

Identifying Preferences for Equal College Access, Income, and Income Equality

AUTHORS

Bernardo Lara

Universidad de Talca

Kenneth Shores

University of Pennsylvania

ABSTRACT

Revealed preferences for equal college access may be due to beliefs that equal access increases societal income or income equality. To isolate preferences for those goods, we implement an online discrete choice experiment using social statistics generated from true variation among commuting zones. We find that, ceteris paribus, the average income that individuals are willing to sacrifice is (i) \$4,998 dollars to increase higher education (HE) enrollment by 1 standard deviation (14%); (ii) \$1,168 dollars to decrease rich/poor gaps in HE enrollment by 1 standard deviation (8%); (iii) \$2,897 to decrease the 90/10 income inequality ratio by 1 standard deviation (1.66). JEL: D31, D63, J62.

VERSION

May 2018

Suggested citation: Lara, B. & Shores, K. (2018). Identifying Preferences for Equal College Access, Income, and Income Equality (CEPA Working Paper No.18-08). Retrieved from Stanford Center for Education Policy Analysis: <http://cepa.stanford.edu/wp18-08>

Identifying Preferences for Equal College Access, Income, and Income Equality

Bernardo Lara E.^{*} and Kenneth A. Shores^{**}

^{*}School of Business and Economics, University of Talca, Santa Elena 2222, Santiago, Chile;

blara@utalca.cl.

^{**}Graduate School of Education, University of Pennsylvania, 3720 Walnut Street,

Philadelphia, PA 19104; kshores@gse.upenn.edu.

Abstract

Revealed preferences for equal college access may be due to beliefs that equal access increases societal income or income equality. To isolate preferences for those goods, we implement an online discrete choice experiment using social statistics generated from true variation among commuting zones. We find that, *ceteris paribus*, the average income that individuals are willing to sacrifice is (i) \$4,998 dollars to increase higher education (HE) enrollment by 1 standard deviation (14%); (ii) \$1,168 dollars to decrease rich/poor gaps in HE enrollment by 1 standard deviation (8%); (iii) \$2,897 to decrease the 90/10 income inequality ratio by 1 standard deviation (1.66). **JEL:** D31, D63, J62.

Keywords: college enrollment gaps, income inequality, social welfare preferences, online experiments.

1 Introduction

Consider a policy decision between allocating governmental funds to an educational intervention that increases college access for low-income students, a social security fund that increases income for low-income retirees or a tax-cut program to increase economic growth. In this example, the education intervention increases equality in college access, social security increases income equality and tax-cuts increase societal income. The policy choice, therefore, has effects on different social dimensions. Supposing the social planner knows the actual costs and effects for each of the policies, two additional pieces of information are needed to determine which of the policies should be pursued. First, we need to know how much citizens value each of the societal variables. Second, in order to make comparisons across different social variables, we need common units of measurement. With this information, it would then be possible to quantify how much societal income individuals would be willing to spend to improve each social value.

In this paper, we are concerned with individual preferences for equality of college access (a sub-component of educational opportunity), and how those preferences relate to preferences for other societal variables, including income and income equality. Traditionally, data about preferences for distributions of social variables have been collected from opinion surveys, such as the General Social Survey in the United States and the World Values Survey at the international level. Meanwhile, the academic community has focused mostly on understanding preferences for equality in income and has not, to our knowledge, considered multi-dimensional preferences for distributions of other variables, such as access to higher education (HE) ([D'Ambrosio and Clark, 2015](#)).

Information regarding individual preferences for multiple social variables is not easily obtained from traditional opinion surveys due to two sources of omitted variable bias. First, preferences for equal college access can be confounded by preferences for either efficiency or equality in income. For example, an individual who expresses an interest in improving college access for low-income students may believe that increased access

has positive spillovers on both efficiency and income equality and is *for those reasons* desirable and not desirable *per se*. Second, individuals make unobserved assumptions about the expected costs to society that a preferred distribution of opportunity or income would require. For example, respondents may prefer equal income distributions, all else constant, but because they believe that equality distorts incentives, they also expect societal costs to be large, and therefore their revealed preferences for equal income will appear attenuated (Piketty, 1995).

To recover preferences, we implement a survey experiment that identifies social preferences for equal college access, efficiency, and income equality. Survey respondents are asked to participate in a discrete choice experiment in which they select between one of two societies. For each society a respondent sees, societal variables are randomly assigned using four statistics: societal income (measured as average median family income), income inequality (measured as the 90/10 income ratio), average education (measured as the enrollment rate in HE) and opportunity for HE (measured as the difference in HE enrollment rates between children from families in the 90th and 10th income percentiles). Variation for these statistics is derived from true variation among commuting zones in the United States, using Census data and the education mobility data from the Chetty et al. (2014) project at <http://www.equality-of-opportunity.org/>. Because societal statistics are randomly assigned, we avoid biases due to beliefs about the relations among societal values. Moreover, because the level of societal income is also randomly assigned, individual beliefs about the costs of equality are no longer unobserved. With these data, we obtain measurements of how much average household income individuals are willing to sacrifice in order to improve other social values, thus providing a common metric for making comparisons across different domains.

We find that (i) individuals are willing to decrease average income by \$4,998 dollars to increase enrollment in HE by 1 standard deviation (SD) (14%); (ii) individuals are willing to exchange \$1,168 dollars of average income to decrease gaps in college

enrollment by 1 SD (8%); (iii) individuals are willing to exchange \$2,897 dollars of average income to decrease the 90/10 income inequality ratio by 1 SD (1.66); (iv) we also evaluate “Rawlsian trades”—so named because of the distributive priority Rawls gives to equality of opportunity over income equality in his theory—and find that individuals are willing to increase gaps in college access by 2.47 SDs to reduce the 90/10 income ratio by 1 SD.

Using additional collected information, we also identify differences based on political affiliation. It is well known that right-leaning voters care less about equality ([Kuziemko et al., 2015](#)). However, it is not known whether this preference is due to beliefs about societal costs or preferences for equality. Moreover, we know little about how political affiliation correlates with preferences for equality in college access and income. We find that Republicans have nearly lexicographic preferences for average income, meaning that they are unwilling to trade any units of income for equality in either dimension. Thus, Republicans are not equality averse because of perceived costs but because societal income is the most important variable in their social welfare functions. We do, however, find overlap among partisans, as both Democrats and Republicans are willing to trade meaningful quantities of average income (over \$2,900) to increase enrollment in HE by 10%. These results suggest that, between parties, there is an overlapping consensus with respect to increasing average levels of education and a large chasm with respect to equalizing educational opportunities or income.

Our primary result is that US citizens are willing to exchange meaningful amounts of average income for other social variables, including overall levels of education (which is often viewed purely as a vehicle for increasing economic growth) and reductions in inequality. Second, our results help clarify some confusion about the relation between access to HE and equality of income. When considered in isolation, individuals may indicate greater preferences for college access relative to equal income; however, our results indicate that some of this rank-ordering is attributable to omitted variable bias.

When respondents consider societal variables simultaneously, they are willing to pay over twice as much for equivalent reductions of income inequality relative to college enrollment inequality. These results suggest that if there is a public policy choice between a social security fund or an educational intervention, all else constant, the preferred policy choice would be income transfers.

The next section reviews the most relevant background literature, while section 3 provides a theoretical and empirical justification for the focus on college access. Section 4 details the experiment that was implemented. Section 5 describes the data and the econometric methodology, and section 6 provides and discusses the results.

2 Background Literature

In general, academic scholarship has focused on preferences for income equality and not equal educational opportunity (D'Ambrosio and Clark, 2015). On the topic of preferences for income equality, D'Ambrosio and Clark (2015) classify academic scholarship into two fields: comparative and normative. In the comparative case, survey respondents think of themselves as the relevant reference group and consider whether their place in a specific distribution of income is better or worse than alternative distributions. In the normative case, the relevant reference group is an ideal or normative standard; therefore, survey respondents consider whether a distribution of income is better or worse relative to the standard and not with respect to the individual's own position.

The work conducted here is most closely related to the normative case. In this branch of research there are two approaches. The first approach estimates empirical correlations between a society's level of income equality and its members' observed level of well-being. Contextual factors—such as credit constraints (Benabou, 2000); observed social mobility (Alesina, Stantcheva and Teso, 2018; Piketty, 1995) and expected social

mobility (Alesina and La Ferrara, 2005; Benabou and Ok, 2001)—can then be used to explain preferences for distributions of income. D’Ambrosio and Clark (2015) provide a summary of such research around the world, and results differ depending on the data source, country of analysis and the inequality metric used. The heterogeneity in these results is not surprising, given that different groups (e.g., socioeconomic, political) residing in different contexts have different beliefs about the relevance of income inequality (Grosfeld and Senik, 2010).

Benjamin et al. (2012) caution against the use of willingness-to-pay statistics based on assessments of subjective well-being. The reason being that respondents understate the importance of money in measures of subjective well-being relative to when they are presented with choice sets. When presented with choice sets (even hypothetical ones), respondents systematically weight income gains more highly than when they are asked whether an equivalent income gain will improve their well-being. These results suggest that forced choice experiments may be a superior way to elicit willingness-to-pay for other social variables.

The second approach uses experiments to estimate individuals’ willingness to pay for equality. To separate respondent preferences for equality from their beliefs about the costs of equality, Johansson-Stenman, Carlsson and Daruvala (2002) provide individuals with hypothetical societies for their future grandchildren and randomly set a uniform distribution of income. They find high levels of inequality aversion in their sample. Similarly, Amiel and Cowell (1999) and Pirttilä and Uusitalo (2010) use a leaky bucket experiment, which imposes a societal cost to redistribute income, and find a wide range of inequality aversion. D’Ambrosio and Clark (2015) provide an extensive overview of experimental evidence about inequality aversion.

Inequality aversion varies among political partisans. For instance, in political science and economics, there is considerable evidence that liberals and conservatives have what appear to be fundamental differences in preferences for income equality. Data

from the GSS show that Democrats are twice as likely as Republicans to favor governmental action to remedy inequality.¹ Data from the Pew Research Center show that Republicans are twice as likely as Democrats to say that a person is rich because of his or her own efforts and nearly three times as likely to say that a person is poor because of lack of effort.²

Researchers have also shown that individuals respond to information differently based on party affiliation and political ideology. [Kuziemko et al. \(2015\)](#) randomly provide accurate information about levels of inequality in the US to a sample of respondents through Amazon’s Mechanical Turk (MTurk) interface and find that this information changes how much individuals care about inequality, but does not change support for redistribution policies. They also demonstrate that liberals care more about inequality overall, and that the effect for liberals of presenting information to respondents is larger. [Alesina, Stantcheva and Teso \(2018\)](#) provide individuals with accurate information about social mobility, and find that liberal respondents increase their support for redistribution when presented pessimistic data about mobility, while conservative respondents are inelastic to information. To our knowledge, empirical research regarding variation in inequality aversion between political partisans has not addressed whether this variation is explained by beliefs about costs or preferences for equality.

Finally, [Lü \(2013\)](#) tests whether educational opportunity mediates inequality aversion. Lü operationalizes educational opportunity as the difference in the percentage of individuals in a high income district attending college versus the percentage in a low income district attending college. The relative differences in college attendance are randomly assigned, and the income differences are held constant. Respondents then report whether they believe the income differences between the two districts are too large. Lü finds that as access to HE becomes more equal, respondents are less likely to

¹NORC Issue Brief - [“Inequality: Trends in Americans’ Attitudes.”](#)

²Pew Research Center online article - [“Why people are rich and poor: Republicans and Democrats have very different views.”](#)

report that the income differences are too large (i.e., inequality aversion declines).

Our study fills two gaps in the research literature. First, we obtain estimates for how much survey respondents are willing to trade average family income for equal college access and equal income jointly. That is, respondents make decisions that require trade-offs between both average income as well as the joint distributions of equal educational opportunity and income equality. Whether individuals care about equal access to HE as means to other ends (such as income equality) or as an end in itself is not known. Our model converts preferences for these two outcomes into a common willingness-to-pay metric; we find that preferences for equal income dominate preferences for equal college access.

