Income Distributions and Happiness: Evidence from the General Social Survey*

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Abstract

Income impacts happiness directly through consumption and indirectly through social standing. This paper explores a possible third channel: projection of future well-being informed by an assessment of society's ability to support individuals with low income. I consider the effect of state-level income inequality on subjective well-being responses from the General Social Survey. Applying an ordered logistic regression to observations from 1981-2018, this paper finds no significant relationship between income inequality and happiness. This is inconsistent with findings from the literature, chiefly Alesina et al., 2004 who found significant results across the full sample and in a sample segmentation of respondents with incomes greater than the median income in their state. This paper attributes the differences between the sets of results to difficulty controlling for redistribution policy, failures of the proportional odds assumption, and increasingly individualized beliefs about inequality among respondents.

Keywords: Inequality; happiness; subjective well-being

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1 Introduction

"Economic performance is not intrinsically interesting. No-one is concerned in a genuine sense about the level of gross national product last year or about next year's exchange rate. People have no innate interest in the money supply, inflation, growth, inequality, unemployment, and the rest. The stolid greyness of the business pages of our newspapers seems to mirror the fact that economic numbers matter only indirectly.

The relevance of economic performance is that it may be a means to an end. That end is not the consumption of beef burgers, nor the accumulation of television sets, nor the vanquishing of some high level of interest rates, but rather the enrichment of mankind's feeling of well-being. Economic things matter only in so far as they make people happier."

- Andrew Oswald[1]

Discussions around economic indicators often lose sight of why the economic indicator matters in the first place. These indicators serve as measures of health and happiness, or more broadly, welfare. They are tools for describing the causes behind our current level of satisfaction and for projecting our satisfaction in the future. Income, whether measured in aggregate or by individual, is a common measure of welfare. This is not so far-fetched; income enables consumption of both necessary and luxury goods. Without income, healthcare, nutrition, and leisure alike become unattainable. In developed economies, humans are conscious of this and generally orient their lives around securing income. Where a person lives and how they spend their time are often decisions determined at least in part by their plan to secure income.

Income also contains social information. A person's rank in the societal hierarchy is largely dependent on their income. This dynamic goes beyond where a person vacations or what kind of car they drive. Income brings with it community and prestige, the admiration and respect of one's peers. It has been said that who you know is what matters in this world, but if who you know is determined by your income, which matters more?

The depth of the information contained in one's earnings is not novel. The dynamics I describe are common knowledge. While the degree of consciousness may vary, the importance of income is well-instilled. This is why differences in income are so troublesome. Some having a great deal more than others, inequality, emphasizes the probability of ending up on the wrong side of the divide.

High levels of inequality can imply a high probability of a person lacking sufficient income for satisfactory levels of consumption and prestige. Increased likelihood of this scenario causes us discomfort. Whether that discomfort stems from a concern for our future selves or for someone else we care about is immaterial. This discomfort, which could be referred

[1] Oswald (1997)

to as unhappiness, reveals a desire for something different.

This paper attempts to investigate this discomfort in the United States. By providing new data to a methodology first introduced by Alberto Alesina, Rafael Di Tella, and Robert MacCulloch in 2004, I explore the impact of state-level income inequality on a person's subjective well-being. This relationship has implications for future innovations in labor policy, social safety-nets, and redistribution. Plans to reduce inequality are often met with the objection that those atop the income and wealth distributions have no incentive to participate. This paper seeks to challenge that objection through insights from subjective well-being data.

The remainder of the paper is outlined as follows. In the next section, I summarize the state of the existing literature on income inequality, subjective well-being, and the relationship between the two. In Section 3, I provide details on the sources and format of the data used for the analysis. In Sections 4 and 5 respectively, I detail my empirical strategy and present the regression estimate tables for each of the models included in that strategy. In Section 6, I discuss the implications of the results. Section 7 concludes.

2 Literature Review

Interest in inequality has spiked over the last decade since Thomas Piketty's bestselling book, *Capital in the Twenty-First Century*, brought the subject into the spotlight (2014). Prior to the mid-1980s, many developed countries had relatively stable income distributions. As a result, questions of economic inequality received less attention in mainstream economic discourse (Coyle, 2017). However, as the share of income belonging the highest-earning and wealthiest individuals has increased, particularly in the United States (Piketty and Saez, 2014), books like Piketty's and the advent of significant economic crises have led to inequality becoming one of the most widely discussed economic indicators.

The Gini index was first introduced in 1912 by Italian statistician Corrado Gini. It is the basis for the Gini coefficient, perhaps the most widely-recognized measure of inequality and the measure used in the analysis described in this paper. The Gini coefficient provides a broad view of the degree of inequality within a society by comparing the income distribution, as measured by the Lorenz curve, to that of a completely equal society (Ceriani and Verme, 2012). Some have criticized the Gini coefficient for not distinguishing between incomes from labor and incomes from other sources (like differential returns on capital) and prefer to measure inequality by the share of income or wealth attributed to the highest decile or percentile (Piketty, 2014). Simon Kuznets introduced this method for national inequality accounting in 1953 when he produced a dataset of income distributions for the United States using individual tax return data going back to 1913. Similar measures based on wealth were introduced in the 1960s and 1970s (Piketty and Saez, 2014). Since then, income data collection efforts have grown more sophisticated and systematic, allowing for the conception of more comprehensive measures of inequality.

The implications of inequality are far-reaching and heavily disputed across disciplines. The link between economic inequality and economic well-being is not immediately clear. In economic research, income has long been viewed as a proxy for well-being, (Easterlin, 1974; Sacks et al., 2010) implying that inequalities of income are thus also inequalities in well-being. This view is not without its skeptics. Mathews and Schwartz (2019) argue that income inequality may not be related to inequality of utility and heavy emphasis on resolving income inequality may not lead to a more egalitarian standard of living. Theloudis (2012) suggests economic inequalities should not be equated to inequalities of welfare without first considering household labor supply decisions.

Increasingly, subjective well-being data is being used as a measure of welfare. Surveys where respondents are asked to describe their own happiness[2] levels provide insight into the factors that directly impact welfare in the eyes of those whose view is most important. Richard Easterlin's initial work on economic growth (1974) revealed the potential for subjective well-being data to yield relevant findings for economic questions. In the half-century since, subjective well-being data has been used to investigate the impact of various economic indicators on well-being including economic growth (Easterlin, 1974; Oswald, 1997; Sacks et al., 2010), inflation (Di Tella et al., 2001, 2003; Wolfers, 2003; Blanchflower, 2007), and unemployment rates (Di Tella et al., 2001, 2003; Blanchflower, 2007).

Similarly, economists have taken increasing interest in the utility of individual characteristics as predictors of happiness. The impact of age, for example, on happiness has long been a topic of interest in the field of psychology where life satisfaction is largely believed to take on an inverted U-shape across the life cycle (Easterlin, 2006). Economists have argued the need for additional control variables which, once included, reveal a U-shape in life satisfaction across the life cycle (Clark, 2007; Blanchflower and Oswald, 2008; Lelkes, 2008). In similar fashion, economists have highlighted differences in happiness across gender (women are happier than men) (Stevenson and Wolfers, 2009), education (those with more education are happier) (Striessnig, 2015), and employment status (the unemployed are less happy) (Clark and Oswald, 1994; Theodossiou, 1998; Winkelmann and Winkelmann, 1997). Specifically in the United States, race plays a significant factor in one's happiness (black persons are less happy) (Blanchflower, 2009). Marital status and family size are also reliable predictors of happiness, with married people and those without children being happier than their counterparts (Blanchflower, 2009).

