**Appendix A: Item Wordings and Descriptive Statistics**

***Items comprising the homo-economicus scale***

*Profit.* Consider the following situation: A small factory produces tables and sells all that it can make at $200 each. Because of changes in the price of materials, the cost of making each table has recently decreased by $20. The factory does not lower its price for the tables. Is this acceptable or unfair?

1 Acceptable

2 Unfair

8 Don’t know

*Trickle Down.* Allowing business to make good profits is the best way to improve everyone's standard of living.

1 Strongly agree

2 Agree

3 Neither

4 Disagree

5 Strongly disagree

8 Can’t choose

*Organ.* A body organ that is much in need and that people may contribute are kidneys. Most people can live with only one kidney, though their chances of survival are better if they have two. Do you believe that people with two healthy kidneys should be permitted to sell a kidney to a hospital or organ center to use for transplants?

1 Definitely not

2 Probably not

3 Perhaps

4 Probably

5 Definitely

*Surrogacy* Recently, some married couples who are unable to have children have paid women, called "surrogate mothers," to bear a child for them. When the child is born, the couple becomes its adoptive parents and the surrogate mother receives a fee. Do you think that this practice should be permitted or forbidden under the law?

1 Forbid it

2 Permit it

8 Don’t know

*Prostitution*. How much do you agree or disagree with the following statements:

There is nothing inherently wrong with prostitution, so long as the health risks can be minimized. If consenting adults agree to exchange money for sex, that is their business.

1 Agree strongly

2 Agree somewhat

3 Disagree somewhat

4 Disagree strongly

8 Don’t know

*Environment.*  How much do you agree or disagree with the following statements:

Natural environments that support scarce or endangered species should be left alone, no matter how great the economic benefits to your community from developing them commercially might be.

1 Agree strongly

2 Agree somewhat

3 Disagree somewhat

4 Disagree strongly

8 Don’t know

*Consumer.* How much do you agree or disagree with the following statements:

It is the responsibility of government to require businesses to provide consumers with the information they need to make informed choices.

1 Agree strongly

2 Agree somewhat

3 Disagree somewhat

4 Disagree strongly

8 Don’t know

For the purpose of the RCA analysis, we transformed “don’t know” responses (where applicable) into mid-scale responses. Respondents who provided 3 or more “don’t know” responses, or at least one missing response, were excluded from the analysis.

***Additional variables***

Education: highest year of schooling, ranging from 1 to 20

Income: self-reported total family income, log transformed

White collar: occupation is classified as either managerial, health professional & engineers, teachers and social scientists, technical, sales, and administrative support, by the census bureau’s two-digit classification

Gender: male = 0, female = 1

Black: Non-African American = 0, African-American = 1

Religiosity: frequency of religious service attendance, per week

Religious denomination: Catholic, Evangelical, Mainline Protestant (including Black Protestants and non-denominational Christians), Non-Christian

Political Ideology: self identification on a 7-point scale ranging from strong liberal to strong conservative

Party: partisan self-identification on a 7-point scale ranging from strong Democrat to strong Republican

Community size: population of place of residence, log transformed

Region: West, South, Northeast, Midwest

Age: in years

Married: is respondent currently

Childs: number of children, ranging from 0 to 8 or more.

Immigrant: respondent born outside the U.S.

The homo-economicus scale (modeled in Table 2) is structured as follows. “Don’t Know” responses are imputed as midpoints, for example, imputed as 2.5 for the variable *Environment* (see above). Each variable is standardized to have a mean of 0 and standard deviation of 1. Let K be the number of variables comprising the scale, and $\tilde{x}\_{k}$ denote standardized variable $k\in K$. The homo-economicus scale is defined as:

$$HE=\frac{1}{K}\sum\_{k=1}^{K}\tilde{x}\_{k}$$

Table A1: Descriptive statistics

|  |  |  |
| --- | --- | --- |
| **Variable** | **Mean** | **Std. Dev.** |
| Education | 13.33542 | 2.947183 |
| Logged Income | 10.27784 | .9544364 |
| White Collar | .5602787 | .4965262 |
| Gender | .552632 | .4973945 |
| Black | .1391967 | .3462716 |
| Religiosity | .4431465 | .5587801 |
| Mainline Protestant | .2963989 | .4568272 |
| Catholic | .2389197 | .4265713 |
| Evangelical | .2527701 | .4347508 |
| Non-Christian | .0914127 | .288295 |
| Political Ideology | 4.225901 | 1.352369 |
| Party | .2834037 | .4508092 |
| Community Size | 3.532967 | 2.141256 |
| West | .2160665 | .4117027 |
| South | .3531856 | .4781253 |
| Northeast | .1932133 | .3949556 |
| Midwest | .2375346 | .4257199 |
| Age | 44.74636 | 17.05602 |
| Married | .4903047 | .5000792 |
| Children | 1.841922 | 1.743703 |
| Immigrant | 0.768698 | .266477 |

