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Income Inequality and Happiness: Is There a Relationship?

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Abstract

This paper uses fixed effects regressions to examine the relationship between happiness and income inequality in 30 countries. It has three major findings. First, happiness and income inequality are correlated in the expected direction; high income inequality correlates with a smaller share of happy people and a higher share of unhappy people. Second, different regions have characteristics that strongly mediate the effect of income inequality on happiness. Third, the correlation between income inequality and happiness is of a similar magnitude to the correlation between median income and happiness.

1 Introduction

The effect of income inequality on society has been a subject of intense scrutiny in recent years, both within academia and the public press. A famous OECD report found a significant negative correlation between inequality and intergenerational mobility (OECD, 2008). Several economists at the International Monetary Fund have found a negative relationship between inequality and economic growth (Berg and Ostry, 2011; Ostry et. al 2014); Keynesian economists have argued that inequality lowers economic growth by reducing demand (Krugman, 2012; Stiglitz, 2013); and many scholars have focused on the deleterious effects of inequality on democracy (Galbraith, 2008; Gilens, 2005; Gilens and Page, 2014; Hacker and Pierson, 2011; Reich, 2012;).

This paper explores the relationship between income inequality and happiness among women. Specifically, it looks at the relationship between five country level measures of income inequality (the GINI coefficient, the 90/10 ratio, the 50/10 ratio, female poverty rates, and single mother poverty rates) and reported happiness among women in 30 countries. These countries were selected because they participate in the Luxembourg Income Study (LIS) Database, which is the gold standard in detailed income data.

The relationship between a country's *average income* and its level of happiness has been examined many times. The famous "Easterlin Paradox," which found that happiness and income are correlated for individuals within countries but not across countries, has been refuted (Easterlin, 1974). One economist, using more recent and higher quality data, found a strong positive relationship between a country's per-capita income and its average level of happiness (Deaton, 2007). This effect was particularly strong among the elderly; i.e. the elderly in poor countries are far more likely to be unhappy than their counterparts in rich countries. This finding was confirmed by a pair of scholars using a different method (Stephenson and Wolfers, 2008). Another researcher tested the importance of income versus other predictors of individual happiness and found that income, although significant, mattered less than other variables (Helliwell, 2009).

In comparison, the literature on happiness and *income inequality* is rather sparse. There have been several studies looking at individuals within countries or comparing a small group of countries. One paper, by a psychologist, finds that more income equality in American neighborhoods predicts higher levels of happiness, although the magnitude of the effect is dwarfed by the effect of household income (Hagerty, 2000). Another paper compares Europeans and Americans, finding different responses to inequality based on socio-economic status and political leanings (Alesina, 2004). The authors find that poor and left-leaning Europeans report lower levels of happiness in countries with higher inequality. They also find that only wealthy, left-leaning Americans report lower levels of happiness in states with higher inequality. The lack of concern by the American poor is explained as a product of the American belief in upward mobility. Another study, this one focusing on Latin America, finds that individual level happiness is not predicted by absolute income but it is strongly predicted by relative income (Graham, 2006). A final paper focuses on happiness *inequality* and various measures on income, including income inequality. Using time-series data from four countries, the authors conclude that income inequality does lower happiness equality, even though the effect is overwhelmed by rising average incomes, which increases happiness equality (Clark, 2012).

When put together, this literature yields two general conclusions. First, income inequality and an individual's relative income matter to happiness. It is unclear, however, whether a country's income inequality matters more than average income. Second, the relationship between income inequality and happiness probably varies across countries and regions.

This paper adds to the literature in a few ways. First, it examines far more countries than any of the studies cited above. Including a broader array of countries allows this paper to draw more generalizable conclusions about the relationship between happiness and income inequality. The second contribution of this paper is its use of LIS's high quality income data. Some of the studies cited above use unreliable measures of income, calling into question the precision of their findings. Third, this paper uses income and happiness data for women, allowing us to examine two gender-specific variables: female poverty rates and single mother poverty rates. Fourth, this study uses country level aggregates for income inequality and happiness, as opposed to individual level data.

Using country level data has pluses and minuses. On the plus side, it allows us to make clear inferences about relationships at the country level and allows simple cross-country comparisons. On the downside, within-country differences get lost when aggregating individual data up to the country level. The broader research project on income inequality and happiness will ultimately require both types of data. Given that individual level data have already been explored, this paper's use of country level data provides a way to cross-check inferences from individual level data.

This paper has three broad findings. First, a country's income inequality does have a strong relationship with its level of happiness. Second, the correlation between income inequality and happiness is mediated by characteristics of a country's region. Third, the magnitude of this relationship is as large as the relationship between happiness and average income.

Part 2 of this paper will discuss the data sources and give details on each measure used here. Part 3 highlights the significant differences across regions and explains why a single correlation for the entire sample could be misleading. Part 4 presents the results from several fixed effects regressions. Part 5 concludes with some thoughts for future research.

2 Data

2.1 Happiness Data

The data on happiness come from two sources: the 2005 wave of the World Values Survey and the Eurobarometer's 2006 survey on European Social Reality. Fortunately, the two surveys ask the respondent the same question: "Taking all things together would you say you are…?" The respondent can choose from four answers:

1. very happy
2. quite happy
3. not very happy

4. not at all happy

The designers of both surveys were well aware of problems that could arise from translation and took steps to ameliorate the issue. They used local partners in each country to ensure that the meaning of the questions and answers were translated properly. More information is available on their websites.[1]

2.2. Happiness Data Transformation

For each country, I calculated the percent of women that gave each answer. Answer 4 posed a challenge because, on average, just 1.5 per cent percent of respondents gave this answer. Instead of discarding the answer, however, I merged 3 and 4 to create a new category, simply called "*Unhappy*." I merged the categories because I assumed that much of the variation in answer 4 was due to individual, not country, characteristics such as clinical depression or mental illness.

After adding answer 3 and 4 together, I had three measures of happiness for each country: *Happy* (i.e. very happy), *Quite Happy*, and *Unhappy*. Table 1 displays the percentage of respondents in each category for each country.