Second, while it is known that liberals and conservatives have different preferences for equality, it is not known whether preferences for equal access to HE or income are weighted differently by political affiliation. Moreover, in general, it is not known whether conservatives' relative indifference to inequalities in different social variables is due to beliefs about costs or preferences. We provide willingness to pay estimates for both equal access to HE and income according to political affiliation and show that Republican voters' willingness to pay for equality of income and college access is close to zero, and that preferences for equal income dominate preferences for equal college access for both Democrat and Republican voters.

3 Theory

3.1 Equal Access to Higher Education

The goal of this paper is to distinguish preferences for equal access to HE from preferences for society's overall level of income, average education, and income equality. Theoretical interest in societal income and income equality are commonplace. However, characterizing and motivating an interest in equal access to HE is worth more

attention. We operationalize equal access to HE as the relative difference in the probabilities that individuals from different parental income percentiles (the 10th and 90th percentiles) attend college. Under certain conditions, such a definition of equal access converges with the traditional notion of fair equality of opportunity articulated by Rawls in *Theory of Justice* and in political philosophy more broadly ([Arneson, 1999](#); [Brighthouse and Swift, 2008](#); [Rawls, 2001, 2009](#)). This conception of access is also widely used in empirical applications. For example, along with income mobility, [Chetty et al. \(2014\)](#) measure equality of opportunity as the probability of college attendance conditional on parental income.

Debate about whether or not public policy should promote equal college access or income equality is salient in both public policy and political philosophy. As is well known, tuition-free HE was a prominently featured populist campaign issue during the Democratic primaries of 2016. As of April, 2016, a Gallup survey of 2,024 adults found that 47% supported tuition-free HE, and less reliable polling data indicate this support has grown.³

It is well known that educational attainment is associated with increased earnings and lower unemployment. As of 2016, the unemployment rate for those with a bachelor's degree was 2.6 percent compared to 5.2 percent for those with a high school diploma. Median weekly earnings were 1.67 times higher for these same groups.⁴ A common policy proposal is to provide subsidies to low income students to increase college attendance. Summarizing the causal literature, [Dynarski \(2002\)](#) estimates that a \$1,000 subsidy increases college attendance by 4 percent. The current federal expenditures on Pell Grants is \$26.6 billion dollars.⁵ Estimates of the population costs required to close the college attendance rate gap are not easily obtained.

³See [Americans Buy Free Pre-K; Split on Tuition-Free College; Is college worth it? Americans see it as a good investment, Bankrate survey finds](#); and [Poll Finds Americans Across Party Lines Support Free College.](#), respectively.

⁴[Bureau of Labor Statistics Employment Projections.](#)

⁵[Total Pell Grant Expenditures and Number of Recipients over Time](#)

In political philosophy, the origin of the debate can be traced back to Rawls' *Theory of Justice*. In the Rawlsian schema, the two principles of distributive justice are fair equality of opportunity and the difference principle; the difference principle is lexically subordinate to the fair equality principle, meaning that the conditions of fair equality are to be satisfied before attention is paid to the difference principle. For our purposes, we can think of the difference principle as any preferred distributive principle, such as equality of income. Thus, for Rawls (2009, 2001), it is allowable to trade equality of income for educational opportunity.

Against this view, Arneson (1999, 2013) has argued that equal opportunity principles have a meritocratic bias. That is, equal opportunity principles that eliminate barriers based on social class (and other observed characteristics) leave open barriers on the basis of ability. Because discrimination on the basis of ability has no greater moral justification than discrimination on the basis of social class, equal opportunity principles need to be given either lower distributive priority or discarded. Such a concern is easily applied to HE subsidies, as those would favor the skilled. Other philosophers have offered various reasons to promote equal opportunity. Each argument has a common feature, which is to identify a benefit promoted by opportunity that is of greater value than the "consumption interest" (Taylor, 2004, p.337) promoted by distributing shares of income. For Shields (2015), the benefit is autonomy; for Shiffrin (2003), the benefit is democratic equality; and for Taylor (2004), the benefit is self-realization. Despite the ongoing disagreement among political theorists, US citizens, and policymakers, our analysis is the first to conduct an empirical test to determine whether individuals prioritize equality of access to HE or income equality.

4 Experimental Design

We now describe the design of the online experiment. We begin with a description of the survey experiment and the definitions of the different variables to be used.

4.1 Discrete Choice Experiment

We use a discrete choice experiment (DCE) to randomly assign societal values, along four dimensions, to two different hypothetical future societies.⁶ Between these two societies, respondents must decide which one is preferable.⁷ The four dimensions isolated are (1) societal income; (2) income inequality; (3) average education; and (4) equal access to HE.

The survey experiment consists of two sections. In the first, we teach respondents about the societal variables and ask diagnostic questions to ensure comprehension. Respondents are first presented with descriptive information about the four variables and asked a series of comprehension questions to determine whether they understand the data. Regardless of whether respondents answer the comprehension questions correctly, the survey tells them the correct answer.⁸

In the second section, respondents are given information about contemporary US statistics in each of these dimensions. In the discrete choice experiment, respondents are then asked to choose between two hypothetical future societies, A and B, in which

⁶We aimed to minimize the possibility of pecuniary self-interest by keeping the number of years into the future ambiguous. Nevertheless, respondents may still consider the skills and income status of their children. However, it is not clear that respondents should be fully veiled. First, what constitutes a veiled experiment is ambiguous and preferences vary by the specification (Amiel, Cowell and Gaertner, 2009). Second, there is evidence that non-veiled respondents have greater justice (or equality) concerns than veiled respondents (Herne and Suojanen, 2004; Traub et al., 2005).

⁷Discrete choice experiments are a method for studying social preferences for discrete outcomes and are widely used in different research areas (Green and Srinivasan, 1978; Louviere, 1988; Ryan and Farrar, 2000; Ryan et al., 2000; Álvarez-Farizo and Hanley, 2002; Poortinga et al., 2003; Hainmueller and Hopkins, 2014, 2015).

⁸Diagnostic questions about how income equality and equal college access are defined in the experiment were answered correctly by 79.4 and 61.2 percent of respondents, respectively. A final diagnostic question asked respondents to identify the difference between two societies in a simulation of the survey; this question was answered correctly by 71.1 percent of respondents. In Appendix A: Survey Platform, we include screen shots of the survey platform.

values for each of the four variables are randomly assigned to each society. For example, Societies A and B may both be assigned the same level of income, but Society A has high levels of income inequality while Society B has large gaps in college access. Respondents choose which bundle of randomly assigned values are optimal, according to their own welfare criteria.

Two additional features of the DCE can be highlighted. First, after respondents are presented with descriptive information and diagnostic questions, they are given four versions of the choice experiment, in which societal values are randomly assigned for each new question. Giving respondents multiple questions is more cost effective than introducing the survey to new respondents an equivalent number of times. Standard errors are therefore clustered at the respondent level. Second, to minimize primacy and recency effects, the four societal attributes were presented in a randomized order across respondents ([Hainmueller, Hopkins and Yamamoto, 2014](#)).

4.2 Social Welfare Variables Construction

As explained, respondents are presented with information about a society’s overall level of income and human capital development, as well as levels of income and equality of access to HE. The variables that are presented to survey respondents are constructed based on means and standard deviations from US commuting zones (CZ) using data made available by [Chetty et al. \(2014\)](#) from the [Equality-of-Opportunity.org](#) project. Respondents are asked to choose values that conform to different combinations of CZ-level family income per capita, income inequality, level of HE and educational mobility. Effectively, respondents are randomly assigned CZ descriptive characteristics and are asked which bundle of descriptive statistics is most desirable.

The primary statistics presented to respondents are household income per capita, the percentage of persons aged 25 and above with at least a Bachelor’s degree, the ratio of average income of the 10% richest to the 10% poorest (90/10 income inequality ratio),

and the equivalent percent of children from the 90th income percentile who attended a 4-year college program by age 21 minus the percent of children from the 10th percentile.⁹ To generate the values that will be presented to respondents, we take values for each variable at the national level and set those as mid-points. For variation, we calculate the CZ-level standard deviations using comparable statistics from [Chetty et al. \(2014\)](#) and the [Equality-of-Opportunity.org](#) project. We then add/subtract one-half and one times the respective standard deviations to the average values. Therefore, lowest values are the average minus one times the standard deviation, while highest values are the average plus one times the standard deviation, for a total of 5 values per variable. For purposes of clarification, we modify the values slightly by rounding so that they are more easily interpretable. These values constitute the final set of variables that are assigned to respondents and are shown in Table 1.¹⁰

[Insert Table 1 Here]

5 Data and Methods

5.1 Data

Data for the survey are collected using Amazon’s Mechanical Turk (MTurk) interface, with the sample drawn from persons living in the United States. Currently, MTurk is an established on-line platform that can be used to carry out social and survey experiments ([Kuziemko et al., 2015](#); [Berinsky, Huber and Lenz, 2012](#); [Horton, Rand and Zeckhauser, 2011](#); [Paolacci, Chandler and Ipeirotis, 2010](#); [Huff and Tingley, 2015](#)). For instance, [Berinsky, Huber and Lenz \(2012\)](#) show that MTurk samples are more representative than in-person convenience samples and less representative than nationally representative probability samples used by firms like YouGov. Importantly, [Berinsky, Huber](#)

⁹Additional details about these data and sources can be found in Appendix B: Variables Construction for DCE.

¹⁰Additional details about how the variables were constructed are available in Appendix B: Variables Construction for DCE.

and Lenz (2012) are able to replicate multiple attitudinal experiments previously conducted with nationally representative sampling designs using MTurk data. In addition, Kuziemko et al. (2015) find that the unweighted MTurk sample for their study was as representative of US Census data as unweighted samples from a nationally representative sample of US adults contacted by Columbia Broadcasting Company (CBS). Finally, Levay, Freese and Druckman (2016) find that differences in political attitudes between the population-based American National Election Studies and an MTurk sample can be substantially reduced once one includes controls for demographic variables.

Chandler, Mueller and Paolacci (2014) raise three concerns regarding the use of MTurk data. First, respondents may participate multiple times on the same survey; second, respondent performance on diagnostic items, such as cognitive reflection tasks, may be inflated due to conceptually related experiments; third, researchers may employ post hoc data cleaning. Our survey is designed to mitigate these threats. First, while our survey was administered in two waves, we used JavaScript to pre-screen and exit respondents if their unique WorkerID appeared in the second wave. Second, the diagnostic items we employ to ensure attention and comprehension are task-specific to the survey instrument and not generic cognitive reflection tasks. Finally, all respondents that completed the survey were included in the main analysis; no post hoc data cleaning was conducted.

The survey was posted in two waves on MTurk, January 5 and January 12 of 2017. We collected complete responses from 999 MTurk participants, at a rate of \$0.75 per response. The average time to completion was 6 minutes 52 seconds; therefore, the hourly rate was \$6.54.¹¹ Descriptive statistics for survey participants, comparable U.S.

¹¹A sample size of 999 was selected based on previous literature. While power calculations for discrete choice experimental designs are not straightforward, de Bekker-Grob et al. (2015) review 83 discrete choice experiments conducted in health care research and find that only 9 percent of them had sample sizes greater than 1,000. Orme (1998) suggests a heuristic for determining sample size of $N = 500c/(t \times a)$, where c is the maximum number of levels for any attribute (i.e., 5), t is the number of choice tasks (i.e., 4), and a is the number of alternatives (i.e., 2). The suggested number of respondents needed according to this heuristic is 313. Based on the prior literature and suggested sample size, we limited data collection to 999.

Census data for 2010, and the [Kuziemko et al. \(2015\)](#) MTurk sample (N=3,741) are shown in Table 2.

