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European egalitarianism is confirmed by a propensity to agree with government intervention to reduce income inequality. This propensity is driven by lower educational level, societal dissatisfaction, liberalism, economic anxiety, and media exposure. These findings are realized with data from the fifth round of the European Social Survey. The regression of agreement propensities on true explanatory values is made possible by correcting for measurement error in explanatory scores. This resolves two major problems in propensity regression, i.e. errors in variables and imputation errors. These resolutions are attained by a pure randomization theory that places fixed measurement error in randomization-based regression. This type of regression (versus model-based regression) is used by statistical agencies and polling organizations for sampling large populations.

keywords: Likert agreement propensity, coefficient alpha, European Social Survey, real-valued measurement error, randomization theory, true-value regression

1 New Looks at Unresolved Issues

1.1 Research Questions and Survey Data

Income inequality, a perennial problem for capitalist economies, has now become a global issue. Aly (2011) views this inequality as the major causal factor in the 2011 Arab Spring and the 2011 Occupy Wall Street demonstrations in the United States. In 2012 the latter movement has morphed into the 99 Percent Spring, protesting the fact that 1% of Americans earn 21% of all U.S. income (Collins, 2012). Skewed and high-variance income distributions are long standing topics treated in the classic economics text by Samuelson and Nordhaus (1985). They warn (p. 47) that the invisible hand of market economies leads to income distributions that "may be unacceptable to voters." They assume that a

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fundamental function of government is to correct market economies through "techniques such as income redistribution to reflect society's concerns for the poor or hapless." They continue (p. 50):

> Let's say that voters through Congress decide to reduce income inequality. What tools could Congress use? First, it could engage in progressive taxation, taxing a larger fraction of incomes of rich than of poor. . . . Second, because low tax rates cannot help those who have no incomes at all, governments have in recent decades built up a system of income support: aid for the elderly, blind, disabled, and those with dependent children, as well as unemployment insurance for the jobless. ... And, finally, governments sometimes subsidize consumption of low income groups by providing food stamps, subsidized medical care, and low-cost housing.

In this well-known economic discourse terms like "unacceptable to voters", "voters decide", and "society's concerns for the poor" beg the following questions:

- What is the public attitude toward government intervention to reduce income inequality?
- What are the factors that drive this attitude?

The present paper addresses these questions with recent data from the European Social Survey (Fitzgerald, 2012).

> The European Social Survey (the ESS) is an academically-driven social survey designed to chart and explain the interaction between Europe's changing institutions and the attitudes, beliefs and behaviour patterns of its diverse populations. . . . the survey covers more than thirty nations and employes the most rigorous methodologies. A repeat cross-sectional survey, it has been funded through the European Commission's Framework Programmes, the European Science Foundation and national funding bodies in each country. . . . The ESS is also among the first social science projects to receive funding to support its infrastructure. In 2005 the ESS was awarded Europe's top annual science award, the Descartes prize. The ESS has also been nominated by ESFRI as a possible future European Research Infrastructure Consortium. In 2007, funding was awarded to the ESS Preparatory Phase Project to prepare for possible selection as a European Research consortium infrastructure by 2013.

The quality and prospects of the ESS position it as a spatial and temporal baseline for investigating public opinion about income inequality–spatial because Europe is a demonstrable egalitarian criterion for other regions of the world (cf. Sections 6.4 and7.1), and temporal because upcoming ESS rounds will monitor change in this public attitude.

1.2 True-value Regression of Public Opinion

Addressing public opinion about income redistribution requires cross-national survey data of the kind collected by the ESS. However, attitudinal constructs scored from these data inevitably contain error. Thus the survey analyst has an uncomfortable choice: a) Deny this error and proceed with traditional randomization-based regression used in government agencies and opinion polling, or b) Declare this error to be random with an unfounded distribution and proceed with the traditional model-based regression common in academia.

Here this choice is circumvented by the placement of real-valued measurement errors into randomization-based regression (cf. Bechtel, 2010, Bechtel, 2011, Bechtel, 2012a, Bechtel, 2012b). We treat the propensity to agree with a Likert attitude item (about income redistribution) as taking continuous values on an interval scale. An individual's coded degree of agreement, or imputation (in the case of item non-response), is interpreted as her (his) propensity to agree plus a fixed measurement error. Each respondent's explanatory score is also interpreted as a true interval-scale value plus a fixed error score. Then, the classical assumptions about measurement error (Bound et al., 2001, Gulliksen, 1950), along with reliability coefficient alpha in psychological test theory (Cronbach, 1951, Lord and Novick, 1968, Nunnally and Bernstein, 1994, StataCorp, 2011), allow the regression of agreement propensities on true explanatory values that a) have been cleansed of error and b) share our common interval scale.

This treatment of errors-in-variables avoids likelihood maximization and its premise that a census of survey scores is sampled from a "superpopulation" with a specified distribution (Chaudhuri and Stenger, 2005, Skinner et al., 1989). We also shun the further assumption in model-based theory that true explanatory values are normally distributed (Bound et al., 2001). Here these true values, and their observed scores, are not distributed at all.

This nonparametric approach to errors-in-variables also avoids the assumption in randomization-based theory that observations are constant and without error (Bellhouse, 1988, Chaudhuri and Stenger, 2005, Lehmann, 1999, Lohr, 2010, Nathan, 1988, Skinner et al., 1989, Valliant et al., 1999). Here real-valued (rather than random-valued) errors preserve and generalize randomization theory by keeping an individual's sample inclusion (or not) as her (his) only random variable. This generalization enhances statistical practice with opinion items and scores that are inevitably laden with measurement error.