In this paper, I only examine the correlation of income inequality with *Happy* and with *Unhappy*. I assume that *Quite Happy* is the default answer for most healthy people, while variation in *Happy* and *Unhappy* will be a function of country characteristics. The correlation between *Happy* and *Unhappy* is only -0.53, so the categories are not inverses.

Predicting two happiness variables, *Happy* and *Unhappy*, is preferable to any attempt to reduce country level happiness to a single number. Any conceivable ratio of *Happy*, *Quite Happy*, and *Unhappy* would raise the question of whether or not variation was caused by change in the numerator, the denominator, or both. One could also calculate a weighted average of reported happiness, but this would be meaningless on a three point scale.

A single country score would also ignore the underlying distribution of happiness. Some countries, for example Guatemala, have a relatively high share of both *Happy* and *Unhappy* people and a relatively low share of *Quite Happy* people. Any single variable would overlook cross-country differences in happiness distribution.

The issue of distribution is a major blind spot in the happiness literature and in cross-country studies more broadly. Many happiness studies use the Pew Global Values Survey, which has a 10 point scale for respondents' happiness. I examined the Pew data and found numerous instances where countries with similar means had very different variances. For example, both India and Poland have a mean happiness of 6.2, but India's standard deviation is 0.086 while Poland's is 0.333. Clearly these countries differ in ways not captured by a simple mean.

Cross-national research on happiness inevitably runs into another problem. Are differences across reported happiness in countries a result of actual differences in happiness, or are they driven by cultural differences? For example, is a "very happy" American happier than a "satisfied" Brit, given the storied English penchant for stoicism and the American preference for superlative language? In general, this problem is quickly mentioned by researchers and then forgotten about. I only found one study that tackled this issue directly. A team of psychologists asked students from different countries to numerically score the favorability of different hypothetical situations. They found that students gave similar scores regardless of their country of origin, and the within-country variance far exceeded the small cross-country variance (Bolle, 2009). This single study hardly settles the matter, but it does suggest that happiness can be compared across countries. Another strong piece of evidence in support of cross-country happiness studies is the persistence of statistically significant correlations between happiness and common-sense effectors of happiness such as income, political freedom, and health. If happiness responses were driven totally by country-specific norms, then one would expect to find a random relationship between country characteristics and happiness.

I decided to only use happiness data only from female respondents so that I could use income inequality measures that apply only to women, specifically Single Mother Poverty Rates and Female Poverty Rates. (Excluding males was not that significant, given that the correlation between male and female happiness scores was 0.95.) Table 1 displays the happiness data used here.

Table 1 Happiness Scores for Each Country (Regional Means in Italics)

Country/Region	Happy	Quite Happy	Unhappy
Australia	37.10%	56.60%	6.30%
Canada	48.90%	46.30%	4.80%
Ireland	46.60%	48.10%	5.30%
United Kingdom	40.00%	51.80%	8.20%
United States	36.30%	56.30%	7.40%
Anglo	*41.78%*	*51.82%*	*6.40%*
Austria	20.80%	63.60%	15.70%
France	31.00%	59.00%	9.00%
Germany	19.30%	60.20%	20.50%
Greece	18.40%	60.00%	21.50%
Italy	17.30%	72.80%	9.90%
Luxembourg	39.60%	53.30%	7.00%
Netherlands	43.90%	50.70%	5.50%
Spain	13.90%	77.20%	8.90%
Switzerland	42.20%	51.80%	6.00%
Europe	*27.38%*	*60.96%*	*11.56%*
Czech Republic	15.40%	71.50%	13.10%
Estonia	12.20%	60.60%	27.30%
Hungary	16.20%	45.80%	38.00%
Poland	23.60%	66.70%	9.70%
Slovenia	18.10%	62.00%	19.90%
Former Communist	*17.10%*	*61.32%*	*21.60%*
Brazil	33.80%	55.60%	10.60%
Colombia	48.80%	36.90%	14.30%
Guatemala	45.40%	31.10%	23.50%
Mexico	57.80%	31.90%	10.20%
Peru	26.50%	38.50%	35.00%
Uruguay	29.00%	54.90%	16.10%
Latin American	*40.22%*	*41.48%*	*18.28%*
Denmark	51.40%	45.40%	3.20%
Finland	28.80%	64.50%	6.70%
Norway	41.10%	55.00%	3.90%
Sweden	44.60%	52.20%	3.20%
Nordic	*41.48%*	*54.28%*	*4.25%*
Taiwan	25.60%	61.90%	12.50%
Correlation between Happy and Unhappy is -0.53.			

2.3 Income Data

Income data in this study come from Wave VI of the Luxembourg Income Study Database (LIS). This mostly contains data from 2004, but some countries report data from 2003, 2005, and 2006. India, Israel, and South Korea were dropped because happiness measures are not available for these countries during this time period. I chose this wave because happiness data is harder to find for older waves and the most recent wave may be confounded by the effects of the 2008 economic crisis.

LIS does not conduct its own income surveys, but rather *harmonizes* household income datasets conducted by governments or data producers that participate in the project. The goal of harmonization is to create comparable variables from each country's data, allowing researchers to compare income data from around the world even when data producers conduct diverse income surveys. LIS also gives researchers access to data that governments are hesitant to share.

LIS data are extremely high quality for several reasons. First, LIS has access to detailed household income surveys, so non-wage income that other datasets overlook are included. This is especially important in countries where a lot of economic activity is not monetized or is informal. Second, the data allow researchers to account for household size, which is important because households have economies of scale. These economies of scale arise because individuals share resources in a household. This makes intuitive sense: a four-person household would not need the four times the income of a one-person household to have equal per-person consumption since individuals in the four-person household would share the kitchen, the TV, the car, etc.

Finally, because LIS allows researchers to construct their own measures, we know we are comparing apples to apples when making cross-country comparisons. This is important because comparisons of official measures (such as poverty rates) can be meaningless if governments have set different poverty lines. With LIS data, poverty rates can be constructed uses the same poverty line, so comparisons are meaningful.