[Insert Table 2 Here]

The data in our sample is especially over-representative of whites, the young, college educated and Democrats. Our data more closely resemble the larger MTurk sampled collected by [Kuziemko et al. \(2015\)](#). In their sample, women are over-represented by the same amount men are over-represented in our data.¹² Whites comprised 78 percent of the [Kuziemko et al. \(2015\)](#) sample compared to 81 percent in our data. The average age of their respondents was 35, whereas our average age (based on the median values of the “binned” age data we collected) is 36. Meanwhile, 43 percent of their sample has at least a college degree, whereas 51 percent of our sample does. Finally, 68 percent of respondents in their sample voted for Obama, whereas 66 percent of our sample either self-identify as Democrat or voted for a Democrat in the previous election. Overall, these statistics confirm that our data are not representative but are typical of MTurk respondents.

In our main econometric specifications below, we weight the data to be representative of the joint distribution of two variables: educational attainment and political affiliation. Educational attainment is taken from the U.S. Census 2010, and political affiliation is taken from the 2010 Gallup poll.¹³ Because party affiliation is not recorded in the U.S. Census, we estimate the joint distribution of these two variables using the raking method described by [Deville, Särndal and Sautory \(1993\)](#) and implemented in [Winter \(2002\)](#). We match the MTurk sample to the population based on education and political affiliation as these two variables were the most implicated by the research questions.

¹²Our sample has more male participants than other MTurk samples that have been evaluated ([Berinsky, Huber and Lenz, 2012](#); [Huff and Tingley, 2015](#)). The samples of [Berinsky, Huber and Lenz \(2012\)](#) and [Huff and Tingley \(2015\)](#) were comprised of 40 and 47 percent male, respectively.

¹³The Gallup poll dichotomizes party affiliation by separating independents (about 38 percent of the sampled respondents) into whether the respondent leans Republican or Democrat. We dichotomize political affiliation similarly. See [Gallup Party Affiliation 2010](#).

5.2 Econometric Methods

Up to this point, we have defined and motivated interest in four statistics. We now describe our econometric models for estimating how much respondents are willing to trade for these social variables. As we are looking to estimate utility parameters, we employ choice modeling methods. We first estimate a non-parametric OLS model to obtain raw estimates of respondent preferences that represent different combinations of social welfare variables. We then model the data using a Cobb-Douglas utility function, allowing us to estimate the relevant trade-offs, which can then be represented as indifference (or iso-welfare) curves. The Cobb-Douglas model imposes additional functional form assumptions on the data; thus, the raw estimates from the OLS model provide information as to whether these assumptions are reasonable. See (Train, 2003, p.62-63) for additional discussion on the relationship between choice models and Cobb-Douglas equations.

In the non-parametric approach, we estimate the normalized level of utility as the probability that society X (independently of whether society A or society B is presented in the question) is chosen. The model includes interactions of indicator variables that correspond to combinations of societal values that a society could have. For example, five levels of average family income and college attendance gaps were randomly assigned to respondents. The interaction of these five variables results in 25 parameter estimates. The following regression model formalizes the approach:

$$\mathbb{1}_i[X \text{ is chosen}] = \sum_{j=1}^5 \sum_{k=1}^5 (\delta_{jk} \mathbb{1}_{jk..}^X) + \sum_{l=1}^5 (\rho_l \mathbb{1}_{..l.}^X) + \sum_{m=1}^5 (\sigma_m \mathbb{1}_{...m}^X) + \varepsilon_{iX} \quad (1)$$

Where $\mathbb{1}_i[X \text{ is chosen}]$ is an indicator equal to 1 if society X is chosen by individual i and 0 otherwise. Meanwhile, $\mathbb{1}_{jklm}^X$ is an indicator equal to 1 (0 otherwise) if society X has j level of income, k level of income inequality, l level of average education and m level of equal access to HE. Therefore, the coefficients δ_{jk} represent fixed effects for each

combination of income and income inequality (of which there are 25). Such fixed effect coefficients are equivalent to utility values of each combination of income/income equality. The coefficients ρ_l and σ_m capture the utility of each level of average education and equal access, respectively. In separate models, we exchange k income inequality with l average education or m equal access, which provide combinations of the interactions of income/average education and income/equal access, respectively. The final specification replaces j level of income with m equal access, which gives the trade-off between equal income and equal access to HE (i.e., “Rawlsian trades”). Finally, ε_{iX} is an individual error term related to heterogeneity in preferences for X . Because the choice sets are randomly assigned to individuals, $\mathbf{E}[\varepsilon_{iX}] = 0$ and, therefore, the OLS model (equivalent to a linear probability model) is an unbiased estimator of the normalized utility levels (Hainmueller, Hopkins and Yamamoto, 2014).

Although the econometric model (1) is flexible and provides interval-scaled estimates for different combinations of societal values, it does not allow us to estimate an indifference curve, nor does it take advantage of the actual structure of the data generation process. Therefore, our second methodological approach is the traditional choice model of McFadden (McFadden, 1980; Train and McFadden, 1978; Train, 2003). We begin by translating the societal preferences of an individual i for society A into a Cobb-Douglas utility function of the form:

$$U_i(A) = \alpha_0 + \alpha_Y \ln(Y_A) + \beta_Y \ln(Y_A^{Ineq}) + \alpha_E \ln(E_A) + \beta_E \ln(E_A^{Ineq}) + \varepsilon_{iA} \quad (2)$$

Where α_Y and α_E are coefficients corresponding to preferences for levels of income and average education, and β_Y and β_E represent the negative preference for inequality of income and educational opportunity, respectively.¹⁴ As usual, we can include a

¹⁴For the variable equal access, recall that respondents are presented with information about the difference in the percentage of children attending college who come from family incomes in the 90th and 10th percentiles. A negative coefficient on β_E indicates dis-utility for higher levels of 90/10 HE attainment, i.e. inequality of access to HE.

constant α_0 in this utility and an error ε_{iA} representing the individual heterogeneity in preferences for societies.

Recall that the survey asks individuals to choose between two societies, A and B . For society A to be chosen it must be the case that $U(A) - U(B) > 0$. Given the functional assumption, this amounts to the following equation:

$$\alpha_Y \ln \left(\frac{Y_A}{Y_B} \right) + \beta_Y \ln \left(\frac{Y_A^{Ineq}}{Y_B^{Ineq}} \right) + \alpha_E \ln \left(\frac{E_A}{E_B} \right) + \beta_E \ln \left(\frac{E_A^{Ineq}}{E_B^{Ineq}} \right) + \eta_i^{AB} > 0 \quad (3)$$

Where the error term $\eta_i^{AB} = \varepsilon_{iA} - \varepsilon_{iB}$. There are four features of equation (3) to highlight. First, if we assume that each error ε_i follows a normal distribution, then η_i^{AB} would also be normally distributed and, therefore, the parameters can be estimated by a Probit Maximum Likelihood Estimator. Second, given that each pair of societies are randomly assigned across individuals, the estimates are unconfounded by preferences for equal college access and societal income. Third, because each society has the same set of features, there is not a constant in the model and, in consequence, we do not include one in our estimation. Fourth, the Cobb-Douglas model imposes the functional form of decreasing marginal returns to each variable, and therefore the marginal rate of substitution varies in the same proportion as the ratio between social statistics and the ratio of the utility parameters of each variable.

6 Results

In this section we present results. Results from equation (2) allow us to plot the ordered preferences that respondents have for the social welfare variables, while results from equation (4) provide marginal rates of substitution (MRS) statistics. From these latter results, we can draw indifference curves. Later, we test for heterogeneous preferences based on political affiliation and educational attainment.

6.1 Non-parametric Results

We start with estimates of the preferences for each social value from equation (1). These results allow us to rank different combinations of social statistics. Figure 1 shows a contour that summarizes the interactions δ_{jl} (income and education levels), δ_{jk} (income and income inequality), δ_{jm} (income and equal access) and δ_{km} (income inequality and equal access), respectively. In each model, 25 possible estimates are available. Cells shaded darker blue indicate that an assigned combination of societal values (e.g., income \$45,000 and 90/10 income ratio 10.5) are less preferred. Cells shaded darker red indicate a stronger preference.¹⁵

[Insert Figure 1 Here]

As expected, higher income per capita, higher levels of college enrollment, lower income inequality and more equal access to HE are preferred, as indicated by the dark red shading in the upper right quadrants and dark blue shade in the lower left quadrants of each panel. These results demonstrate that respondents understood the survey and were providing preferences that were correctly ordered.

More interestingly, we can observe which social statistics appear to be more relevant to individuals. Because variables were generated based on observed standard deviations across CZs in the United States, the shaded cell regions indicate strength of preference in standard deviation units. In general, individuals are willing to trade equivalent units of income for average education (Figure 1(a)), indicated by the uniformity along the diagonal from the upper-left to the lower-right. However, for income equality (Figure 1(c)) and equal access to HE (Figure 1(b)), preferences for income often outweigh equivalent preferences (in standard deviation units) for equality (e.g., \$48,000 income and a 90/10 income ratio of 10.5 is preferred to \$36,000 income and a 90/10 income ratio of 8.8). Indeed, preferences for college access equality are nearly lexicographic, as

¹⁵A table of estimated coefficients and standard errors is shown in Appendix D: Additional Results, Tables D.1, D.2, D.3, and D.4. Results from the unweighted data are available in Appendix C: Unweighted Results, Figure C.1.

increases in estimated utility largely result from increases in societal income along the vertical axis.

Linear probability models are common estimators for discrete choice experiments, but as shown here, they have limited value if the objective is to recover the marginal rate of substitution (MRS, i.e., willingness-to-pay) and to make comparisons across variables. We now turn to results from equation (3), which provide the statistics of interest but require parametric assumptions.

6.2 Parametric Results

Having displayed how bundles are ranked, we can now move on to direct estimation of the indifference curve. We first present direct estimates from equation (3) in Panel (A) of Table 3. We display estimates from the weighted and unweighted data in columns one (Unweighted) and two (Weighted), respectively.

[Insert Table 3 Here]

As expected based on results from Figure 1, increases in income and average education have positive effects on utility, while increases in the statistics measuring inequality have negative signs. All point estimates are statistically significant at $p < .01$.

The estimates of the Cobb-Douglas parameters allow us to map the indifference curves, which are drawn using the utility levels at different points of the y-axis. These parametric results mimic the contour figures generated from the non-parametric models: average education is more relevant than income inequality, while income inequality appears more relevant than equal access to HE. These results indicate that independent improvement in income equality is preferred to equivalent (in standard deviations) independent improvement in educational equality, as shown by the fact that the indifference curve is steeper in Figure 1(c) than in Figure 1(b). Indeed, when compared directly in Figure 1(d), we see that respondents are willing to trade approximately two SD units of equal access to HE for one SD unit of income inequality.

[Insert Figure 2 Here]

Although graphical representation of the indifference curve provides much information, the figures do not give a statistic of the exact trade-offs that individuals are willing to make between social values. For that purpose, we present the estimation results of equation (3) in Panel (B) of Table 3, which are the MRS (or willingness to pay) statistics for certain social variables. As is well known, the MRS can be easily recovered from the Cobb-Douglas utility, as:

$$MRS_{x,y} = \frac{\text{Coefficient } x}{\text{Coefficient } y} \cdot \frac{y}{x} \quad (4)$$

where y is usually a variable for price but in our case is average societal income; x is a vector of the other societal variables of interest (average education and the two inequality statistics). The ratio indicates how much respondents are willing to pay in social income for values of x . In the special Rawlsian trade-off, y is set to equal access and x is equal income; this MRS statistic indicates how much respondents are willing to trade equal access for equal income.¹⁶ Therefore, if we assume that the mean values of x and y provide a reasonable approximation to estimate the MRS,¹⁷ the willingness to pay (WTP) can be expressed as the average income individuals are willing to sacrifice.¹⁸ The findings indicate that:

- Individuals would be willing to decrease average income by \$1,460 dollars to reduce the gap in HE from 54% to 44%. This implies that individuals would have a WTP of \$1,168 dollars for a 1 SD decrease in the HE enrollment gap statistic.
- Individuals would be willing to decrease average income by \$1,745 dollars to

¹⁶Under the Rawlsian schema, fair equality of opportunity is lexicographically superior to equal income, but we have already observed from Figures 1 and C.2 that respondents are not lexicographic with respect to opportunity.