1.3 The Plan of the Paper

Sections 2 and 3 describe the measurement errors in our Likert attitude score and its hypothesized explanatory scores. Section 4 distinguishes a census of these scores from a population of agreement propensities and true predictor values. This defines true regression slopes in terms of estimable census totals. Horvitz-Thompson-type estimates of these totals form our estimated true slopes in Section 5. In Section 6 these estimated slopes confirm our hypothesized effects on European attitudes toward income redistribution. Section 7 argues that European egalitarianism sets a standard for the world-wide reduction of income inequality. It also argues that public opinion about this inequality is realistically monitored with true-value regressions of micro data collected by statistical agencies and polling organizations.

2 The Likert Item on Income Inequality

The following ESS item (Fitzgerald, 2012) measures opinion about government action on income inequality: The government should take measures to reduce differences in income levels.

Disagree				Agree
Strongly 0	Disagree 2.5	Neither 5	Agree 7.5	Strongly 10

We code responses on this Likert scale in equal steps between zero and ten. Missing responses are filled in as imputations that lie among these five coded values. Letting Y_i be individual i's response or imputation, we deconstruct it as

$$Y_i = \eta_i + E_i \tag{1}$$

where η_i is an agreement propensity and E_i is a coding or imputation error in measuring this propensity. The values η_i and E_i lie on a continuous interval scale whose origin and unit are set by the coding of the Likert response labels. Thus, measurement error on this scale is the departure of a coded response value (e.g. $Y_i = 7.5$) or imputation from i's propensity η_i. The items used for imputing missing responses in the present study are exhibited in Table 2. The regression imputation procedure is described in Section 6.3.

3 Hypothesized Explanatory Scales

Table 1 exhibits five survey scales hypothesized to affect the public attitude toward income redistribution. Each hypothesis is justified at the beginning of each of the following five subsections. In order to compare the regression effects of these scales, responses to the items in each explanatory scale are coded between 0 and 10 (like the Likert scale options in Section 2).

3.1 Societal Dissatisfaction (or Anger about Inequality)

The first personal implication of institutionalized income inequality is dissatisfaction with a nation's economy, government, and democratic process. As noted in Section 1.1, Aly (2011) views anger about this inequality as the major cause of the Arab Spring *and* the 99 Percent Spring, the latter protesting the fact that 1% of Americans earn 21% of all U.S. income (Collins, 2012). We measure this personal dissatisfaction by the following coded (or imputed) responses:

$X_{i11} = \tau_{i1} + U_{i11}$ (the state of the economy),
$X_{i12} = \tau_{i1} + U_{i12}$ (the way government is doing its job),
$X_{i13} = \tau_{i1} + U_{i13}$ (the way democracy works).

The interval-scale value τ_{i1} is individual i's true societal satisfaction. The origin and unit of this scale are set by coding *extremely dissatisfied* as 0 and *extremely satisfied* as 10. The difference $U_{i1m} = X_{i1m} - \tau_{i1}$ for $m = 1, 2, 3$ is a coding or imputation error in measuring i's satisfaction by item m. Averaging over these three items gives individual i's satisfaction score as

$$\begin{aligned} X_{i1} &= \frac{X_{i11} + X_{i12} + X_{i13}}{3} \\ &= \tau_{i1} + \frac{U_{i11} + U_{i12} + U_{i13}}{3} \\ &= \tau_{i1} + U_{i1}. \end{aligned} \tag{2}$$

The U_{i1} in (2) is individual i's error score, which can be a mixture of item coding and imputation errors.

3.2 Economic Anxiety (or Fear of No Money)

The second personal implication of income inequality is the anxiety associated with loss of one's income and purchasing power. Bechtel(2012b) has demonstrated that the economic anxiety accompanying this loss has a strong negative impact on consumer spending, which is the major factor in a nation's gross domestic product. It follows that economic anxiety will drive agreement with the Likert item in Section 2. We write respondent i's coded ratings/imputations for our two anxiety items as

$X_{i21} = \tau_{i2} + U_{i21}$ (managing on lower income),
$X_{i22} = \tau_{i2} + U_{i22}$ (drawing on savings or going into debt),

where i's true anxiety τ_{i2} lies on our common interval scale. We keep the origin and unit of this anxiety scale the same as those of our satisfaction scale by coding *not at all* and *a great deal* as zero and ten. The error U_{i2m} for $m = 1, 2$ is a coding or imputation error in measuring i's anxiety by item m. For example, if U_{i21} is a coding error, it is a departure of 0, 1.67, 3.33, 5, 6.67, 8.33, or 10 from τ_{i2} on our anxiety scale. Due to our interpretation of coding error as measurement error, this scale tolerates the equal spacing of response codes that is ubiquitous in survey work. Individual i's anxiety score is the average of her (his) of two item ratings/imputations, i.e.

$$
\begin{aligned}
X_{i2} &= \frac{X_{i21} + X_{i22}}{2} \\
&= \tau_{i2} + \frac{U_{i21} + U_{i22}}{2} \\
&= \tau_{i2} + U_{i2}, \qquad (3)
\end{aligned}
$$

where U_{i2} is an error score in measuring i's true anxiety τ_{i2}.

3.3 Liberalism-Conservatism

Economic liberalism emphasizes that

> highly unequal distributions of wealth create sources of power and coercion that are not constrained by democratic participation or constitutional limits. In such cases, liberals assert that the state must interfere with the market to reestablish proper relations between citizens (Wingenbach, 2005, p. 414).

In contrast, economic conservatism is

> committed not only to fiscal prudence but also to "small government" ... and minimal interference with the operation of private markets.... pure capitalism will always outperform, both absolutely and morally, regulated markets.
>
> The institutional argument, best seen in the work of F. A. Hayek (1976), involves the claim that governments simply are not suited to engage in economic calculation on a large scale.
>
> ... In fact, when the state interferes to change distributive patterns it is acting unjustly, since it is coercing individuals who have done nothing wrong to help some other group of individuals, an act that is clearly immoral (Wingenbach, 2005, pp. 420-421).