Income, as one might expect, is one of the strongest and most commonly discussed predictors of happiness. Income affects happiness through multiple channels. Higher incomes lead to higher consumption and thus directly impacts a person's happiness (Deaton, 2008;

[2] Deaton (2008) and others have argued that happiness and life-satisfaction are not equivalent. As the survey question central to this analysis refers specifically to happiness, I will be using that term to describe a person's subjective welfare.

Blanchflower, 2009). Secondly, higher incomes relative to a person's surrounding community lead to higher social status and prestige, thus affecting their happiness indirectly (Easterlin, 1995; Ferrer-i Carbonell 2005; Luttmer 2005; Clark et al. 2008; Di Tella et al. 2010). A possible third channel involves the development of expectations about the future based on information gleaned from the income distribution. Insofar as they are determined by occupation, tax and transfer policies, and overarching sentiments toward labor, incomes can communicate the values of a society. These values inform one's projection of quality of life in future periods. This paper explores this third channel by using measures of income inequality as a vehicle for the values of society.

This paper is not the first to consider this topic. Senik (2004) investigated the impact of the income distribution on subjective well-being in Russia and found that inequality indices only mattered to individuals insofar as their own position within the distribution, suggesting that the third channel I mentioned above may not be a channel at all. Alesina, Di Tella, and MacCulloch (2004) provided an alternative view; they found happiness levels were lower in periods of high inequality in both Europe and the United States. They also suggested that while high inequality is related to unhappiness in both places, the origins of that unhappiness are quite different. In Europe, inequality has a clear negative impact on the happiness of the poor and the left while the rich and those on the right experience no effect. These results are what one would expect to see if Senik (2004) were correct that income inequality only impacts happiness as a vehicle for relative income: in periods of high inequality, the poor are unhappy and the rich are indifferent. Similarly, high inequality is likely indicative of a lack of government-facilitated redistribution. Such an environment would result in lower happiness for those on the political left. Once again, this follows from intuition and is consistent with the results for Europe from Alesina et al. (2004). The evidence for the United States, however, suggests its dynamics are quite different. In the U.S., Alesina et al. found that happiness among the poor and the left is unaffected by inequality. Conversely, the rich experience a significant decrease in happiness alongside an increase in inequality. These results point to a dynamic in the U.S. where inequality and the policies associated with it are seen as proof of economic mobility, a source of hope for those on the low end of the income spectrum. Meanwhile, the rich may experience a fear of falling behind or perhaps a sense of social responsibility to improve the lives of others. In this sense, equality can be understood as a luxury good where demand rises in proportion with (or even faster than) income. The findings for the U.S. from Alesina et al. (2004) seem to point to the existence of the third channel as described above. Accordingly, their paper serves as the chief reference for this one, providing a launching point for the empirical strategy used in this analysis.

3 Data

Survey data used for this analysis is from the General Social Survey (GSS), a survey of Americans containing questions about a respondent's attitudes, opinions, and behaviors, including questions about the respondent's overall happiness. The survey is conducted by the National Opinion Research Center at the University of Chicago (NORC). For this analysis, respondents' state of residence and survey year were used to pair observations with macro-level variables describing the respondent's environment. These variables include the Consumer Price Index (CPI) and state-level unemployment rates from the United States Bureau of Labor Statistics (BLS), state-level crime data from the United States Federal Bureau of Investigation (FBI), state-level income distribution data from the American Community Survey (ACS), state-level tax data from the Tax Policy Center, minimum wage data from Kavya Vaghul and Ben Zipperer,[3] and state-level inequality data from Dr. Mark Frank at Sam Houston State University.[4] As much as possible, my treatment of the data follows that of Alesina et al. Exceptions are noted in the descriptions below. A summary can be found in Section 5.

3.1 General Social Survey

The GSS was first collected in 1972. Due to data availability challenges, Alesina et al. (2004) were forced limit their analysis to the observations between 1981 and 1996. In this analysis, I include additional, more recent GSS observations from the years the survey was collected, every other year spanning from 1998 to 2018. In total, the GSS collected 52,694 observations between 1981 and 2018. After excluding observations missing happiness responses, reliable income information, or other key demographic information, the analysis was conducted on the remaining 42,757 responses.

The NORC restricts access to the respondents' geographic information, including state of residence. I was granted access to this information after completing an application process verifying sufficient security measures to protect the identities of the survey's respondents.

Survey respondents are asked about their overall happiness in the question, *"Taken all together, how would you say things are these days–would you say that you are very happy, pretty happy, or not too happy?"* The three response options are understood to be ordered with *"very happy"* being the highest degree of happiness and *"not too happy"* the lowest. Further discussion on the ordered nature of these answers and their relationship to one another can be found in Section 6.

[3]Vaghul, Kavya and Ben Zipperer. 2022. "Historical State and Sub-state Minimum Wages." Version 1.4.0, `https://github.com/benzipperer/historicalminwage/releases/tag/v1.4.0`.

[4]Frank, Mark. W. 2014 "A New State-Level Panel of Annual Inequality Measures over the Period 1916 - 2005" Journal of Business Strategies, vol. 31, no. 1, pages 241-263, `https://profiles.shsu.edu/eco_mwf/inequality.html`

General demographic information about respondents is included with the GSS. This includes factors traditionally associated with happiness including employment status, sex, age, education level, marital status, number of children, race, and income.[5] Employment status, education level, and number of children were reformatted to more closely align with the variables used in the Alesina et al. paper. Concerning employment status, answers to the questions *"Last week were you working full time, part time, going to school, keeping house, or what?"* and *"(Are/Were) you self employed or (do/did) you work for someone else?"* were combined to make an employment status variable that distinguished between employment and self-employment. Education levels were grouped together into categories of *"no college degree," "college degree,"* and *"graduate degree."* Number of children was top-coded; all respondents with three or more children were grouped together.

Income is recorded in the GSS in ranges. Respondents are asked *"In which of these groups did your total family income, from all sources, fall last year before taxes, that is?"* The ranges provided are updated periodically to ensure they reflect reasonable ranges for the present period. During the sample period, new range definitions were offered in the years 1982, 1986, 1991, 1998, 2006, and 2016. In order to treat income as a continuous variable, midpoints for each range were used as respondent's nominal incomes. For the highest income range, for which only a lower bound is offered, I estimated a midpoint using the log-normal distribution, which has been shown to resemble income distributions, (Lubrano and Ndoye, 2016) with parameters based on the distribution of responses across the lower income ranges. I then calculated the area under the curve to the right of the lower bound on the highest range and divided that area by two. The sum of the quotient and the lower bound of the highest range provides a midpoint to use for respondent's with incomes in the highest range. All nominal incomes were deflated to 1995 dollars using inflation ratios calculated from the Consumer Price Index.

While not traditionally associated with happiness (and thus not included in this analysis as a control variable), political ideology can be expected to impact to a person's view on inequality. Accordingly, answers to the question *"Generally speaking, do you usually think of yourself as a Republican, Democrat, Independent, or what?"* are used to segment the sample. Respondents answering *"Democrat"* of any degree are categorized as *"left'* and those answering *"Republican"* of any degree are categorized as *"right."*

3.2 Median Incomes

State-level median income data from the Current Population Survey (CPS) was used to split survey respondents into categories *"rich"* and *"poor."* Respondents with nominal incomes above the state median income were categorized as *"rich."* Conversely, respondents with nominal incomes below the state median income were categorized as *"poor."* The CPS

[5] Discussion of the literature pertaining to the relationship between these factors and happiness can be found in Section 2.