¹⁷In other words, that the MRS is stable across different values of x and y ; based on the results from Figure C.2, this assumption seems reasonable.

¹⁸Standard errors for the MRS statistics are calculated using the delta method. All results in the itemized list below are statistically significant at $p < .01$.

decrease the 90/10 income inequality ratio from 9.6 to 8.6. This implies that individuals would have a WTP of \$2,897 dollars for a 1 SD decrease in the income inequality statistic.

- Individuals would be willing to decrease average income by \$3,570 dollars to increase HE enrollment from 28% to 38%. This implies that individuals would have a WTP of \$4,998 dollars for a 1 SD increase in the average education statistic.
- Individuals would be willing to increase the HE enrollment gap by 11.9% to decrease the 90/10 income ratio from 9.6 to 8.6. This implies that individuals would have a WTP of 2.47 SD of the HE enrollment gap statistic for a 1 SD decrease in income inequality.

As shown, individuals are willing to sacrifice important amounts of income in order to improve other social parameters. Indeed, educational attainment, which is often encouraged for its effects on economic growth, is *independently* supported; individuals are willing to sacrifice social income for an educated population. In that sense, economic growth should not be the sole focus of policy, and public policy decisions that require trade-offs between efficiency and other outcomes ought to be considered.

In contrast to popular narratives about the special importance of the “American Dream” and its relation to equal access to HE, our data reveal that individuals care more about income equality than equal access to HE. In traditional survey environments in which respondents are asked how much they value equal access to HE, revealed preferences may be inflated because respondents believe that reducing the gap in college access also reduces income inequality and/or increases average income. When we separate the preferences into the different parts, our results suggest that the actual worth of equal access *per se* is relatively minor, as respondents would take income and equality of income over equal access to HE. These data speak to contemporary debates about minimum wage increases and guaranteed minimum incomes on the one hand (policies

that aim to reduce income inequality at the potential cost of societal income) and free HE and remedies for the achievement gap on the other (policies that aim to increase equal access at the potential cost of societal income). We have presented evidence that can guide policy when the choice is between improving college access for low income students or delivering direct income subsidies to low income families, all else constant. Survey respondents indicate they would support the latter, if the outcomes of the policies were known to them in advance.

6.3 Robustness

Before we show the heterogeneity of results, we first wish to address two possible threats to the validity of our data. The first concern is that by asking respondents multiple questions, they may lose interest in the survey and anchor on familiar variables. The second concern is that our results do not generalize to respondents that did not comprehend the variables.

Regarding the first concern, respondents may become fatigued and begin answering the third and fourth questions by anchoring onto familiar variables, such as income. Such anchoring would bias our results by inflating the value of income. However, it may be that respondents only understood the trade-offs in place once they have responded to several questions. To test whether there are differences in respondent behavior, we estimate equation (2) two times, once including only questions one and two and again including only questions three and four. Table 4 shows the MRS estimations for both groups of questions. Note that these results will not disambiguate fatigue from learning; therefore, it is ambiguous as to whether results from questions one and two should be preferred to results from questions three and four.

Results for questions one and two are shown in column one (First two questions); results for questions three and four are shown in column two (Second two questions); and the differences in the estimated coefficients are shown in column three (First -

Second). If we believed that anchoring would result from fatigue, and if respondents are more likely to anchor on societal income, then these results provide evidence to the contrary. Aversion to income inequality is similar in absolute terms for questions three and four (the MRS for income inequality and income is -1.767 and -1.723, respectively, for the question groupings). The only statistically significant difference (at 10%) is that respondents are willing to exchange less societal income for HE enrollment (estimated MRS of 0.206 and 0.091, respectively, for the question groupings). Overall, these results do not indicate respondent fatigue is leading to bias.¹⁹

[Insert Table 4 Here]

A second concern relates to whether the respondents actually understood the survey. If respondents did not understand the societal statistics, they may anchor on familiar variables, such as income, which could attenuate estimates of the MRS. On the other hand, we cannot disambiguate whether respondents answering incorrectly failed to understand the survey or whether they have different preferences. To test for differences based on comprehension, we leverage the fact that 71 percent of respondents correctly answered the diagnostic question that asks them to make a societal comparison (available in A.4). This comparison question is most closely related to the survey design and therefore it seems reasonable to compare estimates to those 71 percent of respondents that answered correctly to those that did not. Results are displayed in Table 5.²⁰

Compared to those respondents that did not answer the diagnostic correctly, those that did answer correctly have greater aversion to income inequality (estimated MRS of -2.407 and -1.189, respectively) and inequality in access to HE (-0.242 and -0.032, respectively). In addition, respondents answering correctly are willing to trade greater income for increased HE enrollment (estimated MRS of 0.429 and 0.252, respectively).

¹⁹Coefficients taken from Equation 2 are shown in Appendix D: Additional Results, Table D.5.

²⁰In results not shown, we see no evidence that comprehension of the diagnostic question is associated with respondent level of education, political affiliation, gender, race, or age. Summary statistics based on respondent answers to this diagnostic question can be found in Appendix E: Additional Descriptive Tables, Table E.9.

In sum, respondents with lower comprehension of the survey items weighted income more heavily compared to those with greater comprehension. Whether this difference is due to anchoring bias or differences in preferences is not clear.²¹

[Insert Table 5 Here]

6.4 Heterogeneous Preferences

We now turn to whether there is heterogeneity in the social preferences identified here. We identify heterogeneous effects based on political affiliation and respondent educational attainment. Both of these attributes are relevant for the variables included here. While it is well known that right-leaning voters care less about income inequality than left-leaning voters, it is not known whether this preference is due to differences between the political groups in their beliefs about the costs of equality versus preferences for equality. Moreover, it is not known whether right-leaning voters have different preferences for access to HE than left-leaning voters.²² Educational attainment is relevant both because it correlates with individual income, and because individual educational attainment may influence how much educational inequality and overall educational attainment are valued.²³

[Insert Table 6 Here]

Results for political affiliation are presented in Table 6.²⁴ There are important differences in the egalitarian preferences across political groups. Results from Table 6

²¹Coefficients taken from Equation 2 are shown in Appendix D: Additional Results, Table D.6.

²²Our survey asked participants two questions about their political affiliation. We ask them if they self-identify as one of the major political parties (Republican, Democrat, Green, or Libertarian). We then ask them which political party for which they most recently voted. We code as “right-leaning” a respondent who self-identified as Republican or Libertarian or most recently voted for either of those parties. We code as “left-leaning” a respondent who self-identified as Democrat or Green or most recently voted for either of those parties. Identifying political affiliation this way reduces the sample from 3,996 observations to 3,592.

²³Educational attainment is coded as 0 if the respondent has a 4 year college degree or more; 1 if the respondent identified as having “some college”; 3 if the respondent has a high school diploma or less. We exclude trade and vocational schools from the analysis. This reduces the sample to 3,484 observations.

²⁴Table 6 displays the relevant MRS statistics; in Appendix D: Additional Results, Table D.7 displays model coefficients.

show that, compared to Republicans, Democrats are willing to give up nearly 3 times the amount of average income for either of the equality measures. These differences in the willingness to pay are statistically significant at $p < .01$. Democrats also have a greater WTP for average educational attainment ($p < .05$); however, the magnitude of this difference is not large. Both groups are willing to sacrifice important amounts of income (over \$2,500) to increase the average HE enrollment by 10%. This result suggests the presence of an overlapping consensus between parties with respect to increasing average levels of education; however, the parties are far apart with respect to equalizing income or educational opportunities. Finally, it is interesting to note that both groups give greater weight to income equality relative to access to HE, despite having different preferences for equalities of both kinds.

Results based on educational attainment are presented in Table 7.²⁵ Respondents with college degrees have greater WTP for reductions in income inequality than those with some college education. Conversely, those with no college experience have greater WTP for reductions in income inequality than the college educated. Thus, WTP for income equality are not monotonic according to educational attainment. Meanwhile, WTP statistics for access to HE are very similar for all educational groups. This finding is interesting because political affiliation influences preferences for both income equality and access to HE, while educational attainment (an indicator of class status) influences only preferences for income equality. If preferences for equal college access are class *insensitive*, then it may be easier to obtain political consensus for policies promoting equal access to HE, despite the fact that preferences for equal access are weaker on average. This feature of access to HE may be a second explanation (in addition to perceived spillover benefits) for its prominence in US society. Finally, college educated respondents have greater WTP for levels of college enrollment than those with no college experience, but there is no difference when compared to those with some college

²⁵Table 7 displays the relevant MRS statistics; in Appendix D: Additional Results, Table D.8 displays model coefficients.

experience.

[Insert Table 7 Here]

7 Conclusion

In this paper we have estimated social preferences for efficiency, educational attainment, income equality and equal access to HE. Not surprisingly, average income is an important aspect of respondent's social welfare functions. More interestingly, respondents are willing to exchange societal income to increase levels of educational attainment (meaning that educational attainment is not desired purely for economic reasons) as well as both aspects of equality (meaning that respondents have meaningful distributive concerns). Moreover, respondents display a stronger independent preference for income equality relative to expanding access to college. This finding contradicts the traditional notion that equal access to HE is more important than income equality in the United States. Quite possibly, college access is believed to have positive effects on economic growth and income equality; for this reason, narrowing the income gap in college attendance has large popular support, despite it having relatively low independent value.

Finally, we emphasize that the implemented DCE has useful features that can be replicated in subsequent research. First, we use true variation in income, education and inequality statistics. Second, by randomly assigning societal income, we impose a budget constraint, which provides a common metric for making comparisons across different social variables. Third, we integrate different dimensions of societal well-being into a common framework. While DCEs are prevalent in political science and some sub-disciplines of economics, they have not been used to identify the types of social preferences evaluated here. In consequence, additional research with different samples and social statistics could provide deeper understanding of social preferences

for efficiency, income equality and other variants of equality of opportunity, in addition to other social concerns.

Acknowledgements

We want to thank Randall Reback and Ilyana Kuziemko, as well as three anonymous referees, for their insightful comments. All errors are our own.

References

- Alesina, Alberto, and Eliana La Ferrara.** 2005. “Preferences for redistribution in the land of opportunities.” *Journal of public Economics*, 89(5): 897–931.
- Alesina, Alberto, Stefanie Stantcheva, and Edoardo Teso.** 2018. “Intergenerational mobility and preferences for redistribution.” *American Economic Review*, 108(2): 521–54.
- Álvarez-Farizo, Begoña, and Nick Hanley.** 2002. “Using conjoint analysis to quantify public preferences over the environmental impacts of wind farms. An example from Spain.” *Energy policy*, 30(2): 107–116.
- Amiel, Yoram, and Frank Cowell.** 1999. *Thinking about inequality: Personal judgment and income distributions*. Cambridge University Press.
- Amiel, Yoram, Frank A Cowell, and Wulf Gaertner.** 2009. “To be or not to be involved: a questionnaire-experimental view on Harsanyi’s utilitarian ethics.” *Social Choice and Welfare*, 32(2): 299–316.
- Arneson, Richard J.** 1999. “Against Rawlsian equality of opportunity.” *Philosophical Studies*, 93(1): 77–112.
- Arneson, Richard J.** 2013. “Equality of opportunity: Derivative not fundamental.” *Journal of Social Philosophy*, 44(4): 316–330.
- Benabou, Roland.** 2000. “Unequal societies: Income distribution and the social contract.” *American Economic Review*, 96–129.