The endorsement of laissez faire economics, and its market induced inequality, compels strong disagreement with the Likert item in Section 2. Economic liberalism, on the other hand, conveys strong agreement with this item.

The third explanatory scale in Table 1 captures the laissez-faire attitude at its "right" pole and the liberal attitude at its "left" pole. We deconstruct erroneous ratings/imputations for this left-right item as

$$X_{i3} = \tau_{i3} + U_{i3}. \qquad (4)$$

Respondent i's true value τ_{i3} again lies on our common interval scale with origin and unit set by the response coding in Table 1. The departure of X_{i3} from this true value is a coding or imputation error in measuring i's liberal or conservative orientation.

3.4 Media Exposure

As Norpoth (2005, p. 174) notes, "News about the overall economy is something where the public would seem to depend on the mass media for information and interpretation". This dependency, along with European egalitarianism, implies our fourth hypothesis that media exposure facilitates agreement with government-induced redistribution of income. We decompose the fourth item in Table 1 as

$$X_{i4} = \tau_{i4} + U_{i4}, \tag{5}$$

where τ_{i4} is individual i's true exposure to TV news and commentary, and U_{i4} is an error in measuring her (his) exposure by this survey item.

3.5 Education

It is well established that education is strong causal factor in income level (CollegeBoard, 2010). Moreover, Tóth and Keller (2011) find an individual's redistributive preference to be negatively related to her (his) personal material status. These two relationships imply that the more educated tend to disagree with income redistribution. This hypothesis is supported by Tóth and Keller in their pan-European regression of individual-level data from the 2009 Eurobarometer. We reconfirm it here in our pan-European regression of individual-level data from the 2010 ESS. This negative relationship between education and redistributive preference looms as an impediment to alleviating income inequality because government policy is heavily influenced by the more educated. In Table 1 years of education is calibrated on our common interval scale by coding respondents with the least and most education as zero and ten. Respondent i's coded years of education

$$X_{i5} = \tau_{i5}, \tag{6}$$

because this survey variable is without measurement error, i.e. $U_{i5} = 0$. In the present study we regard our education variable as a proxy for affluence.

4 Item Census, Score Census, and Population

We now posit a hypothetical (but possible) census of the inequality item in Section 2, the eight explanatory items in Table 1, and the nine imputation items in Table 2. In this item census missing responses for income redistribution and its eight explanatory items are (assumed to be) imputed in the same manner as their sample imputations described in Section 6.3. Equations (1) through (6) map our imputed 9-item census onto the 6-score census $\{Y_i \; X_{i1} \; X_{i2} \; X_{i3} \; X_{i4} \; \tau_{i5} \; \mid i = 1 \ldots N\}$, where N is the aggregate population size of the countries listed in Section 6.1 (cf. Bechtel, 2010, Bechtel, 2011, Bechtel, 2012a, Bechtel, 2012b). In this census the score Y_i in (1), along with the scores $X_{i1} \; X_{i2} \; X_{i3} \; X_{i4} \; and \; \tau_{i5}$ in (2) through (6) are constants for the i-th individual. These fixed census scores are in keeping with the fact that a census is only conducted once. It follows that i's six error scores in $\{E_i \; U_{i1} \; U_{i2} \; U_{i3} \; U_{i4} \; 0 \mid i = 1 \ldots N\}$ are also fixed because they are differences between i's census scores and true values in the population $\{\eta_i \; \tau_{i1} \; \tau_{i2} \; \tau_{i3} \; \tau_{i4} \; \tau_{i5} \; \mid i = 1 \ldots N\}$.

Table 1: Items in the Explanatory Scales

Construct													Error Sum of Squares
Societal satisfaction													d_1
The present state of your country's economy.													
The way your countrys government is doing its job.													
The way democracy works in your country's.													
Extremely dissatisfied	0	1	2	3	4	5	6	7	8	9	10	Extremely satisfied	
Economic anxiety													d_2
Manage on a lower household income in the last 3 years.													
Draw on my savings or get into debt to cover ordinary living expenses in the last 3 years.													
Not at all	0	1.67	3.33	5	6.67	8.33	10	A great deal					
Liberalism-Conservatism													d_3
In politics where would you place yourself on the following scale?													
Left	0	1	2	3	4	5	6	7	8	9	10	Right	
Media exposure													d_4
Your weekday time watching television news, politics, and current affairs.													
Zero	$< \frac{1}{2}$	$\frac{1}{2}$-1	1-$1\frac{1}{2}$	$1\frac{1}{2}$-2	2-$2\frac{1}{2}$	$2\frac{1}{2}$-3	> 3	hours					
0	1.43	2.86	4.29	5.71	7.14	8.57	10						
Years of education													0
Least	0 10	Most											

Note: The items in this table are adapted from Fitzgerald (2012).

Table 2: Items used for Regression Imputation

How much weekday time do you spend listening to radio news, politics, and current affairs?
How much weekday time do you spend reading newspapers about politics and current affairs?
Did you vote in the last [country] national election in [month, year]?
Is there a particular political party you feel closer to than all the other parties?
Are you a member of any political party?
Gender
Age
Total household income, after tax and compulsory deductions, from all sources
How do you feel about your household's income nowadays?