Table A

	All	Unemployed	Married	Divorced
Very Happy	31.96	17.70	39.69	19.47
Pretty Happy	56.55	53.55	53.22	61.86
Not So Happy	11.48	28.74	7.08	18.66

	Left	Right	Poor	Rich
Very Happy	29.21	37.16	27.06	37.68
Pretty Happy	58.06	54.45	57.16	55.85
Not So Happy	12.73	8.39	15.78	6.48

Figures in percent.

presents the state-level median income data in 2018 dollars, so before comparison with respondents' nominal incomes, the data was re-inflated using inflation ratios calculated from the Consumer Price Index.

The earliest available state median income CPS data is from 1984, so median incomes for 1981-1983 were imputed. The estimates used for imputation were calculated by regressing state median incomes for the rest of the sample period on state unemployment rates and time dummy variables.

3.3 Macroeconomic Indicators

Data from the United States Bureau of Labor Statistics (BLS) was used to account for macroeconomic trends across time and geography. Price data from the Consumer Price Index (CPI) was used to adjust income amounts for inflation. State unemployment rates were used as a control variable in the models as a conduit for the business cycle. Unemployment has been well-documented as a predictor of happiness levels.

3.4 Crime

State crime and population data from the United States Federal Bureau of Investigation's (FBI) Crime in the U.S. series was used to control for crime in the models. The series provides the number of occurrences for various violent crimes in each U.S. state for every year in the sample period. This analysis uses two crimes, homicide and auto-theft, as indicators for the overall feeling of safety in a given state during a particular year. The number of occurrences for each crime is divided by the state population (in hundred thousands).

Table B

	Obs.	Mean	Std. Dev.	Min.	Max.
Income	42,757	37,250.46	26,834.36	303.46	113,392.90
Gini Coefficient	1,750	.5750430	.0464038	.4644108	.7199874
Unemployment Rate	1,750	.0585349	.0213456	.021	.173
Inflation	1,750	.0278504	.0132923	-.0035577	.0616061
Homicide	1,750	5.472589	3.10745	.1567398	20.34924
Motor Vehicle Thefts	1,750	335.3139	197.0071	29.51774	1116.403
Minimum Wage	1,750	4.798743	.4692614	3.893155	6.979495
State Taxes	1,750	6.451995	1.752325	2.143824	30.00985

3.5 Inequality

State-level Gini coefficients for each year of the sample period were provided by Dr. Mark Frank at Sam Houston State University.[6] These measures of inequality are calculated based on the adjusted gross income figures from tax return data provided by the United States Internal Revenue Service (IRS). These figures are before tax, a material difference between this measure on inequality and those used in prior research on this subject. (Alesina et al., 2004). Further discussion on the impacts of this difference on our results can be found in Section 4.

To mitigate the effects of this difference, I incorporated controls for taxes and transfers into the models. Two datasets from the Tax Policy Center, *State and Local Tax Revenue as a Percentage of Personal Income* and *State Percentage of State and Local Tax Revenue*, are combined to yield a single percentage representing the state tax revenue as a percentage of personal income for each state. These datasets are constructed with information from the *Survey of State and Local Government Finances*, a survey collected annually since 2004. Prior to 2004, the survey was collected every five years (1982, 1987, 1992, 1997, and 2002). Figures for the missing years were estimated by evenly distributing the change between surveys across the years in between observations. Because state tax revenue as a percentage of personal income depends heavily on factors the are known to change gradually, population and personal income, I believe this estimation to be reasonable. Annual historical minimum wage rates for each state, a representation of transfer policy, were also included in the model. Minimum wage data came from Kavya Vaghul and Ben Zipperer.[7] Together, these two variables should capture general trends in redistribution

[6]Frank, Mark. W. 2014 "A New State-Level Panel of Annual Inequality Measures over the Period 1916 - 2005" Journal of Business Strategies, vol. 31, no. 1, pages 241-263, https://profiles.shsu.edu/eco_mwf/inequality.html

[7]Vaghul, Kavya and Ben Zipperer. 2022. "Historical State and Sub-state Minimum Wages." Version 1.4.0, https://github.com/benzipperer/historicalminwage/releases/tag/v1.4.0.

policy, a factor I expect to affect our results through disapproval from more politically conservative voters and less disparities in quality of life across the income spectrum leading lower awareness of inequality from the general public. More discussion on this topic can be found in Section 4.

4 Methodology

I begin with a reproduction of the models used in Alesina et al. (2004). Due to differences in data availability, I have chosen to include results from my models for their sample period alongside their results in Table 1. A detailed summary of the differences between the data used in the original models in the Alesina et al. paper and that used in this paper can be found in Section 5.

The structure of the subjective well-being data calls for a discrete choice model. Alesina et al. 2004) chose to use ordered logistic regression. This model is described by the following equation.

$$\text{happiness}^g_{i,s,t} = \alpha^g \, \text{inequality}_{s,t} + \beta^g \, \text{MACRO}_{s,t} + \delta^g \, \text{MICRO}_i + \eta^g_s + \mu^g_t + \epsilon^g_{i,s,t}$$

where each survey respondent, i, lives in a state, s, in year, t. $\text{MACRO}_{s,t}$ is a vector of state-level factors that have been shown to affect happiness. In the base model, this vector consists of only the unemployment rate. Because all income levels, both personal and state medians, have been deflated to 1995 dollars, inflation is omitted. MICRO_i is a vector of individual-level characteristics that have been shown to affect happiness. These include employment status, sex, age, education, marital status, number of children, race, and income. Age is included alongside its square to account for curvilinear effects in the relationship between age and happiness. η_s is a vector of state-level fixed effects and μ_t is a vector of time fixed-effects. $\epsilon^g_{i,s,t}$ is an error term. The model is applied to the entire sample and a series of subsamples denoted by g. These subsamples include:

- *Left* — respondents identifying as Democrats
- *Right* — respondents identifying as Republicans
- *Poor* — respondents with nominal incomes below the median income in their state
- *Rich* — respondents with nominal incomes above the median income in their state

To control for the relative income effects discussed at length in Section 2, MICRO_i is expanded to include a dummy variable for the half of the income distribution in which the respondent falls. Further details on this variable can be found in Section 3.2.

$\text{MACRO}_{s,t}$ is expanded to include state-level violent crime, which is correlated with inequality, in a second variation of the model to control for an individual's feeling of safety, a reasonable predictor of happiness. Violent crime is measured by the number of homicides and the number of motor vehicle thefts in state, s, for year, t divided by the state population in that year in hundred thousands.

One notable difference between the measure of inequality used in Alesina et al. and this paper is the influence of taxes and transfers, the mechanism for redistribution. Alesina et al. used Gini coefficients describing *post-tax* inequality generated from combining data from the CPS and tax simulations from Wu et al. (2006) The inequality measures used for this analysis are *pre-tax* and thus independent of any state-specific redistribution policy. This distinction is important for two reasons. First, high levels of pre-tax inequality may trigger more aggressive redistribution policies which may be displeasing for the rich and those on the right. In this case, their lower happiness levels may actually be a reflection of their disapproval towards such policies and not a reflection of their sentiments towards inequality. Secondly, in states with aggressive redistribution policies (and thus a greater difference between pre-tax and post-tax inequality), the effects of inequality may not be as evident. Inequality is positively correlated with negative outcomes like homelessness and crime. Without capturing redistribution policy, an observation may have a high value for pre-tax inequality but not show the expected shift in happiness. Thus, to account for this difference, in a third variation of the model, I expanded $\text{MACRO}_{s,t}$ to include average state tax rates (taxes) and minimum wage standards (transfers). Together, these two variables should capture a state's general willingness to combat inequality through redistribution.