The income measures used in this paper are derived from one of LIS's central variables: Disposable Household Income (DHI). DHI captures a household's income, net of direct taxes and transfers.

2.4 Income Data Transformation

I began by transforming DHI into individual level data by assigning each individual in the house an income equal to DHI divided by the square root of family size. This takes into account household economies of scale because larger families will have their household income divided into relatively smaller amounts.[2] Other household weights are possible, but using the square root of family size is the most widely used convention.

This transformation yields income data for "equivalized" individuals, meaning that each member of a household is treated equally to all other members with respect to income. The reader should keep in mind that when this paper refers to individual income, the paper is actually referring to "equivalized" individuals. Using this "equivalized" individual level data, I created five income variables (Table 2 displays the values for each country):

1. *Median Income*: This is the median individual's income in each country, measured in thousands of US dollars. The median is a far better measure of a country's "average income" than the mean. In unequal societies, the mean income is distorted by the wealthy, sometimes by a significant amount. Mexico, for example, has a mean of $7,014 and a median of $4,426. As LIS data are calculated using local currencies, I converted all amounts to US dollars using the World Bank's Development Indicators for exchange rates and purchasing power parity (Taiwan's data came from the International Monetary Fund). One flaw with this measure is that it does not fully capture wealth. In a perfect world, we would

have a single measure that incorporates annual income with total net wealth. But wealth data are sparse and there is no convention for integrating it with income data.

2. *GINI*: *GINI* measures the distribution of wealth in a country. A *GINI* of 1 means perfect inequality, while 0 indicates perfect equality. The weakness of the *GINI* is that it is not sensitive to different distributions of income.
3. *90/10* and *50/10 Ratios*: These are the ratios between different income percentiles. These ratios help correct for *GINI's* inability to differentiate between income distributions. The 90/50 ratio is not examined because it correlates with GINI at 0.99.
4. *Female Poverty Rates*: This is the percent of the female population that lives in households where the individual income is below 50% of the country's *Median Income*. Establishing a poverty line at 50% of *Median Income* makes cross-country comparisons more meaningful than using official poverty lines, which may not be comparable across countries. The sample omits females below the age of 25 to exclude minors and college students who appear poor in survey data but are obviously in a different category.
5. *Single Mother Poverty Rates*: This is the fraction of single mothers living in households were the individual income is below 50% of the country's *Median Income*. Defining single mothers is not straightforward; there are many variables to consider. The precise definition of single mothers used in this dataset is mothers who are not living with their partners and have children living in their house. This definition excludes mothers who live with their own parents and are not the household head, and it excludes women whose children do not live with them. It does not take into account legal marriage status, so married mothers whose husbands do not live at home would be counted as single mothers.

Table 2 Income Inequality Data for Each Country

Country/Region	Median Income (thousands)	GINI Score	90/10	50/10	Female Poverty Rate	Single Mother Poverty Rates
Australia	$17.79	0.339	4.54	2.19	0.17	0.31
Canada	$23.03	0.334	4.71	2.34	0.12	0.39
Ireland	$19.68	0.338	4.33	2.12	0.16	0.33
United Kingdom	$20.42	0.368	4.62	2.08	0.12	0.29
United States	$25.72	0.392	6.31	2.84	0.18	0.41
Anglo	*$21.33*	*0.35*	*4.90*	*2.31*	*0.15*	*0.346*
Austria	$22.17	0.281	3.44	1.91	0.08	0.16
France	$22.62	0.289	3.65	1.95	0.08	0.29
Germany	$20.70	0.3	3.67	1.99	0.09	0.36
Greece	$14.55	0.337	4.68	2.25	0.13	0.25
Italy	$15.22	0.35	4.24	2.07	0.12	0.25
Luxembourg	$33.79	0.279	3.6	1.92	0.08	0.25
Netherlands	$20.32	0.282	3.07	1.73	0.04	0.18
Spain	$15.37	0.333	4.75	2.3	0.15	0.25
Switzerland	$26.61	0.283	3.49	1.98	0.08	0.16
European	*21.26*	*0.30*	*3.84*	*2.01*	*0.09*	*0.24*
Czech Republic	$10.00	0.274	3.17	1.69	0.05	0.3
Estonia	$6.13	0.363	4.83	2.06	0.13	0.25
Hungary	$7.70	0.299	3.33	1.76	0.07	0.13
Poland	$6.95	0.321	3.89	1.99	0.08	0.16
Slovenia	$14.48	0.256	3.36	1.97	0.1	0.18
Former Communist	*9.05*	*0.30*	*3.72*	*1.89*	*0.09*	*0.20*
Brazil	$4.93	0.507	9.57	2.81	0.15	0.29
Colombia	$2.55	0.554	14.37	4.06	0.21	0.29
Guatemala	$3.51	0.525	12.3	3.71	0.22	0.23
Mexico	$4.43	0.499	9.28	2.96	0.17	0.2
Peru	$2.97	0.54	16.32	4.87	0.24	0.24
Uruguay	$4.95	0.437	7.32	2.6	0.13	0.31
Latin American	*3.89*	*0.51*	*11.53*	*3.50*	*0.19*	*0.26*
Denmark	$20.34	0.251	2.92	1.75	0.05	0.07
Finland	$18.25	0.288	3.35	1.86	0.07	0.12
Norway	$24.44	0.301	3.21	1.94	0.06	0.14
Sweden	$18.75	0.254	2.94	1.74	0.05	0.1
Nordic	*20.45*	*0.27*	*3.11*	*1.82*	*0.06*	*0.11*
Taiwan	$23.80	0.329	4.62	2.19	0.11	0.16

3 Method I: Analysis of Regions

Initial explorations into the dataset yielded some counterintuitive correlations between happiness and income inequality. Upon further examination, it became clear that different regions have different relationships between happiness and inequality. It is not clear if these differences are due to culture, history, political and economic institutions, or some other factor. This part of the paper will highlight the empirical differences between regions.

3.1 Latin America

The six Latin American countries all have a high share of *Happy* people. Mexico is by far the happiest country in the sample, with Colombia and Guatemala not far behind. The country with the lowest share of *Happy* people in Latin America, Uruguay, is still in the middle of the sample.