4.1 Identification of True Regression Slopes

Our fixed measurement errors allow a generalization of randomization-based regression by replacing the census $\{Y_i\ X_{i1}\ X_{i2}\ X_{i3}\ X_{i4}\ \tau_{i5} \mid i = 1 \dots N\}$ with the population $\{\eta_i\ \tau_{i1}\ \tau_{i2}\ \tau_{i3}\ \tau_{i4}\ \tau_{i5} \mid i = 1 \dots N\}$. Then, linearly deconstructing our propensity η_i gives the set of equations

$$\{\eta_i = \beta_0 + \beta_1\tau_{i1} + \beta_2\tau_{i2} + \beta_3\tau_{i3} + \beta_4\tau_{i4} + \beta_5\tau_{i5} + \epsilon_i \mid i = 1 \dots N\}, \tag{7}$$

where the ϵ_i are fixed specification errors. Requiring $\Sigma{\epsilon_i}^2$ over $i = 1 \dots N$ to be minimal identifies the true-slope vector $\beta = (\beta_1 \dots \beta_5)^T$ as

$$\beta = [\Sigma(\tau_i - \tau_.)(\tau_i - \tau_.)^T]^{-1}\Sigma(\tau_i - \tau_.)(\eta_i - \eta_.), \tag{8}$$

where $\tau_i = (\tau_{i1} \dots \tau_{i5})^T, \tau_. = (\tau_{.1} \dots \tau_{.5})^T$, and the two population totals also run over $i = 1 \dots N$.

4.2 The Classical Measurement-Error Assumptions

We assume that error scores in the set $\{E_i\ U_{i1}\ U_{i2}\ U_{i3}\ U_{i4}\ 0 \mid i = 1 \dots N\}$ sum to zero over $i = 1 \dots N$, are uncorrelated with true scores, and are uncorrelated with each other (cf. Bound et al. 2001, Gulliksen 1950). These assumptions may be written as the vanishing totals

$$\Sigma E_i = \Sigma E_i\tau_{ij} = \Sigma E_i U_{ij} = \Sigma U_{ij} = \Sigma U_{ij}\tau_{ij} = \Sigma U_{ij}\tau_{ik} = \Sigma U_{ik}\tau_{ij} = \Sigma U_{ij}U_{ik} = \Sigma U_{ij}\eta_i = 0, \tag{9}$$

where the explanatory variables $j, k = 1 \dots 5$. It is noteworthy that $\Sigma E_i\eta_i \neq 0$ is allowed in true-value regression theory, i.e. *measurement errors in the response variable may be correlated with their true values.*

4.3 Census-Estimable True Slopes

Under equations (1) through (9) it is easily shown that

$$\Sigma\tau_{ij}\eta_i = \Sigma X_{ij}Y_i, \tag{10a}$$
$$\Sigma\tau_{ij}\tau_{ik} = \Sigma X_{ij}X_{ik} \; for \; j \neq k, \; and \tag{10b}$$
$$\Sigma\tau_{ij}^2 = \Sigma X_{ij}^2 - \Sigma U_{ij}^2 \; for \; j = k. \tag{10c}$$

Our population target (8) may then be written in the estimable form

$$\beta = [\Sigma(X_i - X_.)(X_i - X_.)^T - \Delta]^{-1}\Sigma(X_i - X_.)(Y_i - Y_.), \tag{11}$$

where $X_i = (X_{i1} \dots X_{i5})^T$ and $X_. = (X_{.1} \dots X_{.5})^T$. Again the two census totals run over $i = 1 \dots N$. In (11) the matrix $\Delta = diag(\delta_1, \delta_2, \delta_3, \delta_4, 0)$, where

$$\delta_j = \Sigma U_{ij}^2 = (1 - \alpha_j)\left\{\Sigma X_{ij}^2 - \frac{(\Sigma X_{ij})^2}{N}\right\} \tag{12}$$

for $j = 1 \dots 5$. The diagonal $\delta_5 = 0$ because *years of education* $X_{i5} = \tau_{i5}$ is error-free with $U_{i5} = 0$ and reliability $\alpha_5 = 1$. The census reliability coefficients α_1 and α_2 for satisfaction and anxiety are defined by the well-known formula (A.1) in the Appendix (cf. Bechtel 2010, Cronbach 1951, Lord and Novick 1968, Nunnally and Bernstein 1994, StataCorp 2011). These alpha coefficients provide the error sums of squares δ_1 and δ_2, which follow from (A.2) in the Appendix. Finally, δ_3 and δ_4 are given by our assumptions that $\alpha_3 = \alpha_4 = .7$ for the single- item scores of liberalism-conservatism and media influence.

4.4 The Sufficiency of One Census

Assume a distinct error set $\{E_i \; U_{i1} \; U_{i2} \; U_{i3} \; U_{i4} \; 0 \mid i = 1 \dots N\}$ that satisfies (9). Substituting these new errors into (1) to (6) generates a second score census $\{Y_i \; X_{i1} \; X_{i2} \; X_{i3} \; X_{i4} \; \tau_{i5} \mid i = 1 \dots N\}$ from our population $\{\eta_i \; \tau_{i1} \; \tau_{i2} \; \tau_{i3} \; \tau_{i4} \; \tau_{i5} \mid i = 1 \dots N\}$. These new census scores satisfy (10a), (10b), and (10c) and again generate the same true β in (8) and (11). Hence, one census is sufficient. There is no need to entertain a second census or a super-population of censuses. Nor is it necessary to regard measurement error as a random variable that takes values (within each individual) over different census realizations from this super-population. Fixed individual measurement errors in (1) through (6) maintain a pure randomization theory in which the inclusion (or not) of individual $i = 1, \dots, N$ in a census sample is her (his) only random variable.