- Benabou, Roland, and Efe A Ok.** 2001. "Social mobility and the demand for redistribution: the POUM hypothesis." *The Quarterly Journal of Economics*, 116(2): 447–487.
- Benjamin, Daniel J, Ori Heffetz, Miles S Kimball, and Alex Rees-Jones.** 2012. "What do you think would make you happier? What do you think you would choose?" *American Economic Review*, 102(5): 2083–2110.
- Berinsky, Adam J, Gregory A Huber, and Gabriel S Lenz.** 2012. "Evaluating online labor markets for experimental research: Amazon. com's Mechanical Turk." *Political Analysis*, 20(3): 351–368.
- Brighouse, Harry, and Adam Swift.** 2008. "Putting educational equality in its place." *Education*, 3(4): 444–466.
- Chandler, Jesse, Pam Mueller, and Gabriele Paolacci.** 2014. "Nonnaïveté among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers." *Behavior research methods*, 46(1): 112–130.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner.** 2014. "Is the United States still a land of opportunity? Recent trends in intergenerational mobility." *The American Economic Review*, 104(5): 141–147.
- D'Ambrosio, Conchita, and Andrew E Clark.** 2015. "Attitudes to Income Inequality: Experimental and Survey Evidence." *Handbook of Income Distribution*, 1147–1208.
- de Bekker-Grob, Esther W, Bas Donkers, Marcel F Jonker, and Elly A Stolk.** 2015. "Sample size requirements for discrete-choice experiments in healthcare: a practical guide." *The Patient-Patient-Centered Outcomes Research*, 8(5): 373–384.

- Deville, Jean-Claude, Carl-Erik Särndal, and Olivier Sautory.** 1993. “Generalized raking procedures in survey sampling.” *Journal of the American statistical Association*, 88(423): 1013–1020.
- Dynarski, Susan.** 2002. “The behavioral and distributional implications of aid for college.” *American Economic Review*, 92(2): 279–285.
- Green, Paul E, and Venkatachary Srinivasan.** 1978. “Conjoint analysis in consumer research: issues and outlook.” *Journal of Consumer Research*, 5(2): 103–123.
- Grosfeld, Irena, and Claudia Senik.** 2010. “The emerging aversion to inequality.” *Economics of Transition*, 18(1): 1–26.
- Hainmueller, Jens, and Daniel J Hopkins.** 2014. “Public attitudes toward immigration.” *Annual Review of Political Science*, 17: 225–249.
- Hainmueller, Jens, and Daniel J Hopkins.** 2015. “The hidden American immigration consensus: A conjoint analysis of attitudes toward immigrants.” *American Journal of Political Science*, 59(3): 529–548.
- Hainmueller, Jens, Daniel J Hopkins, and Teppei Yamamoto.** 2014. “Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments.” *Political Analysis*, 22(1): 1–30.
- Herne, Kaisa, and Maria Suojanen.** 2004. “The role of information in choices over income distributions.” *Journal of Conflict Resolution*, 48(2): 173–193.
- Horton, John J, David G Rand, and Richard J Zeckhauser.** 2011. “The online laboratory: Conducting experiments in a real labor market.” *Experimental economics*, 14(3): 399–425.

- Huff, Connor, and Dustin Tingley.** 2015. ““Who are these people?” Evaluating the demographic characteristics and political preferences of MTurk survey respondents.” *Research & Politics*, 2(3): 2053168015604648.
- Johansson-Stenman, Olof, Fredrik Carlsson, and Dinky Daruvala.** 2002. “Measuring Future Grandparents’ Preferences for Equality and Relative Standing.” *Economic Journal*, 362–383.
- Kuziemko, Ilyana, Michael I Norton, Emmanuel Saez, and Stefanie Stantcheva.** 2015. “How elastic are preferences for redistribution? Evidence from randomized survey experiments.” *The American Economic Review*, 105(4): 1478–1508.
- Levay, Kevin E, Jeremy Freese, and James N Druckman.** 2016. “The demographic and political composition of Mechanical Turk samples.” *Sage Open*, 6(1): 2158244016636433.
- Louviere, Jordan J.** 1988. “Conjoint analysis modelling of stated preferences: a review of theory, methods, recent developments and external validity.” *Journal of Transport Economics and Policy*, 93–119.
- Lü, Xiaobo.** 2013. “Equality of Educational Opportunity and Attitudes toward Income Inequality: Evidence from China.” *Quarterly Journal of Political Science*, 8: 271–303.
- McFadden, Daniel.** 1980. “Econometric models for probabilistic choice among products.” *Journal of Business*, S13–S29.
- Orme, Bryan.** 1998. “Sample size issues for conjoint analysis studies.” *Sawthooth Software Research paper Series Squim, WA, USA: Sawthooth Software Inc.*
- Paolacci, Gabriele, Jesse Chandler, and Panagiotis G Ipeirotis.** 2010. “Running experiments on amazon mechanical turk.”

- Piketty, Thomas.** 1995. "Social mobility and redistributive politics." *The Quarterly journal of economics*, 110(3): 551–584.
- Pirttilä, Jukka, and Roope Uusitalo.** 2010. "A 'leaky bucket' in the real world: estimating inequality aversion using survey data." *Economica*, 77(305): 60–76.
- Poortinga, Wouter, Linda Steg, Charles Vlek, and Gerwin Wiersma.** 2003. "Household preferences for energy-saving measures: A conjoint analysis." *Journal of Economic Psychology*, 24(1): 49–64.
- Rawls, John.** 2001. *Justice as fairness: A restatement*. Harvard University Press.
- Rawls, John.** 2009. *A theory of justice*. Harvard university press.
- Ryan, Mandy, and Shelley Farrar.** 2000. "Using conjoint analysis to elicit preferences for health care." *BMJ: British Medical Journal*, 320(7248): 1530.
- Ryan, Mandy, DA Scott, C Reeves, A Bate, ER Van Teijlingen, EM Russell, M Napper, and CM Robb.** 2000. "Eliciting public preferences for healthcare: a systematic review of techniques."
- Shields, Liam.** 2015. "From Rawlsian autonomy to sufficient opportunity in education." *Politics, Philosophy & Economics*, 14(1): 53–66.
- Shiffrin, Seana Valentine.** 2003. "Race, labor, and the fair equality of opportunity principle." *Fordham L. Rev.*, 72: 1643.
- Taylor, Robert S.** 2004. "Self-realization and the priority of fair equality of opportunity." *Journal of Moral Philosophy*, 1(3): 333–347.
- Train, Kenneth.** 2003. *Discrete choice methods with simulation*. Cambridge university press.

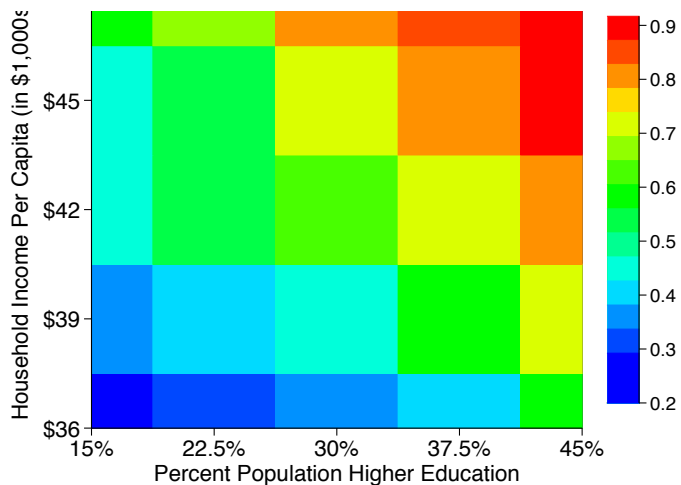
Train, Kenneth, and Daniel McFadden. 1978. “The goods/leisure tradeoff and disaggregate work trip mode choice models.” *Transportation research*, 12(5): 349–353.

Traub, Stefan, Christian Seidl, Ulrich Schmidt, and Maria Vittoria Levati. 2005. “Friedman, Harsanyi, Rawls, Boulding—or somebody else? An experimental investigation of distributive justice.” *Social Choice and Welfare*, 24(2): 283–309.

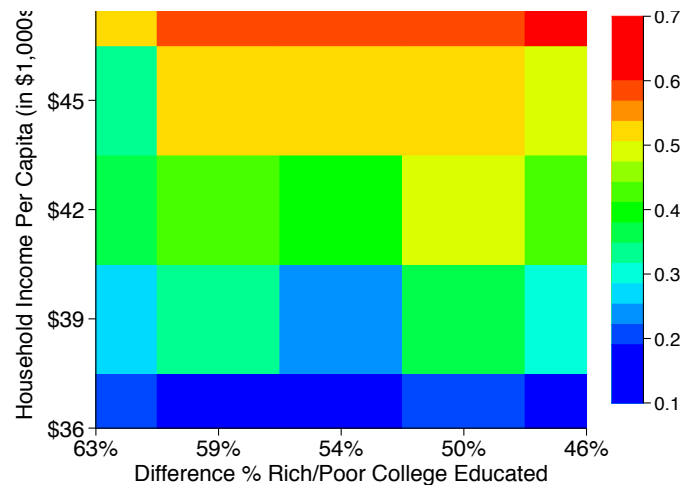
Winter, Nick. 2002. “SURVWGT: Stata module to create and manipulate survey weights.” *Statistical Software Components, Boston College Department of Economics*.

Figures

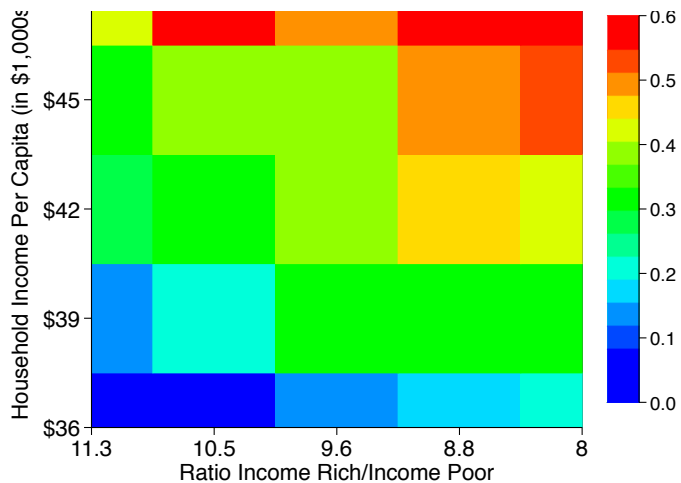
Figure 1: Nonparametric Estimates Social Welfare Preferences, Contour Plots, Weighted Sample



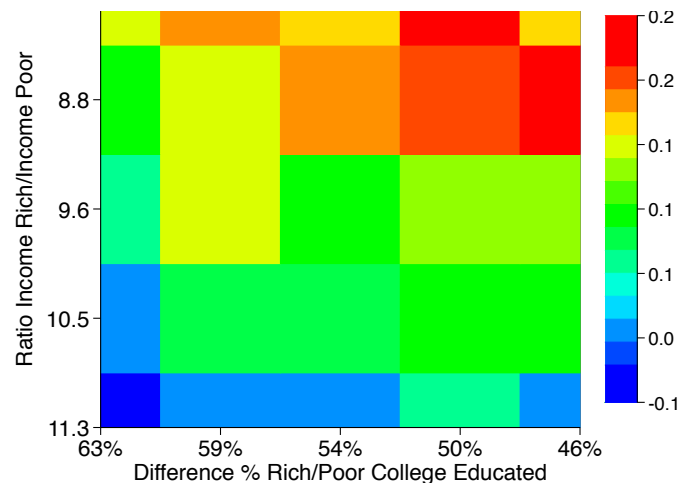
(a) Income/Higher Education



(b) Income/Inequality Higher Education



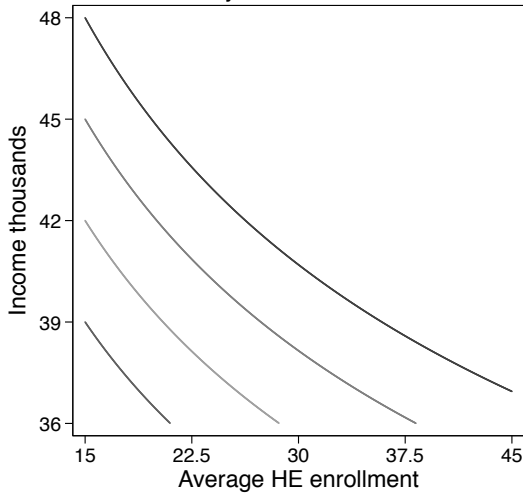
(c) Income/Inequality Income



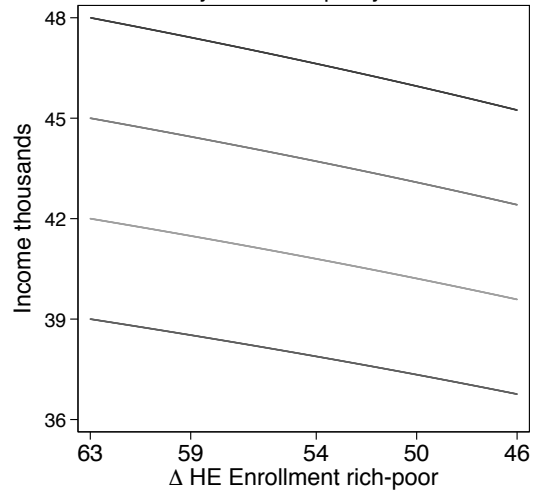
(d) Inequality Income/Inequality Higher Education

Note: Each panel represents a pairwise trade among social variables. Shaded cell regions indicate strength of preference in standard deviation units for pairwise combinations of social variables. Darker red indicates greater utility; darker blue indicates less utility. Utility estimates based on Equation (1). Point estimates and standard errors shown in Appendix D: Additional Results, Tables D.1, D.2, D.3, and D.4.