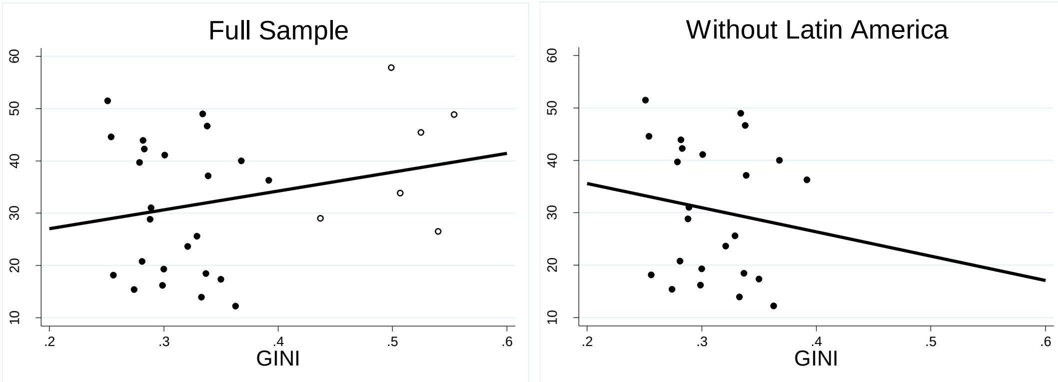
Latin American countries are even more exceptional with respect to income measures, specifically *GINI*, *Female Poverty Rates*, and *Median Income*. Interestingly, the region is not notable for *Single Mother Poverty Rates*, possibly because single mothers face strong pressure to live with their parents.

The six Latin American countries have the six highest *GINI* scores in the sample. As a result, a sample-wide correlation between *Happy* and *GINI* shows a negative correlation, indicating that more unequal countries have a higher share of *Happy* people. This is the opposite of what previous scholarship has found and also violates common sense. But if Latin American countries are excluded from the sample, then the correlation is in the expected direction.

A similar story holds with *Female Poverty Rates*. When Latin American countries are included in the sample, *Happy* and *Female Poverty Rates* are positively correlated. When the region is excluded, the correlation is in the expected negative direction.

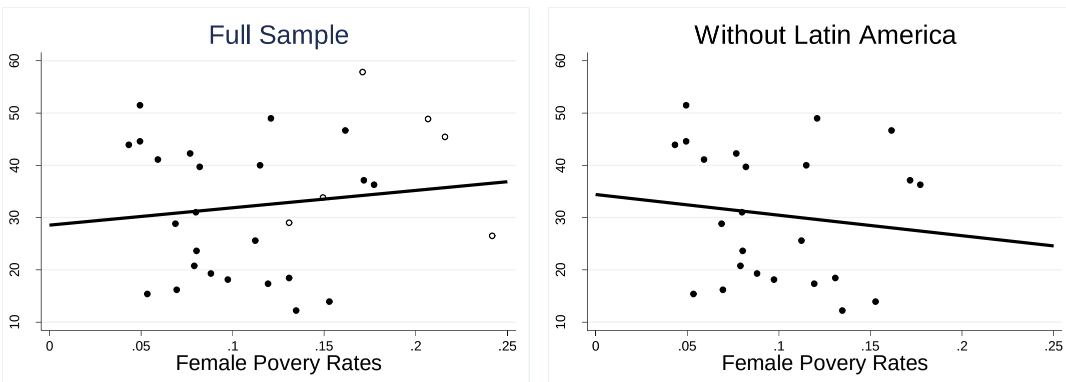
Latin American countries are also the poorest in the sample. When they are included in a correlation between *Happy* and *Median Income*, the correlation is very low and not statistically significant. But when Latin American countries are excluded, one sees a very significant correlation between *Happy* and *Median Income*, as the literature suggests. Figures 1, 2 and 3 compare linear relationships using the full sample of countries with linear relationships of the sample excluding Latin American countries. (Note that the models are simply for illustrative purposes and are not meant to imply causality.)

Figure 1 Happy and GINI, with and without Latin America



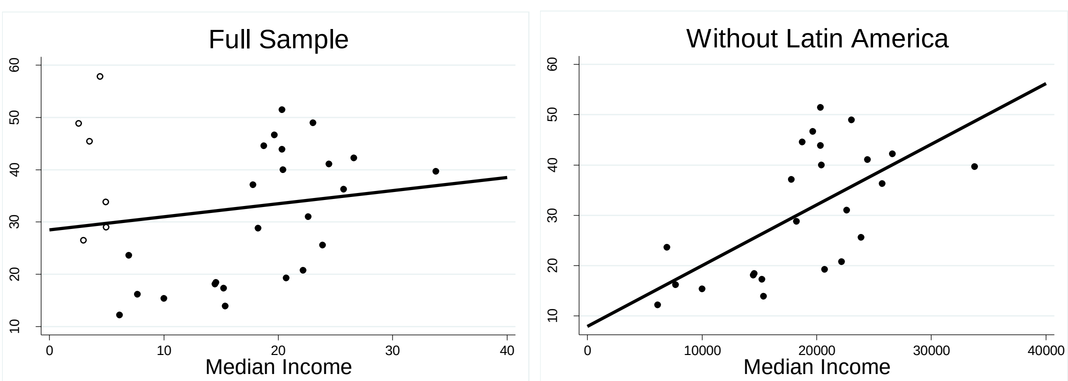
Note: Latin American countries are marked with a hollow circle.

Figure 2 Happy and Female Poverty Rates, with and without Latin America



Note: Latin American countries are marked with a hollow circle.

Figure 3 Happy and Median Income, with and without Latin America



Note: Latin American countries are marked with a hollow circle.

