, the transition from communism to capitalism in the ex-Soviet nations during the time period on which this model is based may be causing a downward bias on the results for these countries that is not directly or wholly attributable to income inequality. Indeed, the sample of countries in the World Values Survey includes a large proportion of countries from Eastern Europe and Central Asia. These data also include very few of the poorest African countries and instead include a number of Latin American countries that are unusually satisfied given their GDP levels. This is a common—and very valid—criticism of the WVS data (Deaton, 2008) and should be taken into consideration when interpreting these results. Other scholars have used life satisfaction or happiness data from the World Poll collected by the Gallup Organization, which appears to have a more balanced sample of countries. Unfortunately, these data are not publicly available.

The quality of data poses an additional challenge in conducting this type of research. Individual panel data would be ideal for a micro-level study of well-being in order to analyze changes over time, as it would allow the researcher to control for unobserved personal characteristics. Panel (or longitudinal) data at the level of the individual would also allow the researcher to isolate more precisely the mechanisms through which inequality affects life satisfaction. However, as Carol Graham (2009) points out, the problem of unobserved error is
common to all economic research that involves the study of individual behavior or attitudes. Thus, pooled cross-sectional analyses are common in this field. Moreover, as discussed in the theoretical section of this paper, subjective measures of well-being based on survey data have become more reliable as psychologists have found consistency in survey responses and physiological measures of satisfaction or happiness (Graham, 2009; Layard, 2010). At the country level, the difficulty in obtaining time series data on inequality also poses a significant challenge, particularly for cross-national studies that include developing nations where data typically are poor. As discussed above, there are also substantial differences in the way inequality is measured across countries. However, the UTIP-EHII data seem promising and have produced robust results (see Appendix for model diagnostics).

**POLICY IMPLICATIONS**

**Self-reported measures of well-being**

British Prime Minister David Cameron recently launched a “Happiness Index”, formalizing efforts to construct a measure of national well-being that reflects feelings of happiness and life satisfaction as well as income-based standards of living (McRae, 2010). In Cameron's view, “When politicians are looking at issues they should be saying to themselves ‘how are we going to try and make sure that we don't just make people better off but we make people happier, we make communities more stable, we make society more cohesive’” (quoted in Easton, 2006). Indeed, growing dissatisfaction with the limitations of national accounts data in predicting well-being (CMEPSP, 2009) has led to an increased emphasis on non-material and self-reported measures of national well-being, or what has been called “emotional prosperity” (Oswald, 2010). Survey data can help to inform policymakers about constituents’ assessments of their own life conditions, shedding light on issues such as perceptions of mobility and trust as well as general levels of satisfaction that would not ordinarily be captured with more conventional economic measures. This type of data can guide policy choices by helping policymakers prioritize goals and challenge dated
assumptions (Bok, 2010). Furthermore, as the concept of emotional prosperity continues to gain traction within the policy community, this should strengthen efforts to collect more data and achieve consensus on methodological approach, allowing for pre- and post-intervention analysis based on measures of subjective well-being.

The hypothesis presented in this paper is based on the assumption that broad economic processes, such as patterns of inequality, can contribute directly to individual levels of happiness and life satisfaction. The results confirm that GDP per capita has a statistically significant impact on life satisfaction, which indicates that absolute income matters for people's well-being. However, based on these data, it appears that the relationship between life satisfaction and GDP per capita weakens somewhat at higher national income levels (see Appendix for details). This is similar to the findings of Inglehart, Foa, Peterson, and Welzel (2008), who describe some societies as doing “a better job of maximizing their citizens' SWB than others do” (Inglehart et al., 2008, p. 268). Indeed, the results presented in this paper demonstrate that the effect of income inequality on life satisfaction is slightly larger than that of GDP per capita. This trend follows the general consensus in the literature that, once basic material needs are met, there are diminishing marginal returns to gains in income (Graham, 2005), implying that while policymakers should not ignore growth-promoting economic policies, they may need to pay more attention to the distributional consequences of these policies. Moreover, the growing gap between rich and poor in advanced nations—despite relatively high average income levels—presents a cautionary tale for developing countries in terms of considering the impact of rising economic prosperity on inequality.