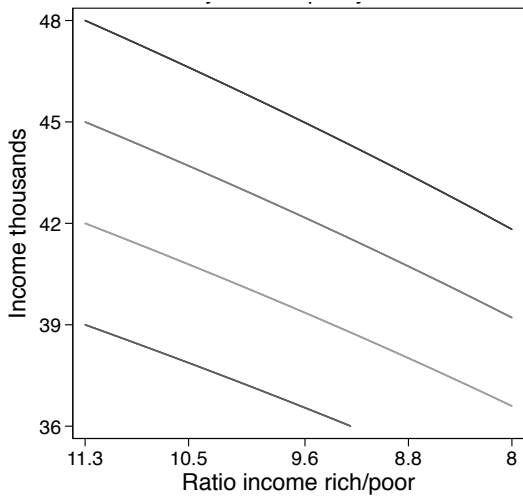
Figure 2: Log Linear Estimates Social Welfare Preferences, Indifference Curves



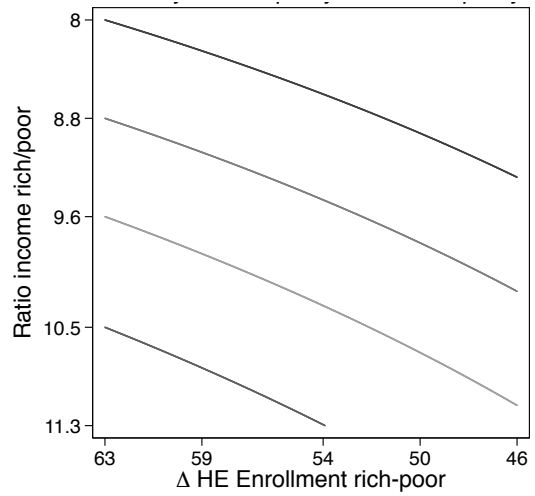
(a) Income/Higher Education



(b) Income/Inequality Higher Education



(c) Income/Inequality Income



(d) Inequality Income/Inequality Higher Education

Note: Each panel represents a pairwise trade among societal variables. Indifference curves derived from estimates from Equation (3).

Tables

Table 1: Discrete Choice Experiment, Randomization Values Actual

Variable	Mean - 1 SD	Mean - $\frac{1}{2}$ SD	Mean	Mean + $\frac{1}{2}$ SD	Mean + 1 SD
Income Per Capita	\$36,000	\$39,000	\$42,000	\$45,000	\$48,000
Inequality Income	8	8.8	9.6	10.5	11.3
Percent College Educated	14%	21%	28%	35%	42%
Inequality Higher Education	46%	50%	54%	59%	63%

Note: Descriptive statistics for the four societal variables randomly assigned to respondents. All values taken from [Chetty et al. \(2014\)](#) from the [Equality-of-Opportunity.org](#) project. Mean corresponds to national mean and variation is based on the estimated between-commuting zone standard deviation.

Table 2: Descriptive Statistics (i) Analytic MTurk sample, (ii) 2010 US Census, and (iii) [Kuziemko et al. \(2015\)](#)

Variable	<i>MTurk Sample</i>		<i>2010 US Census</i>	<i>Kuziemko et al. (2015)</i>
	Freq.	Percent.	Percent.	Percent.
<i>Gender</i>				
Female	420	42.17	50.8	57.2
Male	576	57.83	49.2	42.8
<i>Race/Ethnicity</i>				
Black	72	7.24	12.6	7.8
Other	123	12.37	17.7	7.6
White	799	80.38	63.7	77.8
<i>Age</i>				
18-29	358	35.87	13.0 (18 to 24)	35.41 (sample mean)
30-44	445	44.59	35.0 (25 to 44)	
45-64	164	16.43	34.8 (45 to 64)	
65 or older	31	3.11	17.1 (65 plus)	
<i>Educational Attainment</i>				
Associate's or two-year college degree	95	9.52	5.52	43.3 (at least college)
Did not finish high school	5	0.5	11.6	
Four-year college degree	384	38.47	19.49	
Graduate or professional degree	121	12.12	11.19	
High school diploma or equivalent	109	10.92	28.95	
Some college, no degree	252	25.25	19.1	
Technical or vocational school after HS	32	3.21	4.04	
<i>Lib/Dem</i>				
Democrat	592	59.3	44.8	67.5
Republican	306	30.6	44.3	

This table compares descriptive statistics for the analytic MTurk sample, the 2010 US Census, and the larger MTurk sample obtained in [Kuziemko et al. \(2015\)](#). Statistics on political affiliation are taken from [Gallup Party Affiliation 2010](#).

Table 3: Cobb Douglas Results, Main Effects & Marginal Rate of Substitution

<i>Panel A: Probit Coefficient Estimates</i>		
	Unweighted	Weighted
$\Delta \ln(\text{Income})$	4.280*** (0.206)	4.332*** (0.261)
$\Delta \ln(\text{Inequality Inc.})$	-1.943*** (0.159)	-1.728*** (0.205)
$\Delta \ln(\text{Educ.})$	1.061*** (0.056)	1.032*** (0.064)
$\Delta \ln(\text{Inequality HE})$	-0.968*** (0.157)	-0.815*** (0.197)
<i>Panel B: Marginal Rate of Substitution</i>		
$MRS_{\text{Inequality Inc.,Income}}$	-1.986*** (0.170)	-1.745*** (0.217)
$MRS_{\text{Inequality HE,Income}}$	-0.176*** (0.029)	-0.146*** (0.035)
$MRS_{\text{Avg. HE enrollment,Income}}$	0.372*** (0.022)	0.357*** (0.026)
$MRS_{\text{Inequality Inc.,Inequality HE}}$	11.294*** (1.910)	11.924*** (2.984)
N	3996	3996

Note: Standard errors clustered by respondent in parentheses. MRS measured at the mean values. Probit coefficients based on Equation (3). MRS estimates based on Equation (4). Weighted estimates based on joint distributions of adult education and political affiliation using raking method of Deville, Särndal and Sautory (1993) and implemented by Winter (2002). *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Robustness: Marginal Rate of Substitution, Question Order**

Parameter	First two questions	Second two questions	First - Second
$MRS_{\text{Inequality Inc.,Income}}$	-1.767*** (0.281)	-1.723*** (0.274)	0.043 (0.348)
$MRS_{\text{Inequality HE,Income}}$	-0.206*** (0.051)	-0.091** (0.044)	0.116* (0.063)
$MRS_{\text{Avg. HE enrollment,Income}}$	0.344*** (0.033)	0.368*** (0.036)	0.024 (0.046)
$MRS_{\text{Inequality Inc.,Inequality HE}}$	8.558*** (2.212)	19.036** (9.395)	10.479 (9.336)
N	1998	1998	3996

Note: Standard errors clustered by respondent in parentheses. MRS measured at the mean values. Probit coefficients based on Equation (3) shown in Appendix D: Additional Results, Table D.5. MRS estimates based on Equation (4). Standard errors for tests of significance between question groupings calculated using the delta method. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Robustness: Marginal Rate of Substitution, Respondent Comprehension**

Parameter	Correct answer	Incorrect answer	Correct - Incorrect
$MRS_{\text{Inequality Inc.,Income}}$	-2.407*** (0.215)	-1.189*** (0.256)	1.217*** (0.334)
$MRS_{\text{Inequality HE,Income}}$	-0.242*** (0.036)	-0.032 (0.045)	0.210*** (0.058)
$MRS_{\text{Avg. HE enrollment,Income}}$	0.429*** (0.029)	0.252*** (0.030)	-0.178*** (0.042)
$MRS_{\text{Inequality Inc.,Inequality HE}}$	9.955*** (1.563)	37.170 (52.080)	27.215 (52.103)
N	2840	1156	3996

Note: Standard errors clustered by respondent in parentheses. MRS measured at the mean values. Probit coefficients based on Equation (3) shown in Appendix D: Additional Results, Table D.6. MRS estimates based on Equation (4). Standard errors for tests of significance between respondents' comprehension calculated using the delta method. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Marginal Rate of Substitution, Respondent Political Affiliation

Parameter	Democrats	Republicans	Dem - Repub
$MRS_{\text{Inequality Inc.,Income}}$	-2.575*** (0.243)	-0.893*** (0.252)	-1.683*** (0.350)
$MRS_{\text{Inequality HE,Income}}$	-0.237*** (0.040)	-0.082* (0.046)	-0.154** (0.061)
$MRS_{\text{Avg. HE enrollment,Income}}$	0.407*** (0.031)	0.294*** (0.032)	0.113** (0.045)
$MRS_{\text{Inequality Inc.,Inequality HE}}$	10.888*** (1.858)	10.830* (6.327)	0.058 (6.594)
N	2,368	1,224	3,592

Note: Standard errors clustered by respondent in parentheses. MRS measured at the mean values. Probit coefficients based on Equation (3) shown in Appendix D: Additional Results, Table D.7. MRS estimates based on Equation (4). Standard errors for tests of significance among partisans calculated using the delta method. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Marginal Rate of Substitution, Respondent Level of Education**

Parameter	College or More	Some College	Less than College	College - Some	College - Less
$MRS_{\text{Inequality Inc.,Income}}$	-1.968*** (0.225)	-2.921*** (0.450)	-1.090*** (0.397)	0.952* (0.503)	-0.878* (0.457)
$MRS_{\text{Inequality HE,Income}}$	-0.194*** (0.038)	-0.209*** (0.072)	-0.206*** (0.068)	0.015 (0.081)	0.012 (0.078)
$MRS_{\text{Avg. HE enrollment,Income}}$	0.392*** (0.030)	0.394*** (0.055)	0.211*** (0.034)	-0.002 (0.063)	0.181*** (0.046)
$MRS_{\text{Inequality Inc.,Inequality HE}}$	10.150*** (2.086)	13.991*** (4.696)	5.280** (2.413)	-3.841 (5.138)	4.870 (3.189)
N	2,020	1,008	456	3,028	2,476

Note: Standard errors clustered by respondent in parentheses. MRS measured at the mean values. Probit coefficients based on Equation (3) shown in Appendix D: Additional Results, Table D.8. MRS estimates based on Equation (4). Standard errors for tests of significance among educational level calculated using the delta method. *** p<0.01, ** p<0.05, * p<0.1.

A Appendix: Survey Platform

Figure A.1: Survey Platform: Variables Description

In this study, we want to understand your preferences for different social values. In particular, we want to study preferences for income and education. To better understand your preferences, we show you some information about the United States economy and then we ask you what you would change about the economy.