5 Estimation of the True Slopes

We regard responses to the items in Sections 2 and 3 to be sampled from the item census posited in Section 4. Due to unit non-response, this sample of size n reduces to a net sample of size $r < n$. Like the mapping of the item census onto the score census in Section 4, equations (1) to (6) map our 9-item sample onto a 6-score net sample

$\{Y_i\ X_{i1}\ X_{i2}\ X_{i3}\ X_{i4}\ \tau_{i5} \mid i = 1 \ldots r\}$. This net sample is drawn from the 6-score census $\{Y_i\ X_{i1}\ X_{i2}\ X_{i3}\ X_{i4}\ \tau_{i5} \mid i = 1 \ldots N\}$, which equations (1) to (6) link to our population $\{\eta_i\ \tau_{i1}\ \tau_{i2}\ \tau_{i3}\ \tau_{i4}\ \tau_{i5} \mid i = 1 \ldots N\}$. Our net sample $\{Y_i\ X_{i1}\ X_{i2}\ X_{i3}\ X_{i4}\ \tau_{i5} \mid i = 1 \ldots r\}$ may now be mapped onto

$$B = \left[\Sigma w_i(X_i - X_.)(X_i - X_.)^T - D\right]^{-1} \Sigma w_i(X_i - X_.)(Y_i - Y_.), \tag{13}$$

which is a Horvitz-Thompson type estimator of the mapping β of $\{\eta_i\ \tau_{i1}\ \tau_{i2}\ \tau_{i3}\ \tau_{i4}\ \tau_{i5} \mid i = 1 \ldots N\}$ in (8). The euroweight w_i in (13) is described in Section 6.2. This weight adjusts our micro European data for each respondent's sample inclusion probability, each country's population size, and each country's unit non-response (Bechtel, 2011). The two net sample totals in (13) run over $i = 1 \ldots r$, and the matrix $D = diag(d_1, d_2, d_3, d_4, 0)$, where

$$d_j = (1 - a_j)\left\{\Sigma w_i X_{ij}^2 - \frac{(\Sigma w_i X_{ij})^2}{\Sigma w_i}\right\} \tag{14}$$

for $j = 1 \ldots 5$. The diagonal $d_5 = 0$ because the reliability $a_5 = 1$ for our errorless variable *years of education*. Diagonals d_1 and d_2 are estimated sums of squares for measurement error in our satisfaction and anxiety scores. They are computed using reliability estimates a_1 and a_2 given by formula (A.3) in the Appendix. Diagonals d_3 and d_4 are obtained by setting $a_3 = a_4 = .7$, which is our assumed reliability of the single-item scores for liberalism-conservatism and media influence. Our five alpha coefficients are exhibited in Table 3. The matrix D in (13) corrects the randomization-based regression formula, which holds when $D = 0$ (Chaudhuri and Stenger, 2005, Godambe and Thompson, 2009, Lohr, 2010, Nathan, 1988, Opsomer, 2009, StataCorp, 2011). The weighted net sample totals in (13) and (14) are HT-type estimates of the corresponding census totals in (11) and (12). Finally, formulas for the standard errors of our true-value regression slopes are found in the Appendix of Bechtel (2010). The fourth line in Table 3 displays the five estimated standard errors of $B_1 \ldots B_5$ in B in (13).

6 European opinion about income redistribution

6.1 The ESS dataset

In the European Social Survey (Fitzgerald, 2012)

> Data collection takes place every two years, by means of face to face interviews of around an hour in duration .... The questionnaire consists of a 'core' module lasting about half an hour which remains relatively constant from round to round .... the core module aims .... to monitor change and continuity in a wide range of socio-economic, socio-political, socio-psychological and socio-demographic variables.

The present study uses the 17 ESS items in Tables 1 and 2, along with the income inequality item in Section 2. These items were administered in round 5 of the ESS during the aftermath of the global financial crisis of 2008 and the lead-up to the present Euro Zone crisis. Our pan-European sample includes the following 18 countries: Great Britain, The Netherlands, Belgium, France, Spain, Portugal, Germany, Switzerland, Denmark, Norway, Sweden, Finland, Estonia, The Czech Republic, Poland, Hungary, Slovenia and Bulgaria. In each country a representative probability sample was drawn from the residential population aged 15 and older. Thus, our cross-national dataset is a stratified sample (without replacement) in which each country is a stratum.

6.2 Unit Non-response: A Weighting-class Adjustment

The ESS provides design weights and population size weights that give euroweights representative of the national populations in our sample. The design weight for individual i is the rescaled inverse of her (his) sample inclusion probability. These design weights are normed to sum to each country's net sample size. A country's population size weight is

$$\frac{(country's\ population\ size\ aged \geq 15)}{(country's\ net\ sample\ size * 10000)}.$$

Then

$$w_i \equiv euroweight_i = (design\ weight_i) * (country's\ population\ size\ weight) \tag{15}$$

insures that our weighted regression in Table 3 represents a country in proportion to its population size. Bechtel (2011) shows that this euroweight is also a normed ESS sampling weight that has undergone a weighting-class adjustment for unit non-response (Lohr, 2010). The weighting classes for this adjustment are the 18 countries in our pan-European survey.

6.3 Item Non-response: Regression Imputation

Procedure. Nine regression imputations filled in missing data for the Likert item in Section 2 and its eight explanatory items in Table 1 (Lohr, 2010, StataCorp, 2011). First, one imputation was run for our income-redistribution item and each single-item scale in Table 1. Each of these four single items was regressed on the nine items in Table 2. Second, two imputations were carried out for our anxiety scale, with each item regressed on the other, along with the items in Table 2. Finally, three regression imputations were required for our satisfaction scale. Each item was regressed on the other two items making up this scale, as well as on the items in Table 2. These imputations prevented data loss by preserving 100% of the r = 34085 cases in our net sample.