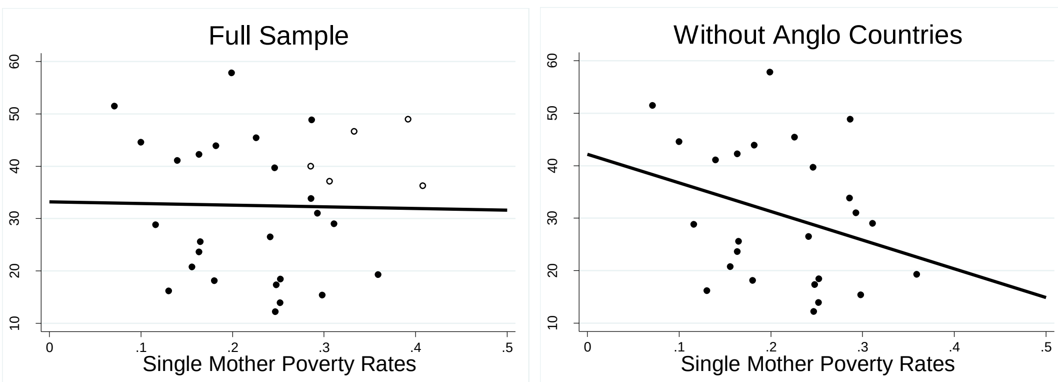
3.2 Anglo Countries

The Anglo countries in the sample (US, UK, Canada, Ireland, and Australia) have exceptionally high values for *Single Mother Poverty Rates* – and yet these countries are relatively happy. All Anglo countries have a high share of *Happy* women and a low share of *Unhappy* women.

A sample-wide correlation between *Single Mother Poverty Rates* and both happiness measures finds low correlations in the expected directions; i.e. higher *Single Mother Poverty Rates* correlates with less *Happy* women and more *Unhappy* women. However, the correlation is very low and not statistically significant. This goes against common sense, since we should expect *Single Mother Poverty Rates* to strongly predict female happiness levels.

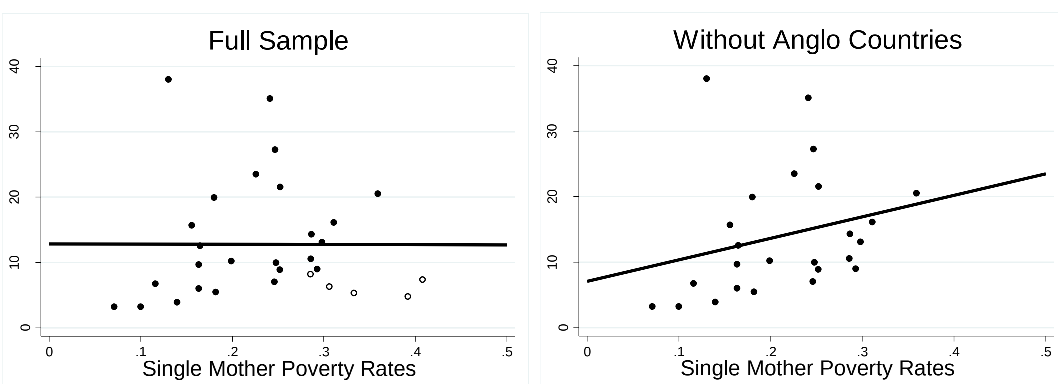
Once Anglo countries are excluded from the sample, however, the correlations look the way we would expect them to. The correlations between *Single Mother Poverty Rates* and happiness measures are much higher and they are statistical significant. Figures 4 and 5 illustrate the effect of Anglo countries on linear relationships.

Figure 4 Happy and Single Mother Poverty Rates, with and without Anglo



Note: Anglo countries are marked with a hollow circle.

Figure 5 Unhappy and Single Mother Poverty Rates, with and without Anglo



Note: Anglo countries are marked with a hollow circle.

3.3 The Importance of Regions

The Latin American and Anglo countries powerfully influence the correlations between happiness and inequality. Other regions, however, are also exceptional in certain measures. Former Communist Countries, for example, tend to have a lot of *Unhappy* people; they also tend to be very equal. Nordic countries have exceptionally low *GINI* and very low poverty rates.

After conducting a region-by-region analysis, it can be concluded that sample-wide correlations are confounded by differences between regions. Regions clearly have unique characteristics that influence the relationship between happiness and inequality. Under these circumstances, a fixed effects regression model has the best chance of estimating this relationship.

4 Data Analysis II: Fixed Effects Models

Fixed effects models are called for when "the unobserved individual effect embodies elements that are correlated with the regressors in the model (Green, 2007 p.183)." In layman's terms, this means that the relationship between happiness and inequality is influenced by variables that we cannot observe, e.g. culture, political institutions, climate, etc. If these unobserved variables affect both happiness and income inequality, then a ordinary least squares regression is biased. A fixed effects model will be less biased because it controls for these unobserved variables.

A fixed effects model works by creating a dummy variable for a group of observations. In this case, the observations are countries and the groups are regions. In theory, each region has unobserved characteristics that influence the relationship between happiness and inequality. By creating a dummy variable for each region, the model controls for these characteristics.

Fixed effects models have two weaknesses. First, the variables that they control for are *unobserved*. Therefore, one can never be sure that these variables exist or even matter. Second, the variables being controlled for may have heterogeneous effects within regions, but using a single dummy variable per region assumes that the variables have homogenous effects within regions. Despite these flaws, however, a fixed effects model presents the best model. Part 3 of this paper strongly indicates than a correlation coefficient or an ordinary least squares model would be biased. Further, there is no theoretically sound reason to use a random effects model (for the sake of completeness, I did run some random effects models; the ensuing Hausman tests rejected the random effects models).

Before proceeding, one important point must be emphasized. This paper uses a fixed effects model as the best way to *describe* the observed relationship between happiness and inequality - the model cannot demonstrate causality. And although it is reasonable to assume that inequality has a causal effect on happiness, this relationship cannot be proven given the available data. The possible directions of causality are discussed in more detail below.