5 Results

5.1 Reproduction of Results from Alesina et al.: 1981-1996

I include a reproduction of the Alesina et al. (2004) results to highlight potential sources of heterogeneity in its extension to a modern sample. Results from the reproduction are shown in Table 1. Included in the table are two regressions from Alesina et al. alongside the respective reproduction from this analysis. The first model, denoted (1), is a regression of happiness on personal characteristics (MICRO_i without the *Rich*/*Poor* dummy).

Table 1: Alesina, Di Tella, and MacCulloch Models

	Alesina et al. (1)	Fitzpatrick (1)	Alesina et al.(2)	Fitzpatrick (2)
Inequality			-2.102*	2.9112
			(1.157)	(2.0688)
Unemployment Rate			-2.328*	-0.3959
			(1.360)	(1.7294)
Unemployed	-0.637**	0.5978**	-0.623**	0.5942**
	(0.106)	(0.1090)	(0.105)	(0.1091)
Self-Employed	0.049	-0.0789	0.055*	-0.0800
	(0.040)	(0.0564)	(0.039)	(0.0564)
Retired	0.011	-0.1000	0.020	-0.1029
	(0.055)	(0.0739)	(0.056)	(0.0741)
School	0.218*	-0.2363**	0.224	-0.2353**
	(0.134)	(0.1023)	(0.135)	(0.1024)
Home	-0.038	-0.0111	-0.030	-0.0124
	(0.048)	(0.0514)	(0.048)	(0.0514)
Other	-0.563**	0.4338**	-0.547**	0.4328**
	(0.107)	(0.1518)	(0.107)	(0.1520)
Male	-0.162**	0.1598**	-0.164**	0.1596**
	(0.029)	(0.0338)	(0.030)	(0.0338)
Age	-0.037**	0.0305**	-0.038**	0.0304**
	(0.007)	(0.0069)	(0.007)	(0.0069)
Age Squared	0.0005**	-0.0004**	0.0004**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
College Degree	0.144**	-0.1467**	0.143**	-0.1467**
	(0.031)	(0.0393)	(0.031)	(0.0394)
Graduate Degree	0.171**	-0.1540**	0.173**	-0.1538**
	(0.055)	(0.0648)	(0.055)	(0.0648)
Married	0.631**	-0.6156**	0.620**	-0.6144**
	(0.047)	(0.0536)	(0.049)	(0.0536)
Divorced	-0.174**	0.1934**	-0.175**	0.1941**
	(0.073)	(0.0688)	(0.073)	(0.0689)
Seperated	-0.487**	0.5294**	-0.486**	0.5292**
	(0.105)	(0.1016)	(0.105)	(0.1015)
Widowed	-0.345**	0.3130**	-0.349**	0.3131**
	(0.078)	(0.0863)	(0.078)	(0.0865)
No. of Children: 1	-0.184**	0.2154**	-0.182**	0.2146**
	(0.035)	(0.0530)	(0.035)	(0.0531)
No. of Children: 2	-0.140**	0.1773**	-0.139**	0.1768**
	(0.044)	(0.0514)	(0.045)	(0.0515)
No. of Children: 3+	-0.164**	0.2000**	-0.161**	0.1994**
	(0.049)	(0.0553)	(0.049)	(0.0552)
Income	9.9e-6**	-9.74e-6**	8.3e-6**	-9.62e-6**
	(8.7e-7)	(8.56e-7)	(9.7e-7)	(1.12e-6)
Black	-0.393**	0.4185**	-0.393**	0.4174**
	(0.049)	(0.0544)	(0.048)	(0.0544)
Rich			0.116**	-0.0085
			(0.056)	(0.0527)
Observations	19895	20627	19895	20627

[1] * denotes significance at a 10% level; ** denotes significance at a 5% level

The full base model, equal to (1) with inequality, $\text{MACRO}_{s,t}$, and the *Rich/Poor* dummy included, is denoted (2).[8]

Due to inequality data availability issues, Alesina et al. excluded 732 state-year observations. It is unclear which observations were excluded and if the data availability issue was related to the CPS or the tax simulations. The CPS data, as presently available, contains no such issues. It is possible the CPS data was incomplete at the time of the Alesina et al. paper's writing and has since been corrected. If the issues are related to the tax simulations, I avoid the challenge by using pre-tax measures of inequality. This explains the difference in sample sizes for the regressions detailed in Table 1. Due to the lack of detail provided in the Alesina et al. paper, it is presumed that the data availability issue was not systematic and the exclusion of these observations is not expected to bias the regression results.

Coefficient estimates on the personal characteristics appear very similar to those from Alesina et al. with minor differences in magnitude likely due to the difference in sample size. The largest differences come from statistically insignificant estimates on less common employment status answers (*Retired*, *Home*, *Other*) where a difference in sample size could have a great deal of impact on the estimate.

As expected, the coefficient estimate on inequality is different, potentially due to the difference in the underlying data used to capture inequality. The direction of the relationship is consistent (more inequality leads to less happiness), but the coefficient estimate from my regression is not statistically significant. The corresponding result from Alesina et al. is significant at a 10% level. A similar difference, though more extreme, can be seen in the unemployment rate. Alesina et al. shows a statistically significant negative result suggesting happiness decreases in periods of high unemployment. The estimated coefficient on the unemployment rate from my regressions is not statistically significant, suggesting potential correlation between the unemployment rate and tax and transfer policy.

5.2 Full Sample: 1981-2018

Table 2 contains regression results from the extension of the sample period to include additional survey responses from the years 1997-2018. In total, these years provide an additional 22,130 observations, yielding a final sample size of 42,757. The table includes

[8]Ordered logit is a model with three distinct parameterization methods. The method used by statistical software varies across program. It is unclear which program was used for the calculations in Alesina et al., but the parameterization method used differs from the one used in this analysis such that the sign on each of the coefficient estimates is opposite. When comparing the results from this paper to those from Alesina et al., coefficient estimate magnitudes are expected to be equal, but their signs are expected to be opposite. In the Alesina et al. results, a positive coefficient is associated with an increase in happiness and a negative coefficient is associated with a decrease in happiness. For the results from this paper, the opposite is true.