Rationale. The imputation of missing *census* data in Section 4 is assumed to mimic the imputation of missing sample ratings just described (cf. Bechtel, 2010, Bechtel, 2011, Bechtel, 2012a, Bechtel, 2012b). Thus each of our sample imputations closely estimates its corresponding census imputation which is hypothetically carried out over the larger census dataset. For example, in equation (2) if X_{i11} is an imputed economic satisfaction, it is a weighted sum of individual i's rated governmental and democratic satisfactions as well as her (his) responses to the nine items in Table 2. Due to our large sample, the eleven weights in this sum are extremely close to those obtained from the even larger census imputation. Because these similar census weights are applied to i's same governmental and democratic satisfactions, along with her (his) same other nine responses, the census imputation of i's economic satisfaction closely approximates our sample imputation X_{i11}. Hence, individual i's societal satisfaction score X_{i1} in (2), which is the average of her (his) two item scores and one item imputation, differs negligibly from her (his) census score on this construct. These score differences will (approximately) sum to zero over a large sample. Therefore, our weighted totals using sample imputations in formulas (13) and (14) are almost identical to those that would be obtained had we been able to draw census imputations in our sample.

6.4 Macro Attitude toward Income Redistribution

True value theory enables inference to the population mean propensity as well as to population regression coefficients explaining micro propensities. Summing both sides of (1) over $i = 1 \ldots N$ and using $\Sigma E_i = 0$ gives

$$\frac{\Sigma Y_i}{N} = \frac{\Sigma \eta_i}{N}. \tag{16}$$

The left side of (16) is an estimable form of the true population mean on the right side. Our HT-type estimator of this macro attitude is

$$m = \frac{\Sigma w_i Y_i}{\Sigma w_i}, \tag{17}$$

where the two net sample summations run over $i = 1 \ldots r$, and w_i is the euroweight in (15). This macro agreement propensity, which is 7.17 on the common interval scale described in Sections 2 and 3, shows pan-European endorsement of income redistribution.

This egalitarian European attitude stands in sharp contrast to recent polling results in the United States. Less than fifty percent of Americans favor income redistribution (Jacobe 2008, Saad 2011). Other surveys show that "the gap between the rich and poor" is rated near the bottom of lists of national problems presented to American respondents (Newport 2011, 2012). This opinion data may account for the fact that a moderator from the Public Broadcasting Service put no question about poverty to either presidential candidate in their debate on the economy on October 3, 2012. On September 12, 2012 the United States Census Bureau released its report stating that 15% of the population, or 46.2 million Americans, fall below the poverty line (United States Census Bureau, 2012). The non-egalitarian American attitude versus the egalitarian European one reflects actual income inequality in the United States versus Europe. (See Table 4 below.)

6.5 Micro-Attitude Regressions

We explain European egalitarianism by regressing this propensity over individual Europeans[1].

Preparation. The variance inflation factor for each explanatory scale $j = 1 \ldots 5$ in Table 1 is

$$VIF_j = \frac{1}{(1 - R_j^2)}.$$

R_j^2 is the squared multiple correlation coefficient when scale j is regressed on the other four scales (StataCorp, 2011). These five VIF values in the first row of Table 3 are all close to one. Therefore, there is negligible co-linearity among the explanatory variables in our true-value regression. The second row of Table 3 reveals that our two multiple-item scores, satisfaction and anxiety, are measured with reliabilities .79 and .77. Years of education, presumably recalled without error, has reliability 1.00. The remaining single item scores, liberalism-conservatism and media exposure, are each assumed to be measured with reliability .70. These computed and assigned alpha coefficients correct our regression slopes for unreliability in four of the explanatory scales in Table 1. These slopes, in the third line of Table 3, were computed by formulas (13) and (14) from our net sample of the 18 countries listed in Section 6.1. The number of cases in this true-value regression is 34085.

Hypothesis tests. The highly significant regression effects in the third line of Table 3 confirm all five hypotheses laid out in Section 3 concerning our Likert response and its explanatory variables. Sections 2 and 3 describe the coding of these variables on the *same* interval scale. Therefore, in addition to being tested separately, the five explanatory variables in Table 1 may also be compared as to their influence on agreement propensity with income redistribution. Table 3 shows that the strongest effect is exerted by years of education, which is associated with disapproval of government intervention to reduce income inequality. This disapproval is also strongly associated with societal satisfaction and political conservatism. In contrast, economic anxiety and media influence elevate one's approval of income redistribution. These cross-national results confirm anecdotal evidence that the well off would preserve the status quo. In contrast, the dissatisfied, anxious, and liberal look to their government for relief.

Comparison with traditional regression. The traditional randomization-based regression slopes are exhibited in the last line of Table 3. The formula for computing these slopes may be found in Opsomer (2009, p. 7), Godambe and Thompson (2009, p. 89), and Lohr (2010, p. 442). In Table 3 the errorless predictor *years of education* serves as a marker whose coefficient stays (almost) constant between our true-value and randomization-based regressions. The attenuating effect of measurement error on the slopes of the erroneous predictors is revealed in the last line of the table. True-value regression corrects the relative influence of these four psychological predictors in relation to that of *years of education,* which is our demographic proxy for affluence. The standard errors in Table 3 follow the same pattern as their regression slopes. The

[1] The Stata .do file and documentation for running true-value regression may be obtained by email from the author.

traditional standard errors for our psychological predictors are spuriously low because they fail to allow for measurement errors that inflate coefficient variation.