4.1 Evidence for Selection of Regions

Dividing countries into regions is strongly supported by previous scholarship. Alesina et al., find that Americans and Europeans are affected by inequality differently. Another paper argues that high levels of religiosity in the US compensate for high inequality (Scheve and Stasavage, 2006). Esping-Andersen's famous typology of welfare states divides the western world into Liberal, Corporatist-Statist, and Social Democratic, which roughly correspond to Anglo, European, and Nordic countries (Esping-Andersen, 1990). The research team behind the World Values Survey has generated a famous graph called "The Cultural Map of the World," in which the regions used in the paper are shown to have similar values (World Values Survey, 2014a). Table 3 displays how this paper divides the sample of countries into five regions.

Table 3 Regional Groupings

Anglo	**Europe**	**Former Communist**	**Latin American**	**Nordic**
Australia	Austria	Czech Republic	Brazil	Denmark
Canada	Germany	Estonia	Colombia	Finland
Ireland	Greece	Hungary	Guatemala	Norway
United States	Italy	Poland	Mexico	Sweden
United Kingdom	Luxembourg	Slovenia	Peru	
	Netherlands		Uruguay	
	Spain			
	Switzerland			
Taiwan is the reference category				

This regional division is also supported by this paper's data on income inequality. For a fixed effects model to be appropriate, groups must have unobserved characteristics that are correlated with the regressors. Figures 6, 7, and 8 show that the different regions have very different ranges for measures of inequality; these differences in ranges demonstrate the effects of the unobserved regional characteristics on the countries in the sample.

Figure 6 displays the ranges for *GINI*. Nordic countries have such low *GINI* scores that the most unequal country in the region is more equal than the most equal Anglo country. The Anglo countries, meanwhile, are more unequal than almost all the Former Communist and European countries. And the Latin American countries are in a category all of their own. The lowest *GINI* in Latin America is well above the highest *GINI* among the Anglo countries. A similar situation holds for *Female Poverty Rates* and *Single Mother Poverty Rates*; these results are presented in Figures 7 and 8. These figures demonstrate empirically that the five regions used here have characteristics that are correlated with measures of income inequality.

Figure 6 Range of GINI in each Region

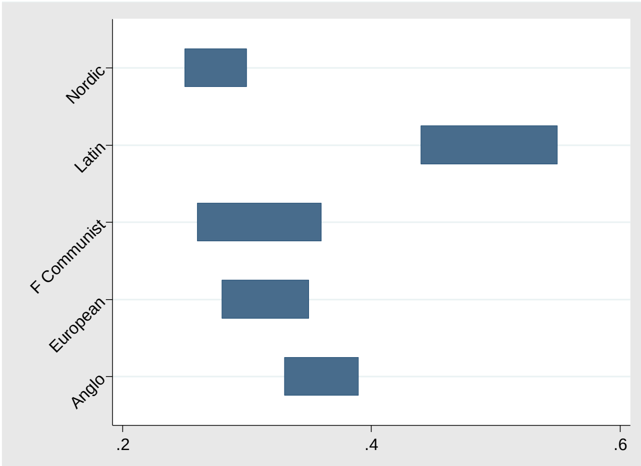


Figure 7 Range of Female Poverty Rates in each Region

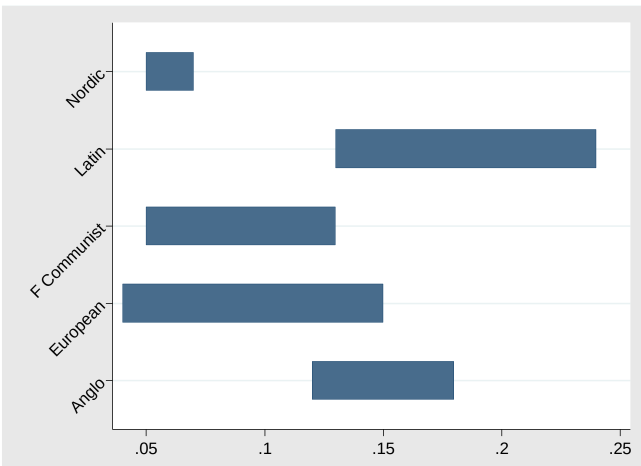
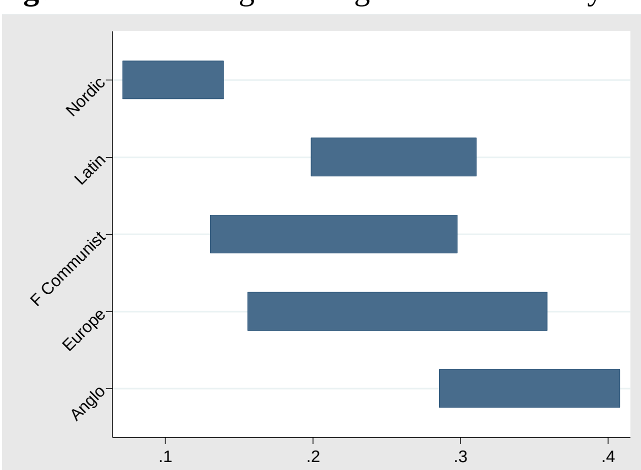


Figure 8 Range of Single Mother Poverty Rates by Region



4.2 The Fixed Effects Models

Table 4 contains the results from fixed effects regressions on *Happy*; Table 5 contains the results from regressions on *Unhappy*. Each model regresses just one measure of inequality on a measure of happiness. A dummy variable has been included for each region (the coefficients are omitted for brevity). Taiwan, which is not categorized, serves as the reference category.

This simple model is not motivated by the small sample size. A great deal of recent scholarship in political methodology has argued persuasively that large multivariate models often do more harm than good (Achen, 2005; Clark, 2005; Ray, 2002). This body of literature points out that multivariate models often bias the estimator of interest because of multicollinearity, non-linearity, outliers, and causality running between control variables. One paper in particular, Clark 2005, uses Monte Carlo simulations to demonstrate the control variables only improve the accuracy of a regression if the model is *perfectly* specified.

As this paper is one of the first attempts to study cross-country happiness and income inequality, it seemed best to avoid the pitfalls of large models and focus directly on the variables of interest (I did run the inequality models with *Median Income* as a control and results did not change substantially). Tables 4 and 5 present the results of the fixed effects regressions.