Table 2: Extended Sample Period

	(1)	(2)	(3)	(4)	(5)	(6)
Inequality		-0.0030	-0.0275	-0.0249	0.5528	0.5510
		(0.7580)	(0.7583)	(0.7584)	(0.8042)	(0.8056)
State Taxes						0.0126
						(0.0304)
Minimum Wage						-0.0103
						(0.0418)
Unemployment Rate			-0.8423	-0.8442	-0.9232	-0.9354
			(1.2079)	(1.2079)	(1.2083)	(1.2178)
Murder Rate					0.0018	0.0014
					(0.0094)	(0.0094)
Auto Theft Rate					0.0002*	0.0002*
					(0.0001)	(0.0001)
Unemployed	0.6736**	0.6736**	0.6734**	0.6731**	0.6731**	0.6733**
	(0.0737)	(0.0737)	(0.0737)	(0.0738)	(0.0738)	(0.0738)
Self-Employed	-0.0357	-0.0357	-0.0357	-0.0365	-0.0358	-0.0357
	(0.0416)	(0.0416)	(0.0416)	(0.0416)	(0.0416)	(0.0416)
Retired	-0.0435	-0.0435	-0.0436	-0.0442	-0.0446	-0.0446
	(0.0491)	(0.0491)	(0.0491)	(0.0491)	(0.0491)	(0.0491)
School	-0.2036**	-0.2036**	-0.2030**	-0.2031**	-0.2024**	-0.2024**
	(0.0717)	(0.0717)	(0.0717)	(0.0717)	(0.0716)	(0.0716)
Home	0.0706*	0.0706*	0.0707*	0.0702*	0.0702*	0.0703*
	(0.0387)	(0.0387)	(0.0387)	(0.0387)	(0.0387)	(0.0387)
Other	0.6060**	0.6060**	0.6061**	0.6051**	0.6053**	0.6052**
	(0.0936)	(0.0936)	(0.0936)	(0.0937)	(0.0936)	(0.0937)
Male	0.1362**	0.1362**	0.1363**	0.1362**	0.1362**	0.1362**
	(0.0234)	(0.0234)	(0.0234)	(0.0234)	(0.0234)	(0.0234)
Age	0.0393**	0.0393**	0.0393**	0.0394**	0.0395**	0.0395**
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Age Squared	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
College Degree	-0.1724**	-0.1724**	-0.1723**	-0.1720**	-0.1719**	-0.1720**
	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0275)
Graduate Degree	-0.1513**	-0.1513**	-0.1515**	-0.1516**	-0.1503**	-0.1504**
	(0.0431)	(0.0431)	(0.0431)	(0.0431)	(0.0431)	(0.0432)
Married	-0.7365**	-0.7365**	-0.7365**	-0.7354**	-0.7356**	-0.7356**
	(0.0374)	(0.0374)	(0.0374)	(0.0375)	(0.0375)	(0.0375)
Divorced	0.0936**	0.0936**	0.0937**	0.0937**	0.0930**	0.0930**
	(0.0458)	(0.0458)	(0.0458)	(0.0458)	(0.0458)	(0.0458)
Seperated	0.4545**	0.4545**	0.4542**	0.4541**	0.4544**	0.4543**
	(0.0756)	(0.0756)	(0.0756)	(0.0757)	(0.0757)	(0.0757)
Widowed	0.1900**	0.1900**	0.1898**	0.1903**	0.1910**	0.1912**
	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)
No. of Children: 1	0.1414**	0.1414**	0.1410**	0.1408**	0.1403**	0.1402**
	(0.0367)	(0.0367)	(0.0367)	(0.0367)	(0.0368)	(0.0368)
No. of Children: 2	0.0956**	0.0956**	0.0953**	0.0951**	0.0948**	0.0947**
	(0.0354)	(0.0354)	(0.0354)	(0.0354)	(0.0354)	(0.0354)
No. of Children: 3+	0.0864**	0.0864**	0.0863**	0.0860**	0.0857**	0.0856**
	(0.0367)	(0.0367)	(0.0367)	(0.0367)	(0.0367)	(0.0368)
Income	-9.04e-6**	-9.04e-6**	-9.04e-6**	-8.81e-6**	-8.82e-6**	-8.82e-6**
	(5.37e-7)	(5.38e-7)	(5.38e-7)	(7.38e-7)	(7.37e-7)	(7.37e-7)
Black	0.3039**	0.3039**	0.3036**	0.3034**	0.3036**	0.3039**
	(0.0374)	(0.0374)	(0.0374)	(0.0374)	(0.0374)	(0.0374)
Rich				-0.0175	-0.0168	-0.0169
				(0.0376)	(0.0376)	(0.0376)
Observations	42757	42757	42757	42757	42757	42757

[1] * denotes significance at a 10% level; ** denotes significance at a 5% level

a regression of happiness on personal characteristics, denoted (1). Column (2) contains results from the same regression when inequality is included. In each ensuing column, an additional control variable is added. These variables are the unemployment rate, the *Rich/Poor* dummy, crime, and tax and transfer policy, respectively.

The estimated coefficients on the personal characteristics are consistent with present understanding of their relationship to happiness as described by the existing literature including Alesina et al. The regressions suggest unemployment is associated with a decrease in happiness as is marital distress and having children. Education and income are both associated with increases in happiness. On average, men are less happy than women and black people are less happy than white people. These results are all statistically significant.

Unlike the results from Alesina et al., this analysis does not show any kind of substantial impact of inequality on happiness until crime is included. Even then, the results are not statistically significant. In direction, the coefficients on inequality in the models that include crime are consistent with the idea that inequality produces unhappiness. Including state tax and minimum wage policy does not appear to account for the difference between pre-tax and post-tax inequality as the change in the estimated effect of inequality is minimal.

Crime is often correlated with inequality (Di Tella and MacCulloch, 2006). These results suggest its omission from the models may be a source of endogeneity. Auto thefts appear to be associated with a small decrease in happiness. The estimated coefficient for homicides is not statistically significant.

The estimated coefficient for the unemployment rate continues to be statistically insignificant, similar to the results found during the reproduction of the Alesina et al. results. In each model in which it is included, a higher unemployment rate appears to be associated with an increase in happiness, a result in direct opposition to intuition and an extensive literature investigating the relationship. Once again, this is likely due to correlation between the unemployment rate and redistribution policy.