Table 3: Traditional and True-value Regressions of Attitude toward Income Redistribution

Explanatory variable	Societal Satisfaction	Economic Anxiety	Liberalism Conservatism	Media Exposure	Years of Education
Variance inflation factor	1.10	1.06	1.04	1.00	1.02
Alpha coefficient	.79	.77	.70	.70	1.00
True value slope	-.284	.086	-.253	.080	-.466
	(.017)	(.010)	(.018)	(.018)	(.025)
Randomization-based slope	-.241	.074	-.187	.054	-.473
	(.011)	(.007)	(.010)	(.011)	(.025)

Note: The formula for each variance inflation factor is given in Section 6.5.
The alpha coefficients for satisfaction and anxiety are given by formula (A.3) in the Appendix. Those for the other three single-item scales are assigned. The true-value regression slopes were computed by formulas (13) and (14). Their standard errors (in parentheses)were obtained from the iterative procedure given in the Appendix of Bechtel (2010). The traditional randomization-based slopes and standard errors were computed from Stata software (StataCorp, 2011)

Limitations of the present analysis. Each of five predictors in Table 3 was put through a sensitivity analysis called an "added variable plot" (Graubard and Korn 2009, pp. 397-419, Mosteller and Tukey 1977, pp. 271-279, StataCorp 2011). This procedure a) regressed our Likert response in Section 2 on four predictors *without* the predictor in question and b) regressed the predictor in question on these same four predictors. The regression residuals for a) were then plotted against those for b). None of the five plots (not shown) reveal outlying points that would tend to invalidate our linear model (7). The plots for economic anxiety and liberalism-conservatism show lowest variation about their regression lines, i.e. most sensitivity to an individual's residual error in predicting her (his) attitude toward income redistribution. However, even these two predictors have considerable variation about their regression lines. High-variation added variable plots would appear to characterize public opinion data, where sensitive *individual-level* predictors are hard to find. This situation, of course, does not gainsay the usefulness of survey regressions in diagnosing societal problems and informing public policy.

Finally, we caution that our true-value regression in Table 3 rests on the classical assumptions about measurement error in Section 4.2. The robustness of true-value coefficients and standard errors to departures from these assumptions awaits clarification by future Monte Carlo analyses.

7 Future Directions

7.1 Can Europe Lead the Way?

This question is answered in the book *Why Europe Will Run the 21st Century* (Leonard, 2005), which has been summarized by Brookes (2005):

> What Europe has, argues Mark Leonard in his provocatively titled book, is a model, one centered around a new understanding of power and embodied in the institutions and norms of the European Union. The EU exerts an irresistible attraction on the countries around it, Leonard says, drawing them into its orbit, embedding them in its legal and economic framework and changing them from the inside out. Next to this "transformative power," the United States' military might, which can change regimes but not societies, and whose application is necessarily fleeting, seems a weak instrument indeed. Increasingly, Leonard tells us, we'll see more regional groupings emerge bound, as the EU is, by mutual self-interest and common values. It's in this sense, he argues, that Europe-or, more precisely, the "European way"-will dominate the 21st century.

Evidence that European institutions and norms do guide the 21st century is provided by the Gini coefficient (Wikipedia, 2012), which is the most widely used measure of income inequality. This coefficient is zero if everyone in a country earns the same income. It is one if a single person earns all of a nation's income, with everyone else earning nothing. Table 4 exhibits the range of Gini coefficients in 2009 for the western market economies and the developing BRICS nations. The message is clear: Europe sets an egalitarian standard for the rest of the world. This evidence-based message is reinforced in Section 6.4, where a mean agreement of 7.17 on our propensity scale gives a solid European endorsement to government action on income inequality. In Section 6.5 this propensity is micro-regressed on five explanatory variables. Education, societal satisfaction, and conservatism show the strongest (negative) effects in Table 3, indicating that the affluent prefer to maintain their privileged situation. In contrast, television has a positive influence on agreement propensity, suggesting that media news and commentary can counteract the status quo. Also, those who are anxious about income loss agree with governmental reduction of income inequality. The specter haunting loss of household income and purchasing power, i.e. unemployment, has been described by Samuelson and Nordhaus (1985, pp. 207-209):

> However large the economic costs of unemployment, a recounting of dollars does not adequately convey the human, social, and psychological toll that persistent periods of involuntary unemployment bring. ... recent studies indicate that unemployment leads to a deterioration of both physical and psychological health - higher levels of heart disease, alcoholism, and suicide. ... other studies indicate that involuntary joblessness is a highly traumatic event for many people.

Clearly, reduction of economic anxiety and societal dissatisfaction, through reduction in income inequality, should be a global goal in the 21st century. Such policy can be informed by comparing public opinion about inequity in egalitarian Europe with that in Japan, the United States, and the BRICS nations.

Table 4: Income Inequality in Western and BRICS Economies

	European Countries	Japan & India	Russia	U.S.A. & China	Brazil	South Africa
Gini coefficient	.23-.34	.35-.39	.40-.44	.45-.49	.50-.54	>.60

Note: Each country is within the Gini-coefficient range indicated.
These 2009 data are found in Wikipedia (2012).

7.2 Real-valued (Rather than Random-valued) Measurement Error

Our results have been obtained from a generalization of the orthodox randomization theory used by statistical agencies and polling organizations. The competition between randomization theory and model-based theory in societal data analysis has been brisk and persistent for many years (Bellhouse, 1988, Brewer and Gregoire, 2009, Chaudhuri and Stenger, 2005, Lohr, 2010, Nathan, 1988, Opsomer, 2009, Skinner et al., 1989, Thompson, 1997, Valliant et al., 1999). Curiously, despite the continuing use of randomization theory by governments and the survey industry, the academic treatment of measurement error in survey data has remained model-based (Bound et al., 2001). Recently, Bechtel(2010, 2011, 2012a, 2012b) has attempted to correct this imbalance by including measurement error in a pure randomization framework.

This inclusion is especially important because (a) opinion polling with micro data has become a world-wide commercial and governmental activity, and (b) it has long been known that measurement error attenuates survey regression slopes (Johnston, 1972). True-value theory corrects these slopes by relaxing the randomization-based assumption that a finite population is a set of *errorless* constants (Chaudhuri and Stenger, 2005, Lehmann, 1999, Lohr, 2010, Nathan, 1988, Opsomer, 2009, Skinner et al., 1989, Thompson, 1997). Here this traditional population is replaced by two finite sets of vectors. The first set is a population of N true vectors, and the second is a census of N erroneous vectors. Each of these sets consists of real, rather than random, numbers.