The economic information includes **levels** of income and educational attainment and **inequalities** of income and educational attainment. We will use the words “rich” and “poor” to mean persons who are in the top 90th income percentile (the richest 10% of people) and persons who are in the bottom 10th income percentile (the poorest 10% of people).

1. Levels of income is measured as the amount of income in the average household.

2. Inequality in income is measured as the amount of money the richest 10% of individuals have divided by the amount of money the poorest 10% of persons have. A value of 1 would mean there is income equality.

3. Level of education is measured as the percent of the population with a Bachelor's degree or more.

4. Inequality in education is measured as the percentage of kids from the richest 10% of families who earn a Bachelor's degree minus the percentage of kids from the poorest 10% of families who earned a Bachelor's degree. A value of zero would mean there is no education inequality.

We want to see if you understand these values. Please answer the following questions.

Figure A.2: Survey Platform: Diagnostic Question, Inequality Income

In this survey, what is meant by "rich" and "poor" persons?

- Persons who are in the top and bottom 20th income percentile
- Persons who are in the top and bottom 1st income percentile
- The top 1 percent and the bottom 99 percent
- Persons who are in the top and bottom 10th income percentile

Figure A.3: Survey Platform: Diagnostic Question, Inequality HE

If 80% of kids from rich families earn a Bachelor's degree and 40% of kids from poor families earn a Bachelor's degree, what is the education inequality in the society? (using the measure described above)

- 2
- 40%
- 1/2
- 0%
- 200%

Figure A.4: Survey Platform: Diagnostic Question, Societal Comparison

Now compare between Countries A and B.

	Country A	Country B
Level of Income	\$42,354	\$45,230
Income Inequality	9.6	10.5
Level of Education	28%	21%
Education Inequality	54%	50%

Which of the following statements is true?

- Country B is richer but Country A has more income inequality.
- Country A has more educated people but Country B has less education inequality.
- Country B has more income inequality but Country A is richer.

Figure A.5: Survey Platform: Societal Preferences

Here are U.S. statistics for 2010.

Level of Income	\$42,354	The average household in the US makes about \$42,000 per year
Income Inequality	9.6	The income of the rich is 9.6 times higher than the income of the poor.
Level of Education	28%	28 percent of the population has a Bachelor's degree or higher
Education Inequality	54%	On average, people from rich families go to college 54% more than people from poor families.

Please indicate which of the following future society would be better, all things considered.

Question 1

Please carefully review the options detailed below, then please answer the questions.

Which of these choices do you prefer?

	Society 1	Society 2
Income Levels	Average household has \$48,000	Average household has \$48,000
Income Inequality	Average income of the rich is 11.3 times higher than average income of the poor	Average income of the rich is 8.0 times higher than average income of the poor
Education Levels	21% of people have at least a college education	35% of people have at least a college education
Education Inequality	On average, kids from rich families go to college 59% more than kids who come from poor families	On average, kids from rich families go to college 50% more than kids who come from poor families

Which of these societies would be better, all things considered?

Society 1

Society 2

B Appendix: Variables Construction for DCE

The variables that are presented to survey respondents are constructed based on means and standard deviations from US commuting zones (CZ) using data made available by Chetty et al. (2014) from the [Equality-of-Opportunity.org](https://equalityofopportunity.org) project. We ask respondents to choose values that conform to different combinations of CZ-level family income per capita, income inequality, level of HE and educational mobility. Effectively, respondents are randomly assigned CZ descriptive characteristics and are asked which bundle of descriptive statistics is most desirable.

Our goal in constructing these variables is two-fold: plausibility and interpretability. We generate the variables based on actual averages corresponding to contemporary United States economic conditions, using national averages and variation between CZs to provide plausible regional descriptions.

Variable means are defined as follows. For average income, we use aggregate household income per capita, which is the total household income in the United States divided by the total number of persons in the United States ages 18-65, for Census survey years 2006-2010.²⁶ Income inequality is the income of the 90th percentile divided by the income of the 10th percentile in the United States, for year 2010.²⁷ Percent college educated is the percent of the population with a Bachelor’s degree or more in year 2010.²⁸ Education inequality is the percent of children from the 90th income percentile who attend a 4-year college program by age 18-21 minus the percent of children from the 10th income percentile who attend a 4-year college program by age 18-21.²⁹

Variable standard deviations are defined as follows. Household income per capita is taken from the Chetty data, which is defined as aggregate household income in the

²⁶Aggregate household income and counts of persons by age are downloaded from the National Center for Education Statistics <https://nces.ed.gov/programs/edge/>.

²⁷Downloaded from [Equality of Opportunity](https://equalityofopportunity.org) project. See Online Data Table 2, Parent Family Income Column, centile 90 divided by centile 10.

²⁸Downloaded from the [Census webpage](https://census.gov).

²⁹Downloaded from [Equality of Opportunity](https://equalityofopportunity.org) project. See Online Data Table 10, Sheet “By Parent Income Percentile,” Column College, centile 90 minus centile 10.

2000 census divided by the number of people aged 16-64. These data are available for every CZ in the United States and the standard deviation is the unweighted between-CZ standard deviation. Income inequality is defined as the 90/10 income ratio for each CZ using the Chetty data, and the standard deviation is the unweighted between-CZ standard deviation.³⁰ The percent of college educated by CZ, net of income, is taken from the Chetty data, which is defined as the residual from a linear regression of graduation rate (defined as the share of undergraduate students that complete their degree within 1.5 times the program duration) on household income per capita in 2000. Variation is defined as the unweighted between-CZ standard deviation.³¹ The rich/poor difference in college education is taken from the Chetty data, where the difference for each CZ is calculated using the relative mobility measure to predict college attendance. Percentages of children attending college at the 10th and 90th percentiles are calculated for each CZ; we then take the p90-p10 difference and calculate the unweighted between-CZ standard deviation.³² Means and standard deviations are shown in Table B.1.

Table B.1: Discrete Choice Experiment, Randomization Values Descriptives

Variable	Mean	Std. Deviation
Household Income Per Capita	42,354.24	5,750.70
90/10 Income Ratio	9.63	1.66
Percent College Educated	0.28	0.14
Education Inequality	0.54	0.08

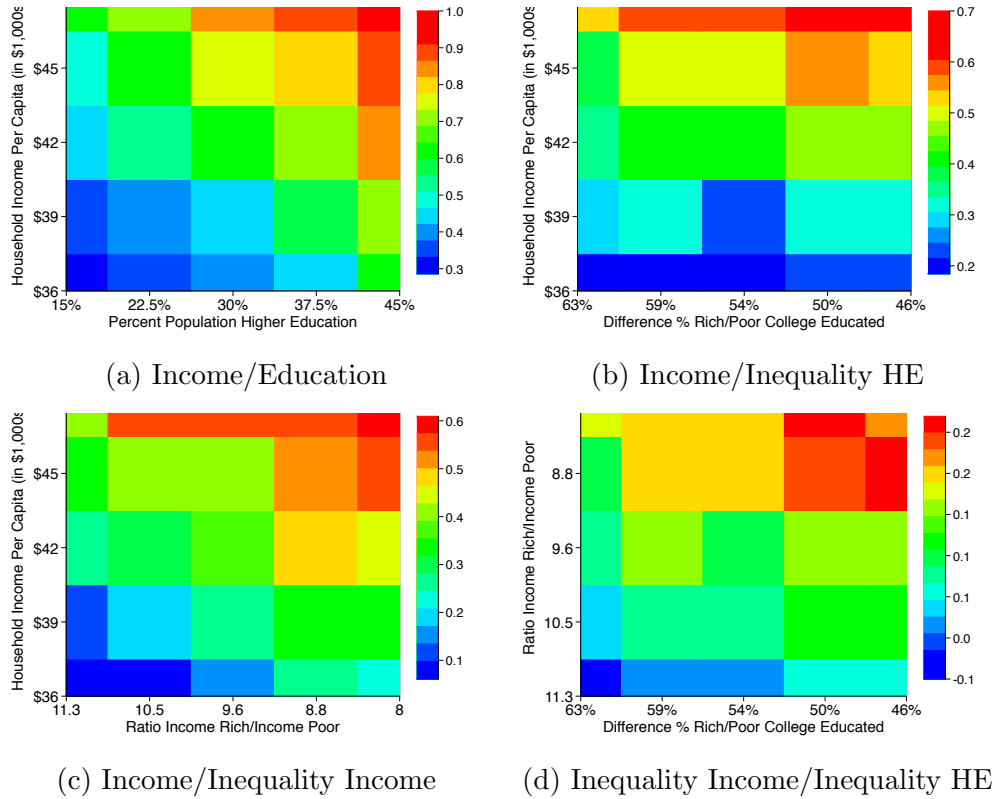
³⁰Downloaded from [Equality of Opportunity](#) project. See Online Data Table 7, using columns Parent Income P90 and Parent Income P10.

³¹See Online Data Table 8 and 9, for description of variable. The average of this variable is not easily interpretable, but we use only its standard deviation between CZs.

³²[Equality of Opportunity](#) project online data Table 5. The variable “RM, College Attendance” is defined as the slope of OLS regression of indicator for college attendance between ages 18-21 on parent income rank in core sample. A ratio of college attendance between 90th and 10th parent income percentiles is not available from the data, as the OLS slope estimate is fitted through the origin; thus, the 90/10 ratio will always be equal to the slope.

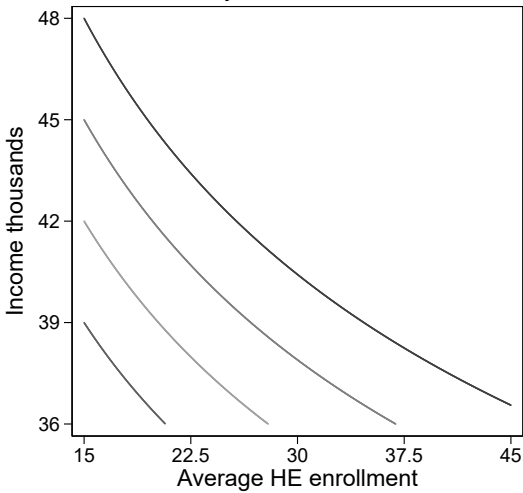
C Appendix: Unweighted Results

Figure C.1: Nonparametric Estimates Social Welfare Preferences, Contour Plots, Unweighted

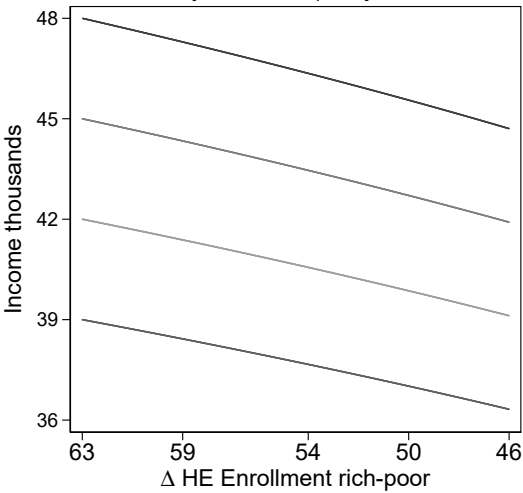


Note: Each panel represents a pairwise trade among social variables. Shaded cell regions indicate strength of preference in standard deviation units for pairwise combinations of social variables. Darker red indicates greater utility; darker blue indicates less utility. Utility estimates based on Equation (1).