Table 3: Extended Sample Period

	(1)	(2)	(3)	(4)	(5)	(6)
Inequality		-0.0030	-0.0275	-0.0249	0.5528	0.5510
		(0.7580)	(0.7583)	(0.7584)	(0.8042)	(0.8056)
State Taxes						0.0126
						(0.0304)
Minimum Wage						-0.0103
						(0.0418)
Unemployment Rate			-0.8423	-0.8442	-0.9232	-0.9354
			(1.2079)	(1.2079)	(1.2083)	(1.2178)
Murder Rate					0.0018	0.0014
					(0.0094)	(0.0094)
Auto Theft Rate					0.0002*	0.0002*
					(0.0001)	(0.0001)
Unemployed	0.6736**	0.6736**	0.6734**	0.6731**	0.6731**	0.6733**
	(0.0737)	(0.0737)	(0.0737)	(0.0738)	(0.0738)	(0.0738)
Self-Employed	-0.0357	-0.0357	-0.0357	-0.0365	-0.0358	-0.0357
	(0.0416)	(0.0416)	(0.0416)	(0.0416)	(0.0416)	(0.0416)
Retired	-0.0435	-0.0435	-0.0436	-0.0442	-0.0446	-0.0446
	(0.0491)	(0.0491)	(0.0491)	(0.0491)	(0.0491)	(0.0491)
School	-0.2036**	-0.2036**	-0.2030**	-0.2031**	-0.2024**	-0.2024**
	(0.0717)	(0.0717)	(0.0717)	(0.0717)	(0.0716)	(0.0716)
Home	0.0706*	0.0706*	0.0707*	0.0702*	0.0702*	0.0703*
	(0.0387)	(0.0387)	(0.0387)	(0.0387)	(0.0387)	(0.0387)
Other	0.6060**	0.6060**	0.6061**	0.6051**	0.6053**	0.6052**
	(0.0936)	(0.0936)	(0.0936)	(0.0937)	(0.0936)	(0.0937)
Male	0.1362**	0.1362**	0.1363**	0.1362**	0.1362**	0.1362**
	(0.0234)	(0.0234)	(0.0234)	(0.0234)	(0.0234)	(0.0234)
Age	0.0393**	0.0393**	0.0393**	0.0394**	0.0395**	0.0395**
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Age Squared	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
College Degree	-0.1724**	-0.1724**	-0.1723**	-0.1720**	-0.1719**	-0.1720**
	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0275)
Graduate Degree	-0.1513**	-0.1513**	-0.1515**	-0.1516**	-0.1503**	-0.1504**
	(0.0431)	(0.0431)	(0.0431)	(0.0431)	(0.0431)	(0.0432)
Married	-0.7365**	-0.7365**	-0.7365**	-0.7354**	-0.7356**	-0.7356**
	(0.0374)	(0.0374)	(0.0374)	(0.0375)	(0.0375)	(0.0375)
Divorced	0.0936**	0.0936**	0.0937**	0.0937**	0.0930**	0.0930**
	(0.0458)	(0.0458)	(0.0458)	(0.0458)	(0.0458)	(0.0458)
Seperated	0.4545**	0.4545**	0.4542**	0.4541**	0.4544**	0.4543**
	(0.0756)	(0.0756)	(0.0756)	(0.0757)	(0.0757)	(0.0757)
Widowed	0.1900**	0.1900**	0.1898**	0.1903**	0.1910**	0.1912**
	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)
No. of Children: 1	0.1414**	0.1414**	0.1410**	0.1408**	0.1403**	0.1402**
	(0.0367)	(0.0367)	(0.0367)	(0.0367)	(0.0368)	(0.0368)
No. of Children: 2	0.0956**	0.0956**	0.0953**	0.0951**	0.0948**	0.0947**
	(0.0354)	(0.0354)	(0.0354)	(0.0354)	(0.0354)	(0.0354)
No. of Children: 3+	0.0864**	0.0864**	0.0863**	0.0860**	0.0857**	0.0856**
	(0.0367)	(0.0367)	(0.0367)	(0.0367)	(0.0367)	(0.0368)
Income	-9.04e-6**	-9.04e-6**	-9.04e-6**	-8.81e-6**	-8.82e-6**	-8.82e-6**
	(5.37e-7)	(5.38e-7)	(5.38e-7)	(7.38e-7)	(7.37e-7)	(7.37e-7)
Black	0.3039**	0.3039**	0.3036**	0.3034**	0.3036**	0.3039**
	(0.0374)	(0.0374)	(0.0374)	(0.0374)	(0.0374)	(0.0374)
Rich				-0.0175	-0.0168	-0.0169
				(0.0376)	(0.0376)	(0.0376)
Observations	42757	42757	42757	42757	42757	42757

[1] * denotes significance at a 10% level; ** denotes significance at a 5% level

5.3 Sample Segments: 1981-2018

Table 3 contains regression results for each of the sample segments, *Left*, *Right*, *Poor*, and *Rich*. These regressions include crime, but not tax and transfer policies. Results for segment regressions containing the tax and transfer policies can be found in the appendix.

No segment experiences a statistically significant change in happiness due to inequality. This is in contrast to the results from the Alesina et al. paper where they found a significant inverse relationship between inequality and happiness for those with incomes above the median. Both the *Poor* and *Left* segments are associated with a decrease in happiness due to inequality, but it is not statistically significant. This is the same result seen in the Alesina et al. paper. The results suggests the *Right* segment actually sees an increase in happiness in periods of high inequality, but the estimate is again not statistically significant. The previously observed effects of gender, education, marital status, age, race, and being unemployed persist throughout all four segments. However, having children is not associated with a statistically significant decrease in happiness for those on the right and those earning more than the median income. Income remains a significant driver of happiness in all four groups though the poor feel its impact the strongest.

The poor appear to experience a decrease in happiness in periods of high unemployment. Albeit statistically insignificant, this is a result not seen in the full sample or in any of the other segments. No segment yielded statistically significant coefficient estimates on the unemployment rate or crime rates. The *Rich/Poor* dummy was not significant for either political ideology segment.

Table 4: Sample Segments

	Left	Right	Poor	Rich
Inequality	0.9988	-0.0844	0.5140	0.2722
	(1.1983)	(1.5354)	(1.1843)	(1.2951)
Unemployment Rate	-0.2593	-1.8769	0.6187	-3.3502
	(1.8855)	(2.2232)	(1.6130)	(2.0615)
Murder Rate	0.0069	-0.0084	-0.0043	0.0062
	(0.0138)	(0.0178)	(0.0128)	(0.0168)
Auto Theft Rate	0.0001	0.0003	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Unemployed	0.5138**	0.7957**	0.5984**	0.7516**
	(0.1052)	(0.1524)	(0.0831)	(0.1765)
Self-Employed	0.0463	-0.0901	-0.0543	-0.0355
	(0.0677)	(0.0690)	(0.0671)	(0.0600)
Retired	-0.0102	-0.0721	-0.0492	-0.0405
	(0.0719)	(0.0866)	(0.0629)	(0.0865)
School	-0.1310	-0.2774**	-0.2934**	-0.0282
	(0.0986)	(0.1334)	(0.0857)	(0.1347)
Home	0.0627	-0.0127	0.0952*	-0.0471
	(0.0584)	(0.0726)	(0.0516)	(0.0669)
Other	0.5488**	0.7437**	0.5416**	0.5719**
	(0.1342)	(0.2223)	(0.1030)	(0.2452)
Male	0.1056**	0.1937**	0.1680**	0.1030**
	(0.0351)	(0.0435)	(0.0343)	(0.0373)
Age	0.0369**	0.0354**	0.0404**	0.0402**
	(0.0066)	(0.0086)	(0.0061)	(0.0089)
Age Squared	-0.0004**	-0.0004**	-0.0005**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
College Degree	-0.1758**	-0.1692**	-0.1953**	-0.1545**
	(0.0449)	(0.0466)	(0.0435)	(0.0404)
Graduate Degree	-0.2196**	-0.1299*	-0.2356**	-0.1463**
	(0.0606)	(0.0753)	(0.0857)	(0.0543)
Married	-0.6986**	-0.6552**	-0.7215**	-0.7168**
	(0.0563)	(0.0756)	(0.0513)	(0.0689)
Divorced	0.1561**	0.1832*	0.0915	0.0799
	(0.0640)	(0.0986)	(0.0558)	(0.0929)
Seperated	0.4968**	0.5587**	0.3575**	0.7386**
	(0.1031)	(0.1658)	(0.0877)	(0.1886)
Widowed	0.1902**	0.3234**	0.2368**	-0.0473
	(0.0843)	(0.1234)	(0.0719)	(0.1367)
No. of Children: 1	0.1673**	0.0770	0.2142**	0.0251
	(0.0538)	(0.0742)	(0.0510)	(0.0582)
No. of Children: 2	0.0901*	0.0573	0.1499**	0.0028
	(0.0539)	(0.0688)	(0.0523)	(0.0557)
No. of Children: 3+	0.0949*	0.0487	0.1403**	-0.0128
	(0.0555)	(0.0715)	(0.0505)	(0.0581)
Income	-7.28e-6**	-9.15e-6**	-1.25e-5**	-7.67e-6**
	(1.16e-6)	(1.27e-6)	(1.42e-6)	(9.93e-7)
Black	0.2453**	0.4670**	0.2548**	0.3258**
	(0.0477)	(0.1350)	(0.0473)	(0.0734)
Rich	-0.0686	0.0282		
	(0.0579)	(0.0676)		
Observations	20568	15133	24794	17963

[1] * denotes significance at a 10% level; ** denotes significance at a 5% level

6 Discussion

The results from the updated sample do not reaffirm the dynamics reported by Alesina et al. in their original paper. Starting with the full sample, the authors demonstrated a consistent association between inequality and decreases in happiness in the United States. In each variation of the model, the full sample showed evidence of a statistically significant inverse relationship between inequality and happiness. In this analysis, the models found statistically significant evidence of such a relationship during the Alesina et al. sample time period (1981-1996), but only when crime was included.[9] Similarly, when sample segments were evaluated, Alesina et al. found a statistically significant inverse relationship between inequality and happiness among the wealthy. When observations from 1997-2018 were added, this analysis found no strong evidence of such a relationship.