**Redistributive policies**

Two heavy-hitters in the economics field—Raghuram Rajan, previously the chief economist at the International Monetary Fund, and Robert Reich, Secretary of Labor under President Clinton—both published books last year warning that rising income inequality presents a serious problem not only for social cohesion but also for economic growth (Rajan, 2010; Reich, 2010). Similarly, Alesina and Perotti (1996) found that the destabilizing effects of income inequality, from a
socio-political perspective, actually decrease investment. These findings, along with the results presented in this paper, may lend credence to supporters of more progressive tax policies to directly redistribute income from the rich to the poor. Discussing the implications of redistribution for investment and economic growth, Alesina and Perotti (1996) explain: “Fiscal redistribution, by increasing the tax burden on capitalists and investors, reduces the propensity to invest. However, the same policies may reduce social tensions and, as a result, create a socio-political climate more conducive to productive activities and capital accumulation. …Therefore the net effect of redistributive policies on growth has to weigh the costs of distortionary taxation against the benefits of reduced social tensions” (p. 1226).

While a discussion of the merits and limitations of redistribution are well beyond the scope of this paper, it is worth noting that the feasibility of raising taxes or benefits for redistributive purposes is conditional upon public opinion and political will. Attitudes towards inequality differ across cultures (Alesina et al., 2004; Bok, 2010), suggesting that even if we were to accept that income inequality tends to breed unhappiness—and that happiness is indeed a worthy policy goal—political ideology, attitudes towards the poor, and tolerance for inequality may prevent redistributive policies. Public opinion on the determinants of poverty—beliefs in society about whether poverty results mainly from misfortune or from laziness—is closely related to public perceptions of upward social mobility. People who believe that they live in a fair and mobile society, for instance, will be less inclined to support redistributive policies (Alesina, Glaeser, & Sacerdote 2001; Alesina et al., 2004). Comparing the United States to Europe, Alesina, Glaeser, and Sacerdote (2001) found a significant positive relationship between the perception that “luck drives success” and the country’s share of social spending as a percentage of GDP (p. 238). While the differences between countries in terms of their propensity for social spending are both considerable and complex, the authors suggest that beliefs about poverty may explain some of the differences in redistributive policies in Europe and the U.S.
**Broader policy issues**

Growing income inequality may also have broader political consequences. In his seminal work on social capital and community in America, *Bowling Alone*, Robert Putnam (2000) draws a parallel between the period during which the U.S. had the most egalitarian distribution of income—the 1950s and 1960s—and that during which it also had the highest levels of social capital and civic engagement (chap. 22). Discussing the direction of causality between inequality and social capital, he writes, “Great disparities of wealth and power are inimical to widespread participation and broadly shared community integration, so it is... plausible that the causal arrow points from equality toward civic engagement and social capital” (p. 359). Thus, greater disparity in income may not only exacerbate disparities in social outcomes but also in political outcomes such as participation, voting behavior, and political power. Furthermore, when income inequality rises, quality of life worsens for a growing proportion of the population, as access to fundamental public services such as education and health care is effectively restricted to those with higher incomes, or the quality of service becomes so inadequate that the rich go elsewhere and the poor have no alternatives (Reich, 2010). As purchasing power becomes more concentrated among those in the top brackets of the income distribution, the wealthy become increasingly insular, magnifying the differences between income groups and leading to increased segregation (Reich, 2010). Reich concludes, “Concentrated income and wealth will threaten the integrity and cohesion of our society, and will undermine democracy” (Reich, 2010, p. 65). While the focus of this paper has not been on social capital, trust, or other factors that may potentially mediate the impact of income inequality, these issues present important policy implications as well as additional opportunities for empirical research.
CONCLUSION

A regional fixed effects model using data from the World Values Survey and the University of Texas Inequality Project (UTIP-EHII) was employed to empirically test the relationship between income inequality and aggregate levels of life satisfaction in a sample of 51 countries during the period 1981-2002. While further study is required to understand the impact of inequality on well-being over time, and the varying determinants of well-being within countries, the empirical relationship presented in this paper appears to provide some evidence of the negative impact of income inequality at the global level. Indeed, what these results show is that—all else equal—people living in egalitarian societies are, on average, more satisfied with their lives.