Our use of erroneous real variables avoids the model-based postulate that a census of scores is sampled from a "superpopulation" with a specified distribution (Chaudhuri and Stenger, 2005, Skinner et al., 1989). It also evades the further unrealistic assumption that our true explanatory values $\tau_{i1} \dots \tau_{i5}$ are normally distributed (Bound et al., 2001). Here these true real values, and our real census scores, are not distributed at all. This nonparametric interpretation of census scores $Y_i\ X_{i1} \dots X_{i5}$ in (1) to (6) as deviations from interval-scale values $\eta_i\ \tau_{i1} \dots \tau_{i5}$ is a step forward within the Neyman paradigm (Bellhouse, 1988, Brewer and Gregoire, 2009, Neyman, 1934, Opsomer, 2009). These deviant census scores, which arise from *fixed* response coding and imputation errors in (1) to (6), elude extreme interpretations of micro-data as errorless constants on the one hand or specifically distributed random variables on the other. Then, the classical assumptions in (9) about our real-valued measurement errors enable the estimation of the true regression slopes in Table 3 within a pure randomization theory.

Appendix: Census reliability and its estimation

A.1. Coefficient Alpha as the Ratio of True and Observed Variances

Referring to multiple-item scores (2) and (3), along with their component items, we suppress the subscripts 1 and 2 signifying our first and second explanatory variables. We then denote item and score variables (which take values over individuals) by suppressing the subscript i. Thus the variable for an item m is X_m for $m = 1, \ldots, M$. Its observed score variable is X, its true score variable is τ, and its error-score variable is U. Also, the summative (rather than average) score variable is MX (cf. Section 3.1 for $M = 3$ and Section 3.2 for $M = 2$). With this notation the census coefficient alpha for an M-item score is

$$\alpha = \frac{M}{M-1}\left\{1 - \frac{\Sigma_m Var(X_m)}{Var(MX)}\right\}, \tag{A.1}$$

where the summation (over items) runs over $m = 1, \ldots, M$ (Bechtel, 2010, Cronbach, 1951, Lord and Novick, 1968, Chapter 4, Nunnally and Bernstein, 1994, StataCorp, 2011). The variances in (A.1) are

$$Var(X_m) = \frac{\left\{\Sigma X_{im}^2 - \frac{(\Sigma X_{im})^2}{N}\right\}}{N}$$

and

$$Var(MX) = M^2 Var(X) = \frac{M^2\left\{\Sigma X_i^2 - \frac{(\Sigma X_i)^2}{N}\right\}}{N},$$

where the census summations (over individuals) run over $i = 1 \ldots N$. If the item errors U_{im} for $m = 1, \ldots, M$ are uncorrelated (over individuals) with each other and with the true construct values τ_i, we show that coefficient alpha is the ratio of the unobserved true variance to the observed variance of a score variable.

First, as in Sections 3.1 and 3.2, we have $X_m = \tau + U_m$ and $Var(X_m) = Var(\tau) + Var(U_m)$. Letting $T = M\tau$, $Var(T) = M^2 Var(\tau)$ so that $Var(X_m) = \frac{Var(T)}{M^2} + Var(U_m)$. Then the summative score $MX = T + MU$ and $Var(MX) = Var(T) + M^2 Var(U)$. Substituting for $Var(X_m)$ and $Var(MX)$ in (A.1) gives

$$\alpha = \frac{M}{M-1}\left\{1 - \frac{\frac{Var(T)}{M} + \Sigma_m Var(U_m)}{Var(T) + M^2 Var(U)}\right\}$$

Finally, writing the number one as

$$\frac{Var(T) + M^2 Var(U)}{Var(T) + M^2 Var(U)},$$

and noting that $M^2Var(U) = \Sigma_m Var(U_m)$, we have

$$\begin{aligned}\alpha &= \frac{M}{M-1}\left\{\frac{Var(T) - \frac{Var(T)}{M}}{Var(T) + M^2Var(U)}\right\} \\ &= \frac{Var(T)}{Var(MX)} \\ &= \frac{Var(\tau)}{Var(X)},\end{aligned} \tag{A.2}$$

where

$$Var(\tau) = \frac{\Sigma\tau_i^2 - \frac{(\Sigma\tau_i)^2}{N}}{N}.$$

Thus, access to this unknown true variance is provided by the observable coefficient alpha in (A.1), conditioned on the classical error assumptions(Bound et al., 2001, Gulliksen, 1950, pp. 4-7, Lord and Novick, 1968, p. 36).

A.2. A Horvitz-Thompson Type Estimator of Alpha

Let Var denote the sample estimate of a census variance Var. For example, $Var(X)$ is an estimate of Var(X). Using this notation the sample coefficient alpha for an M-item score X is

$$A = \frac{M}{M-1}\left\{1 - \frac{\Sigma_m Var(X_m)}{Var(MX)}\right\}, \tag{A.3}$$

where

$$Var(X_m) = \frac{\Sigma w_i X_{im}^2 - \frac{(\Sigma w_i X_{im})^2}{\Sigma w_i}}{\Sigma w_i}$$

and

$$Var(MX) = M^2Var(X) = \frac{M^2\left\{\Sigma w_i X_i^2 - \frac{(\Sigma w_i X_i)^2}{\Sigma w_i}\right\}}{\Sigma w_i}$$

In these estimated variances w_i is respondent i's euroweight in (15), and the summations over *respondents* run over $i = 1, \ldots, r$ (= the *net* cross-national sample size). Each of the weighted net sample totals in (A.3) is a Horvitz-Thompson type estimator of its corresponding census total in (A.1). Table 3 exhibits the estimated alpha coefficients, computed by (A.3), for our societal satisfaction and economic anxiety scores (2) and (3).

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