However, Alesina et al. also reported the absence of a statistically significant relationship between inequality and happiness for the poor and those on the left in the United States, a result found in this paper as well. In Alesina et al., the authors highlight the stark contrast in this area between the U.S. and Europe where the poor and the left are most bothered by the existence of inequality. While I do not find a statistically significant relationship between happiness and inequality among the poor and the left, I am not confident the results from this paper should be used as conclusive proof that the trends uncovered by Alesina et al. continue on in modern day, given the differences between my results and those of Alesina et al. in other areas of the analysis.

If the results found in this paper were accepted to be true, one could suspect the outlook on inequality in America has begun to change. Perhaps the wealthy are beginning to accept the safeguards of their resources, believing now they will never find themselves on the other end of the income spectrum. Some may be now seeing inequality as a necessary evil, a price to pay for a capitalist system that has allowed them to achieve a great deal of security. While the rich might have cared about inequality in the past, the results in this paper suggests that care has at least begun to dissipate.

Similarly, the results in this paper may point to continually diverging beliefs about inequality across the general populace. In the age of the internet, each individual decides where to receive their information. Thus, their beliefs about inequality, its existence, its causes, and its remedies are increasingly idiosyncratic. What a person believes about inequality may now have more to do with their personality than their income or their political affiliation. This dynamic could explain the lack of significant results from the full sample.

Before believing the results found in this paper and accepting that the rich no longer care about equality or that Americans are not convinced inequality is problematic, a few primary concerns from the analysis must be addressed.

[9] These results can be found in Appendix B.

First, it is evident that pre-tax inequality and post-tax inequality are not the same thing. Adequately controlling for redistribution policies, taxes, and transfers is a crucial aspect of understanding sentiments toward inequality. It is not clear that including state tax rates and minimum wage policy are an effective means for doing so. Using pre-tax measures of inequality leaves open the possibility that the happiness levels of the respondents are also impacted by the redistribution policies themselves. For example, it is possible that a conservative or wealthy person might be unhappy in times of high inequality as a result of increased taxes of which they do not approve. Alternatively, it is possible that respondents do care a great deal about inequality, but its impact on their subjective well-being is offset by a state government that sees addressing it as a priority. Pre-tax measures of inequality may also fail to capture the experienced level of inequality in a state. If a state's redistribution policy mitigates the needs among the low-income households, a wealthy person might not be aware of the degree to which inequality actually exists.

Secondly, ordered logistic regression models depend on the proportional odds assumption, the idea that each discrete choice option in the dependent variable must be evenly spaced or that moving from one option to the next is equally likely at all points along the spectrum. In this case, the assumption applies to the happiness levels of the survey respondents. Aversion toward being viewed as extreme or dramatic may incentivize respondents to answer a question about their happiness with *"Pretty happy"* instead of *"Very happy"* or *"Not too happy"*. If this were the case, the likelihood of moving from one answer to another is not consistent and the proportional odds assumption does not hold. A generalized ordered choice model will relax this assumption and may provide more reliable estimates as to the impact of inequality on happiness.

Third, the influence of personality and idiosyncrasies on sentiments toward inequality can be controlled for through individual-level fixed effects when panel data is available. The GSS released a panel data set in 2018 consisting of survey responses from the same individuals in 2006, 2008, and 2010. Using a fixed-effects model on this data set would likely provide greater insights on the impact of income inequality on happiness.

7 Conclusion

Sentiments toward inequality have heavy implications for policy makers, as any proposed redistribution requires those at the top of the income spectrum to participate. The literature, Alesina et al. (2004) in particular, suggests, in the United States, their happiness might be improved if inequality is reduced. This analysis could not confirm the same conclusion. In this paper, I applied the ordered logistic regression model introduced in Alesina et al. (2004) to an updated sample containing GSS responses from 1981-2018. The results showed no significant relationship between income inequality and subjective well-being. A reproduction of the Alesina et al. results, based on observations from 1981-1996, highlighted an important distinction between my analysis and that of Alesina et al.. In this paper, I used a pre-tax measure of income inequality. Alesina et al. used a post-tax measure, allowing for taxes and transfers to have redistributive effects. I suspect these effects make a material difference in the regression results and must be included in the model for an assessment of the relationship between inequality and happiness to be meaningful.

Additionally, this paper raises concerns about the Alesina et al. model. The structure of the subjective well-being question may entice respondents who wish not to appear extreme to offer one particular response. This casts doubt on whether the proportional odds assumption, a critical assumption for the validity of an ordered logistic regression model, will hold. A generalized logistic regression model may yield more reliable results.

Beliefs about inequality may also be growing more individualized. The introduction of individual-level fixed effects, made possible through the availability of panel data from the GSS published in 2018, is a natural continuation of the exploration of the impact of inequality on personal happiness.

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Appendices

A Cut Points

Cut points (standard errors) for the regressions included in this paper are listed below.

Table 1: -2.76 (0.14), 0.3 (0.15) for Alesina et al. (1); -0.57 (0.18), 2.5 (0.18) for Fitzpatrick (1); -3.70 (0.47), -0.63 (0.48) for Alesina et al. (2); 0.78 (1.05), 3.85 (1.05) for Fitzpatrick (2).

Table 2: -0.49 (0.13), 2.52 (0.13) for regression (1); -0.49 (0.38), 2.52 (0.38) for regression (2); -0.60 (0.41), 2.42 (0.41) for regression (3); -0.59 (0.41), 2.42 (0.41) for regression (4); -0.24 (0.46), 2.78 (0.46) for regression (5); -0.23 (0.50), 2.79 (0.50) for regression (6);

Table 3: -0.06 (0.69), 2.96 (0.69) for regression (1); -0.64 (0.85), 2.49 (0.85) for regression (2); -0.19 (0.66), 2.67 (0.66) for regression (3); -0.33 (0.76), 2.99 (0.76) for regression (4).

Table 4: -3.70 (0.47), -0.63 (0.48) for Alesina et al. (1); 1.97 (1.22), 5.05 (1.22) for Fitzpatrick (1); -3.80 (0.45), -0.73 (0.46) for Alesina et al. (2); 2.10 (1.25), 5.17 (1.25) for Fitzpatrick (2).

Table 5: -0.21 (0.76), 2.82 (0.76) for regression (1); -0.83 (0.95), 2.30 (0.95) for regression (2); 0.13 (0.72), 2.99 (0.72) for regression (3); -0.73 (0.84), 2.59 (0.84) for regression (4).

B Additional Regression Tables

Table 4 contains a comparison of regression results from Alesina et al. (2004) to results of this analysis for when taxes and minimum wage rates are included.

Table 5 contains regressions results from the 4 sample segments when taxes and minimum wage rates are included.