Table 4 Fixed Effects Regressions on *Happy*

Model	Regressor	Coefficient	Standard Error	P-value	Standardized Coefficient
1	Median Income	1.042*	0.446	0.029	0.674*
2	GINI	-89.479	59.769	0.148	-0.616
3	90/10	-1.178	1.230	0.348	-0.313
4	50/10	-5.270	4.625	0.266	-0.297
5	Female Poverty	-123.409*	58.043	0.044	-0.505*
6	Single Mother Poverty	-66.340*	34.347	0.066	-0.437*

* indicates p-value < 0.1
For all models, N=30.
Coefficients on regions have been omitted.

Table 5 Fixed Effects Regressions on *Unhappy*

Model	Regressor	Coefficient	Standard Error	P-value	Standardized Coefficient
1	Median Income	-0.448	0.354	0.218	-0.419
2	GINI	64.559	44.228	0.158	0.643
3	90/10	2.011*	0.826	0.023	0.772*
4	50/10	8.001*	3.088	0.016	0.652*
5	Female Poverty	96.094*	42.381	0.033	0.568*
6	Single Mother Poverty	-3.879	27.327	0.888	-0.037

* indicates p-value < 0.1
For all models, N=30.
Coefficients on regions have been omitted.

4.3 Discussion of Findings

The standard way to interpret a regression table is to search for coefficients with acceptably low p-values and discuss why the model "proves" that these variables matter. This method is flawed because it allows statistical models to do our thinking for us. Focusing too intently on the results of null hypothesis testing, we ignore our common sense. Even worse, a focus on p-values ignores all previous research on the subject being studied.

Two alternatives methods for analyzing results have been recommended (Cohen 1994 has a useful discussion; Gill 1999 writes specifically for political scientists). One solution is the standard scientific practice of replication. If findings can be replicated repeatedly using multiple research methods, then the findings are probably true. Another solution is to report confidence intervals. Confidence intervals present the same basic information as a T-test, but they present the information in a way that forces the reader to think about the reasonableness of the results instead of taking refuge in a formal test

Both methods should be used to interpret the results here. Think of each fixed effects regression as a single experiment that attempts to capture the true relationship between happiness and an unobservable variable, a country's true *Income Inequality*. Each variable used in this paper looks at *Income Inequality* from a different angle, and so each regression paints a slightly different picture of the truth. Interpreted this way, this paper replicates a test five times. Rather than interpreting each test in isolation and accepting or rejecting its findings, it makes far more sense to consider all the tests together and draw conclusions based on all the evidence.[3]

Figures 9 and 10 present the "standardized confidence intervals" for the regressions above. The purpose of this standardization is to allow simple, meaningful comparisons between different variables. The intervals were standardized by dividing the lower and upper bounds by the coefficient, and then multiplying both by the standardized coefficient. For example: *GINI* has a coefficient of -89.48, a lower bound of -191.92, an upper bound of 12.96, and a standardized coefficient of -0.616. Dividing lower and upper bounds by the coefficient, then multiplying both by the standardized coefficient creates a "standardized confidence interval" of -1.32 to 0.089.

The important information in these figures is how much of the confidence interval for each variable extends beyond 0. The more that the interval extends past zero, the less confident we can be in the estimated relationship between happiness and income inequality.

Figure 9 Confidence Intervals for Fixed Effects Regressions on Happy

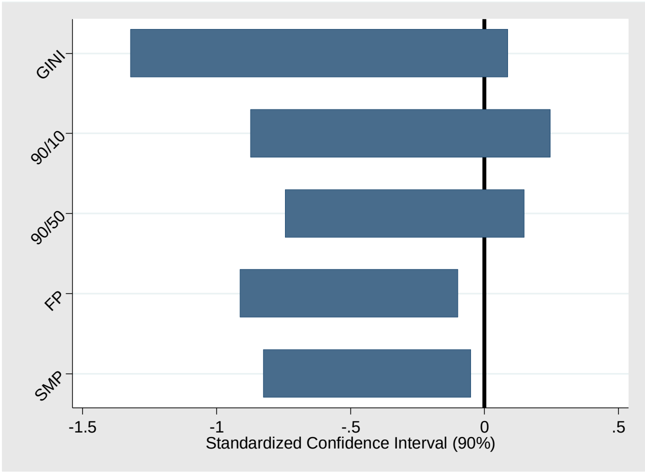
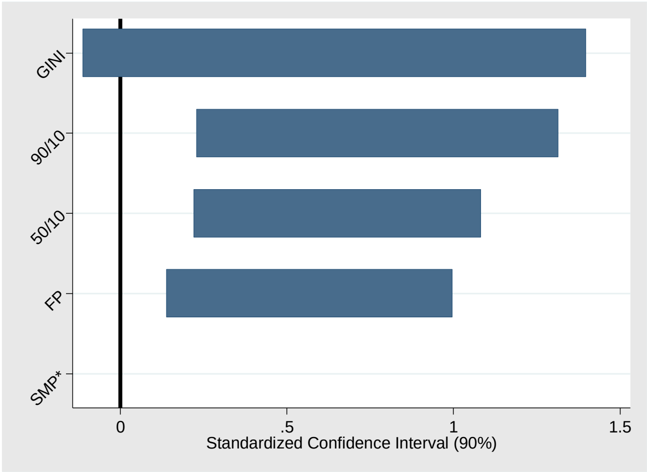


Figure 10 Confidence Intervals for Fixed Effects Regressions on Unhappy



** The coefficient on Single Mother Poverty is negative and the CI bounds extend far beyond this figure.*

These figures present strong evidence that income inequality and happiness are related in the expected direction. If we just look at the coefficients, we see that they are all in the expected direction and have a sizable magnitude (expect for *Single Mother Poverty Rates* and *Unhappy*, whose insignificant correlation is driven by a strong negative correlation in Latin America). From this, we can conclude that inequality predicts a country having a lower share of *Happy* people and higher share of *Unhappy* people.

The evidence also strongly suggests that the observed relationship between happiness and inequality is not random. The confidence intervals show that two of the five variables regressed on *Happy* pass the formal test of significance, while three of the five variables regressed on *Unhappy* pass. *GINI* is insignificant when regressed on both happiness measures, but it is close to significant (p-value of 0.15).