Building on relative deprivation theory, the model is based on the idea that the less equitable the distribution of income is in a particular society, the greater the social distance between members of that society, creating greater social divisiveness that, in turn, leads to negative health and social outcomes (Wilkinson & Pickett, 2009). Indeed, Wilkinson and Pickett (2007) believe that it is precisely at the societal, or national, level that the processes of social stratification manifest themselves. These processes are captured by the degree of income inequality at the aggregate level. As evidenced here, higher levels of income inequality are associated with a reduction in life satisfaction, controlling for average national income, inflation, and total unemployment in each country. These findings are based on data on income inequality that, to date, do not appear to have been utilized in the happiness literature, producing robust results at the global level and filling a gap in the literature that has included few cross-country analyses of well-being and macroeconomic factors such as inequality.

As Alesina, Glaeser, and Sacerdote (2001) note, “As is well known, comparing inequality and poverty rates across countries is a minefield. However, it is quite clear that after-tax income inequality is relatively low in the Nordic countries, intermediate in central and southern Europe, higher in the United Kingdom, and higher still in the United States” (p. 200). The UTIP-EHII data
generally mirror this pattern of inequality in the advanced industrialized nations. The cross-country regression results also support the popular perception that Nordic countries—characterized by their large welfare states and relatively low income inequality—are more satisfied with their lives than individuals in other nations. Furthermore, the results support Melgar and Rossi's (2010) recent findings of the negative impact of income inequality on incidence of depression across countries. Among all the countries in their sample (both developing and advanced), the Scandinavian countries were least likely to be depressed. Indeed, the authors point not only to income inequality as a significant “stressor”, but also to the importance of a country’s social conditions to individual well-being (Melgar & Rossi, 2010, p. 15-16). While the happiness data that are available today may not capture directly, or adequately, the long-term impact of the social consequences of economic inequality, these findings nonetheless provide evidence—in spite of these limitations—of the potential negative consequences of greater income inequality.
### Appendix

#### I. Summary statistics for regression sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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<td>6.300058</td>
<td>26.53046</td>
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Distribution of key predictor variable (ehii)

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<th>Percentiles</th>
<th>Smallest</th>
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<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Sum of Wgt.</th>
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Distribution of dependent variable (lifesat)

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<tr>
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<td>90%</td>
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</table>
II. Distribution of happiness and life satisfaction data where life satisfaction is measured on a scale from 1-10 and happiness is measured on a scale from 1-4 (World Values Survey)
III. Diagnostics Output

Linear Relationships

Two-way scatter plot between Life satisfaction and EHII

Relationship between Life satisfaction and GDP per capita
Relationship between EHII and GDP per capita
Tests for multi-collinearity

### Independent variable correlations

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<th></th>
<th>ehii</th>
<th>gdp</th>
<th>infl</th>
<th>tot</th>
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<th>eur</th>
<th>asia</th>
<th>eca</th>
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<th>na</th>
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<tr>
<td>GDP per capita</td>
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<td>Inflation rate</td>
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<tr>
<td>Total unemployment</td>
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<td>0.007</td>
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<td>1.21</td>
<td>0.825057</td>
</tr>
<tr>
<td>infl</td>
<td>1.08</td>
<td>0.922318</td>
</tr>
</tbody>
</table>

Mean VIF: **1.76**
Tests for normality/homoskedasticity

Cameron & Trivedi's decomposition of IM-test

<table>
<thead>
<tr>
<th>Source</th>
<th>chi2</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heteroskedasticity</td>
<td>69.52</td>
<td>37</td>
<td>0.001</td>
</tr>
<tr>
<td>Skewness</td>
<td>23.7</td>
<td>9</td>
<td>0.0048</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.01</td>
<td>1</td>
<td>0.9362</td>
</tr>
<tr>
<td>Total</td>
<td>93.22</td>
<td>47</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance
Variables: fitted values of lifesat

\[
\text{chi2}(1) = 8.58 \\
\text{Prob > chi2} = 0.0034
\]

Plotting residuals against predicted values
Plotting residuals against observed values

Plotting residuals against EHII
Checking for normality of residuals

Kernel density estimate

Kernel density estimate
Normal density

Kernel = epanechnikov, bandwidth = 0.1862

Checking for non-linearity

Augmented component plus residual

(mean) ehii
REFERENCES