Table 5: Alesina, Di Tella, and MacCulloch Models (with Taxes, Transfers, and Crime)

	Alesina et al. (1)	Fitzpatrick (1)	Alesina et al.(2)	Fitzpatrick (2)
Inequality	-2.102*	3.5314*	-2.077*	3.5924*
	(1.157)	(2.0398)	(1.147)	(2.0484)
State Taxes		0.1966**		0.1905**
		(0.0653)		(0.0656)
Minimum Wage		-0.0368		-0.0354
		(0.1045)		(0.1050)
Unemployment Rate	-2.2328*	-0.8499	-2.516*	-0.9191
	(1.360)	(1.7718)	(1.472)	(1.7730)
Murder Rate			-0.009	0.0102
			(0.156)	(0.0155)
Auto Theft Rate			0.0000	0.0001
			(0.0002)	(0.0002)
Unemployed	-0.623**	0.5944**	-0.623**	0.5948**
	(0.105)	(0.1090)	(0.105)	(0.1090)
Self-Employed	0.055*	-0.0801	0.055	-0.0800
	(0.039)	(0.0565)	(0.039)	(0.0565)
Retired	0.020	-0.1011	0.021	-0.1024
	(0.056)	(0.0741)	(0.056)	(0.0740)
School	0.224	-0.2365**	0.224	-0.2383**
	(0.135)	(0.1023)	(0.135)	(0.1021)
Home	-0.030	-0.0121	-0.030	-0.0128
	(0.048)	(0.0514)	(0.048)	(0.0514)
Other	-0.547**	0.4316**	-0.547**	0.4318**
	(0.107)	(0.1519)	(0.107)	(0.1520)
Male	-0.164**	0.1608**	-0.164**	0.1609**
	(0.030)	(0.0338)	(0.030)	(0.0338)
Age	-0.038**	0.0308**	-0.038**	0.0309**
	(0.007)	(0.0069)	(0.007)	(0.0069)
Age Squared	0.0004**	-0.0004**	0.0005**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
College Degree	0.143**	-0.1473**	0.143**	-0.1474**
	(0.031)	(0.0393)	(0.031)	(0.0393)
Graduate Degree	0.173**	-0.1527**	0.173**	-0.1526**
	(0.055)	(0.0648)	(0.056)	(0.0648)
Married	0.620**	-0.6149**	0.620**	-0.6145**
	(0.049)	(0.0536)	(0.049)	(0.0536)
Divorced	-0.175**	0.1942**	-0.176**	0.1944**
	(0.073)	(0.0689)	(0.073)	(0.0689)
Seperated	-0.486**	0.5281**	-0.487**	0.5296**
	(0.105)	(0.1014)	(0.105)	(0.1015)
Widowed	-0.349**	0.3159**	-0.349**	0.3170**
	(0.078)	(0.0865)	(0.078)	(0.0865)
No. of Children: 1	-0.182**	0.2148**	-0.182**	0.2150**
	(0.035)	(0.0530)	(0.035)	(0.0530)
No. of Children: 2	-0.139**	0.1755**	-0.138**	0.1754**
	(0.045)	(0.0515)	(0.044)	(0.0515)
No. of Children: 3+	-0.161**	0.1982**	-0.161**	0.1983**
	(0.049)	(0.0552)	(0.049)	(0.0552)
Income	8.3e-6**	-9.63e-6**	8.3e-6**	-9.65e-6**
	(9.7e-7)	(1.12e-6)	(9.7e-7)	(1.12e-6)
Black	-0.393**	0.4141**	-0.393**	0.4140**
	(0.048)	(0.0545)	(0.048)	(0.0546)
Rich	0.116**	-0.0085	0.116**	-0.0080
	(0.056)	(0.0527)	(0.056)	(0.0527)
Observations	19895	20627	19895	20627

[1] * denotes significance at a 10% level; ** denotes significance at a 5% level

Table 6: Sample Segments (with Taxes and Transfers)

	Left	Right	Poor	Rich
Inequality	1.0733	-0.0267	0.3757	0.3711
	(1.2015)	(1.5339)	(1.1879)	(1.2933)
State Taxes	0.0433	-0.0148	0.0251	-0.0046
	(0.0446)	(0.0576)	(0.0447)	(0.0489)
Minimum Wage	-0.0782	-0.0278	0.0498	-0.0855
	(0.0598)	(0.0812)	(0.0605)	(0.0650)
Unemployment Rate	-0.1903	-1.7524	0.3818	-3.1595
	(1.8924)	(2.2600)	(1.6244)	(2.0729)
Murder Rate	0.0045	-0.0089	-0.0038	0.0033
	(0.0138)	(0.0178)	(0.0128)	(0.0168)
Auto Theft Rate	0.0000	0.0003	0.0003	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Unemployed	0.5143**	0.7947**	0.5990**	0.7524**
	(0.1052)	(0.1525)	(0.0831)	(0.1766)
Self-Employed	0.0460	-0.0905	-0.0543	-0.0353
	(0.0677)	(0.0690)	(0.0671)	(0.0600)
Retired	-0.0104	-0.0722	-0.0493	-0.0387
	(0.0719)	(0.0865)	(0.0629)	(0.0864)
School	-0.1313	-0.2773**	-0.2938**	-0.0276
	(0.0986)	(0.1334)	(0.0858)	(0.1348)
Home	0.0631	-0.0126	0.0948*	-0.0469
	(0.0583)	(0.0726)	(0.0517)	(0.0669)
Other	0.5480**	0.7427**	0.5433**	0.5712**
	(0.1343)	(0.2225)	(0.1029)	(0.2449)
Male	0.1057**	0.1937**	0.1683**	0.1032**
	(0.0351)	(0.0435)	(0.0343)	(0.0373)
Age	0.0368**	0.0354**	0.0405**	0.0401**
	(0.0066)	(0.0086)	(0.0061)	(0.0089)
Age Squared	-0.0004**	-0.0004**	-0.0005**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
College Degree	-0.1764**	-0.1695**	-0.1946**	-0.1548**
	(0.0449)	(0.0466)	(0.0435)	(0.0404)
Graduate Degree	-0.2191**	-0.1306*	-0.2362**	-0.1462**
	(0.0606)	(0.0754)	(0.0856)	(0.0543)
Married	-0.6964**	-0.6550**	-0.7218**	-0.7154**
	(0.0563)	(0.0757)	(0.0513)	(0.0690)
Divorced	0.1572**	0.1835*	0.0918	0.0807
	(0.0640)	(0.0986)	(0.0558)	(0.0929)
Seperated	0.4967**	0.5592**	0.3571**	0.7398**
	(0.1030)	(0.1660)	(0.0879)	(0.1882)
Widowed	0.1919**	0.3235**	0.2365**	-0.0453
	(0.0842)	(0.1235)	(0.0719)	(0.1363)
No. of Children: 1	0.1663**	0.0771	0.2146**	0.0246
	(0.0538)	(0.0742)	(0.0510)	(0.0582)
No. of Children: 2	0.0891*	0.0568	0.1506**	0.0018
	(0.0539)	(0.0688)	(0.0523)	(0.0558)
No. of Children: 3+	0.0937*	0.0486	0.1408**	-0.0145
	(0.0555)	(0.0715)	(0.0505)	(0.0581)
Income	-7.25e-6**	-9.15e-6**	-1.25e-5**	-7.66e-6**
	(1.16e-6)	(1.27e-6)	(1.42e-6)	(9.92e-7)
Black	0.2465**	0.4667**	0.2550**	0.3271**
	(0.0477)	(0.1350)	(0.0474)	(0.0736)
Rich	-0.0709	0.0280		
	(0.0579)	(0.0676)		
Observations	20568	15133	24794	17963

[1] * denotes significance at a 10% level; ** denotes significance at a 5% level