So after conducting ten tests, we have five that are significant, two that are slightly less than significant, two that are marginally insignificant, and one that is totally insignificant. While these tests do not settle the matter, it is more reasonable than not to conclude that inequality and happiness are related.

The magnitudes of the income inequality variables are in the same range as the magnitude of *Median Income*. The far-right columns in Tables 4 and 5 show the standardized coefficients for each variable. *Median Income* has a magnitude of 0.67 when regressed on *Happy* and 0.42 when regressed on *Unhappy*. The inequality variables range between 0.30 and 0.62 for *Happy* and 0.57 and 0.77 for *Unhappy*. These ranges show that income inequality is just as important a predictor of happiness as income overall.

There are two important finding about the relationship between *Median Income* and happiness. First, when *Median Income* is regressed on *Happy*, the coefficient is significant, as previous literature suggests. But when *Median Income* is regressed on *Unhappy*, the coefficient is insignificant and has a lower magnitude. This suggests that *Median Income* can predict movements between *Quite Happy* and *Happy*, but cannot predict movements between *Unhappy* into *Quite Happy*. This may be because *Unhappy* responses are caused by persistent inequality and rising *Median Incomes* may not lead to any economic benefits for the poor. It may also be that *Happy* responses are partly driven by international comparisons, where people in wealthy countries feel well off relative to the poorer people they see on TV.

At this point, the data only allow us to determine correlation and not the direction of causation; but it is worth speculating about different causal stories. It seems most likely that income inequality has a causal effect on happiness. Inequality violates people's natural sense of equity and justice, making the culture less happy. Inequality may also create insecurity among middle income groups who fear falling below the poverty line. Finally, inequality could make the poor lose hope in upward mobility and the possibility of a better life for their children.

It may also be that happiness drives economic equality. In this story, people who are more content with their lives will be more likely to vote for policies that redistribute income, thus lowering inequality and poverty rates. This story is supported by the overwhelming data showing that cross-country inequality is driven by the level of government redistribution and not market wages (Brady, 2005; Brandolini and Smeeding, 2007; Scruggs and Allen, 2006).

The correlation between inequality and happiness may also be caused by third variables. Higher inequality could increase crime, making people less secure and thus less happy. Latin America, which is by far the most unequal region in this sample, also has the highest crime rates. Inequality's potential to distort political and legal institutions, which would give people less faith in their government, may also make people less happy. Inequality may also make labor markets more exploitative; workers facing poverty would have to accept longer hours and lower wages than they might otherwise want. This would make the workplace less enjoyable and thus lower happiness.

5 Conclusion

This paper finds that income inequality is correlated with a country's level of happiness: more equal countries have more *Happy* people and less *Unhappy* people. This relationship, however, is strongly mediated by the characteristics of different regions. Further, the magnitude of this relationship is similar to the magnitude that a country's *Median Income* has on its level of happiness.

The findings presented here corroborate previous research, both on *Median Income* and income inequality. This paper contributes in two important ways. First, its sample of countries is much larger than samples used in previous papers. This paper controlled for characteristics of different regions and still found a significant relationship between inequality and happiness, suggesting that this relationship is universal. Second, this paper shows that income inequality is just as important as *Median Income*. Based on this finding, it seems that societies should be just as concerned about distribution as they are about growth.

I will end by suggesting four ways to improve research on this topic. The first method is simply to have data on more countries. This obvious improvement is constrained by the challenge of measuring income in most economies. In non-industrialized countries, a majority of economic activity is conducted outside the formal sector. Often, economic activity does not even involve the exchange of money as much as the exchange of favors or bartering. As such, measures of income can fluctuate wildly. For example, numerous expenditure-based studies have calculated that India's *GINI* is between 0.30 and 0.35; a recent income-based approach, however, concluded that India's *GINI* is actually 0.52 (Desai et al. 2010). Given that both approaches were conducted by sincere, knowledgeable, well-funded researchers, we can only conclude that measuring incomes in India cannot be done with any precision.

A second way to improve research would be to look at changes in happiness and income inequality over time. At present, however, this path is also constrained by lack of available data. Income inequality changes very slowly, and we can surmise that national happiness also changes slowly. In addition, a population's *perception* of income inequality may change even more slowly than actual income inequality. As such, it will take decades of continuous data collection before a time-series analysis can be conducted.

A third avenue for improving research would be to combine neighborhood, city, country, and regional data. This paper looks at cross-country variation, but country level inequality may not be the strongest predictor of happiness. Individuals may care more about inequality within their immediate neighborhoods, cities, or counties. Conversely, individuals may be more concerned about their income in an international context. For example, a rich Guatemalan who frequently travels to Europe may be unhappy because she compares herself to Europeans rather than her countrymen.

Finally, this research project can be improved by ironing out the differences in cross-country analysis and individual level analysis. For example, one paper argues that Latin Americans are more concerned about inequality than Americans and Europeans (Graham 2006). This conclusion somewhat contradicts the findings present here, given that Latin Americans have a very high share of *Happy* despite extreme inequality (of course, Latin Americans also have a high share of *Unhappy*). This difference is hard to reconcile, as their paper and mine use different data. Nevertheless, an ideal research project would reconcile the different inferences made by different levels of analysis.

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Notes

1. http://www.worldvaluessurvey.org/ and http://ec.europa.eu/public_opinion/index_en.htm
2. Consider an example where two families of different sizes both have an income of $100,000. A four person family will have per-capita income of $50,000 [100,000/√4], while an eight person household will have per-capita income of $35,360 [100,000/√8], not $25,000.
3. If this seems odd, consider the strangeness of the common practice of interpreting each regression in isolation. Imagine if 19 of 20 similar regressions returned p-values of over 0.5, but the 20th regression returned a p-value of 0.001. Should we conclude that this final regression has proven something? Or should we conclude that this tiny p-value is the result of randomness? I would interpret this final regression as meaningless, but could only do so based on the other 19 results.