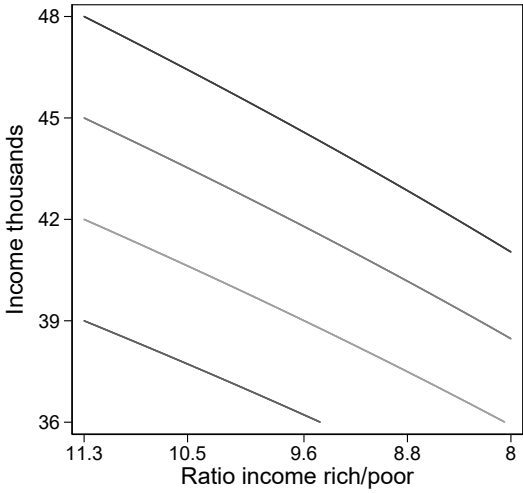
Figure C.2: Log Linear Estimates Social Welfare Preferences, Iso-curves, Unweighted data



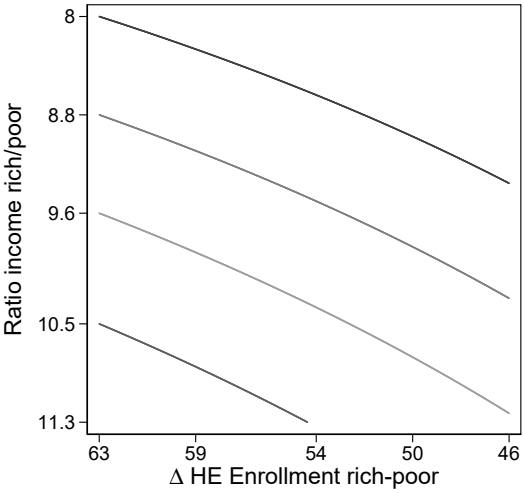
(a) Income/Education



(b) Income/Inequality HE



(c) Income/Inequality Income



(d) Inequality Income/Inequality HE

Note: Each panel represents a pairwise trade among societal variables. Iso-welfare curves derived from estimates from Equation (3).

D Appendix: Additional Results

Table D.1: **Non-Parametric Results: Point Estimates and Standard Errors**

<i>Panel A: Income/ Higher Education (HE)</i>					
	HE 1	HE 2	HE 3	HE 4	HE 5
Income 5	0.638 *** (0.032)	0.691 *** (0.029)	0.832 *** (0.028)	0.884 *** (0.025)	0.952 *** (0.025)
Income 4	0.468 *** (0.031)	0.599 *** (0.031)	0.746 *** (0.030)	0.802 *** (0.029)	0.888 *** (0.027)
Income 3	0.425 *** (0.031)	0.550 *** (0.030)	0.632 *** (0.030)	0.728 *** (0.030)	0.829 *** (0.030)
Income 2	0.356 *** (0.030)	0.408 *** (0.029)	0.458 *** (0.030)	0.587 *** (0.032)	0.712 *** (0.030)
Income 1	0.286 *** (0.027)	0.336 *** (0.029)	0.388 *** (0.028)	0.462 *** (0.030)	0.610 *** (0.029)

Table D.2: **Non-Parametric Results: Point Estimates and Standard Errors**

<i>Panel B: Income/Inequality Higher Education (HE)</i>					
	Ineq HE 5	Ineq HE 4	Ineq HE 3	Ineq HE 2	Ineq HE 1
Income 5	0.517 *** (0.031)	0.595 *** (0.030)	0.603 *** (0.029)	0.611 *** (0.029)	0.633 *** (0.029)
Income 4	0.367 *** (0.032)	0.512 *** (0.028)	0.510 *** (0.029)	0.555 *** (0.029)	0.516 *** (0.032)
Income 3	0.359 *** (0.030)	0.408 *** (0.032)	0.408 *** (0.030)	0.475 *** (0.032)	0.475 *** (0.030)
Income 2	0.285 *** (0.030)	0.312 *** (0.029)	0.230 *** (0.030)	0.324 *** (0.028)	0.327 *** (0.031)
Income 1	0.185 *** (0.027)	0.194 *** (0.030)	0.211 *** (0.030)	0.233 *** (0.028)	0.218 *** (0.028)

Note: Standard errors clustered by respondent in parentheses. OLS estimates based on Equation (1). Weighted estimates based on joint distributions of adult education and political affiliation using raking method of [Deville, Särndal and Sautory \(1993\)](#) and implemented by [Winter \(2002\)](#). *** p<0.01, ** p<0.05, * p<0.1.

Table D.3: **Non-Parametric Results: Point Estimates and Standard Errors**

<i>Panel C: Income/Inequality Income</i>					
	Ineq Inc 5	Ineq Inc 4	Ineq Inc 3	Ineq Inc 2	Ineq Inc 1
Income 5	0.426 *** (0.033)	0.562 *** (0.029)	0.552 *** (0.029)	0.565 *** (0.028)	0.610 *** (0.028)
Income 4	0.334 *** (0.031)	0.403 *** (0.032)	0.417 *** (0.030)	0.527 *** (0.030)	0.544 *** (0.028)
Income 3	0.274 *** (0.029)	0.311 *** (0.031)	0.369 *** (0.031)	0.472 *** (0.030)	0.459 *** (0.031)
Income 2	0.125 *** (0.029)	0.185 *** (0.029)	0.267 *** (0.031)	0.330 *** (0.030)	0.332 *** (0.032)
Income 1	0.061 ** (0.025)	0.088 *** (0.028)	0.162 *** (0.029)	0.251 *** (0.030)	0.235 *** (0.030)

Table D.4: **Non-Parametric Results: Point Estimates and Standard Errors**

<i>Panel D: Inequality Income/Inequality Higher Education (HE)</i>					
	Ineq HE 5	Ineq HE 4	Ineq HE 3	Ineq HE 2	Ineq HE 1
Ineq Income 1	0.172 *** (0.031)	0.203 *** (0.028)	0.197 *** (0.029)	0.257 *** (0.029)	0.212 *** (0.031)
Ineq Income 2	0.103 *** (0.030)	0.198 *** (0.030)	0.206 *** (0.029)	0.231 *** (0.028)	0.269 *** (0.028)
Ineq Income 3	0.069 ** (0.027)	0.163 *** (0.031)	0.091 *** (0.028)	0.159 *** (0.029)	0.148 *** (0.030)
Ineq Income 4	0.031 (0.030)	0.070 ** (0.029)	0.083 *** (0.030)	0.119 *** (0.028)	0.110 *** (0.027)
Ineq Income 5	-0.036 (0.029)	0.006 (0.029)	0.010 (0.027)	0.052 * (0.027)	0.051 * (0.028)

Note: Standard errors clustered by respondent in parentheses. OLS estimates based on Equation (1). Weighted estimates based on joint distributions of adult education and political affiliation using raking method of [Deville, Särndal and Sautory \(1993\)](#) and implemented by [Winter \(2002\)](#). *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: **Cobb-Douglas Parameters Probit Estimation, Question Group**

Variable	Coeff.
First two questions $\times \Delta \ln(\text{income})$	4.337*** (0.269)
Second two questions $\times \Delta \ln(\text{income})$	4.231*** (0.281)
First two questions $\times \Delta \ln(\text{Inequality Inc.})$	-1.805*** (0.202)
Second two questions $\times \Delta \ln(\text{Inequality Inc.})$	-2.098*** (0.215)
First two questions $\times \Delta \ln(\text{Educ.})$	0.997*** (0.072)
Second two questions $\times \Delta \ln(\text{Educ.})$	1.127*** (0.076)
First two questions $\times \Delta \ln(\text{Inequality HE})$	-1.290*** (0.224)
Second two questions $\times \Delta \ln(\text{Inequality HE})$	-0.661*** (0.208)
N	3996

Note: Standard errors clustered by respondent in parentheses. Probit estimates based on Equation (3) used to calculate MRS for Table 4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.6: **Cobb-Douglas Parameters Probit Estimation, Comprehension Group**

Variable	Coeff.
Right in Diagnostic $\times \Delta \ln(\text{income})$	4.240*** (0.253)
Wrong in Diagnostic $\times \Delta \ln(\text{income})$	4.612*** (0.372)
Right in Diagnostic $\times \Delta \ln(\text{Inequality Inc.})$	-2.332*** (0.199)
Wrong in Diagnostic $\times \Delta \ln(\text{Inequality Inc.})$	-1.254*** (0.261)
Right in Diagnostic $\times \Delta \ln(\text{Educ.})$	1.213*** (0.070)
Wrong in Diagnostic $\times \Delta \ln(\text{Educ.})$	0.773*** (0.092)
Right in Diagnostic $\times \Delta \ln(\text{Inequality HE})$	-1.318*** (0.194)
Wrong in Diagnostic $\times \Delta \ln(\text{Inequality HE})$	-0.190 (0.268)
N	3996

Note: Standard errors clustered by respondent in parentheses. Probit estimates based on Equation (3) used to calculate MRS for Table 5. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.7: **Cobb-Douglas Parameters Probit Estimation, Political Affiliation**

Democrat $\times \Delta \ln(\text{Income})$	4.149*** (0.263)
Republican $\times \Delta \ln(\text{Income})$	4.728*** (0.391)
Democrat $\times \Delta \ln(\text{Inequality Inc.})$	-2.442*** (0.214)
Republican $\times \Delta \ln(\text{Inequality Inc.})$	-0.965*** (0.274)
Democrat $\times \Delta \ln(\text{Avg. HE enrollment, Income})$	1.127*** (0.077)
Republican $\times \Delta \ln(\text{Avg. HE enrollment, Income})$	0.927*** (0.093)
Democrat $\times \Delta \ln(\text{Inequality HE})$	-1.262*** (0.206)
Republican $\times \Delta \ln(\text{Inequality HE})$	-0.501* (0.281)
N	3,592

Note: Standard errors clustered by respondent in parentheses. Probit estimates based on Equation (3) used to calculate MRS for Table 6. *** p<0.01, ** p<0.05, * p<0.1.

Table D.8: **Cobb-Douglas Parameters Probit Estimation, Educational Attainment**

Variable	Coeff.
College or More $\times \Delta \ln(\text{income})$	4.822*** (0.301)
Some College $\times \Delta \ln(\text{income})$	3.412*** (0.375)
Less than College $\times \Delta \ln(\text{income})$	5.212*** (0.637)
College or More $\times \Delta \ln(\text{Inequality Inc.})$	-2.169*** (0.245)
Some College $\times \Delta \ln(\text{Inequality Inc.})$	-2.278*** (0.301)
Less than College $\times \Delta \ln(\text{Inequality Inc.})$	-1.298*** (0.473)
College or More $\times \Delta \ln(\text{Educ.})$	1.260*** (0.084)
Some College $\times \Delta \ln(\text{Educ.})$	0.897*** (0.106)
Less than College $\times \Delta \ln(\text{Educ.})$	0.732*** (0.124)
College or More $\times \Delta \ln(\text{Inequality HE})$	-1.202*** (0.235)
Some College $\times \Delta \ln(\text{Inequality HE})$	-0.916*** (0.305)
Less than College $\times \Delta \ln(\text{Inequality HE})$	-1.383*** (0.466)
N	3484

Note: Standard errors clustered by respondent in parentheses. Probit estimates based on Equation (3) used to calculate MRS for Table 7. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E Appendix: Additional Descriptive Tables

Table E.9: Descriptive Statistics by Diagnostic Question Performance

Variable	Correct Response		Incorrect Response	
	Frequency	Percent	Frequency	Percent
<i>Gender</i>				
Female	291	41.10	129	44.79
Male	417	58.90	159	55.21
<i>Race/Ethnicity</i>				
Black	44	6.21	28	9.79
Other	92	13.0	31	10.84
White	572	80.79	227	79.37
<i>Age</i>				
18-29	252	35.49	106	36.81
30-44	319	44.93	126	43.75
45-64	119	16.76	45	15.62
65 or older	20	2.82	11	3.82
<i>Educational Attainment</i>				
Associate's or two-year college degree	71	10.01	24	8.30
Did not finish high school	5	0.71	0	0
Four-year college degree	273	38.51	111	38.40
Graduate or professional degree	92	12.98	29	10.03
High school diploma or equivalent	76	10.72	33	11.42
Some college, no degree	174	24.54	78	26.99
Technical or vocational school after HS	18	2.54	14	4.84
<i>Lib/Dem</i>				
Democrat	429	66.93	163	63.42
Republican	212	33.07	94	36.58

This table provides descriptive statistics for respondents based the diagnostic question response.