**Appendix B: RCA procedure and statistical significance**

A useful way to understand the analytical purchase that RCA affords is to com­pare it to other latent variable models. Some such models reduce *item* dimensionality: methods such as factor analysis, multidimensional scaling, principal component analysis and correspondence analysis reduce a set of variables onto a smaller set of factors or dimensions. Other such mod­els reduce *respondent* dimension­ality by placing respondents in dif­fer­ent groups. Latent class models divide sets of observations into subgroups such that variables are un­cor­related within each subgroup. RCA, by contrast, sim­ultaneously reduces inter-item and inter-respondent variability. Like latent class analysis (LCA), it divides a population into sub­groups, and like factor analysis, each subgroup is identified by a reduction of the set of variables onto a smaller number of factors. Note, however, that because the input to RCA is a distance matrix based on the difference of differences matrix, RCA solutions cannot be recovered by LCA or *vice versa.*[[1]](#footnote-1)

RCA measures schematic similarity between respondents using a metric called *re­lat­ion­ality*. Relationality measures the extent to which two respondents’ responses follow the same pattern. It does so by calculating the relative difference between all pairs of responses pro­vided by each respondent, and then averaging the difference in differences across the two re­spondents. Like the Pearson correlation coefficient, relationality is bounded by –1 and +1. Pairs of respondents with high absolute relationality (namely, with values close to 1 or –1) are said to be schematically similar.

Let *K* be the number of variables in the dataset, and *X* be the *NxK* set of observations where each column is standardized to range from 0 to 1. Formally, relationality $R\_{ij}$ between observations *i* and *j* is defined as follows:

$$Rij\_{}=\frac{2}{K(K-1)}\sum\_{k=1}^{K-1}\sum\_{l=k+1}^{K}\left(λ\_{ij}^{kl}∙δ\_{ij}^{kl}\right)$$

where

$$δ\_{ij}^{kl}=1-\left|\left|∆X\_{i}^{kl}\right|-\left|∆X\_{j}^{kl}\right|\right|$$

is the relational similarity for the variable pair *{k,l}* between observations *i* and *j*,

$$∆X\_{i}^{kl}=X\_{i}^{k}-X\_{i}^{l}$$

is the distance between the values of variables *k* and *l* for observation *i*, and

$$λ\_{ij}^{kl}=\left\{\begin{array}{c} 1 ∆X\_{i}^{kl}∙∆X\_{j}^{kl}\geq 0\\-1 ∆X\_{i}^{kl}∙∆X\_{j}^{kl}<0\end{array}\right.$$

is a binary operator that changes the sign of relational similarity if both distances are in opposite directions.

The overall schematic similarity between respondents can be represented as a weighted network. RCA calculates relationality between all pairs of respondents to generate such a net­work, and removes edges with insignificant relationality. A spectral network-partitioning algor­ithm (Newman 2006) is used to partition the network into groups of schematically similar re­spondents. The algorithm partitions the network by maximizing a property known as modularity (see Newman and Girvan [2004] for details). The algorithm follows an iterative procedure whereby classes are recursively partitioned until modularity cannot be maximized further.

Initially, the RCA procedure partitioned the dataset into five classes. Because the mod­ularity maximization procedure only stops when modularity cannot be maximized any further, it may include steps that only contribute marginally to modularity, and therefore do not produce a meaningful partition. The last two steps of the partitioning algorithm contributed only modestly to overall modularity, increasing it by 9.5% and 1.5%, respectively. Our subjective examination of these two classes suggested that they were not substantively distinguishable. We therefore de­cided to reverse these last two steps and stop the procedure with a tri-partite partition.

Until now, there has been no statistical method for assessing the optimal number of classes. This appendix presents such a procedure and uses it to evaluate the model presented in this paper.

We produced a set of Monte Carlo simulations to generate random null distributions of data. We used those to calculate:

1. The expected modularity at random. If the modularity produced by our tri-partite partition is significantly greater than that expected at random, we could determine that the RCA classes we have produced indeed represent a meaningful partition.

2. Using a method known as the gap statistic (Tibshirani, Walther and Hastie 2001, see below), we estimate the optimal number of classes.

The Monte Carlo simulations generate a set of randomly drawn datasets that are identical in size to the original dataset, and which are used to obtain a reference null distribution (in ex­pect­ation, these datasets should not naturally partition into classes). We generated these datasets by permuting the rows of the original dataset such that each observation retained the same distrib­ution of attitudes, but these attitudes were randomly assigned to variables. In other words, each “respondent” in our simulated datasets is equally opinionated as the original respondent, but these opinions are applied to random items. Because we constrain the simulated datasets to adhere to observed distributional properties, the statistical estimates we obtain are highly conservative.

We generated 1,000 simulated datasets, and applied the RCA procedure to partition each into classes of schematically similar respondents. On average, RCA identified 7.32 classes, ranging from 5 to 10. The mean modularity for these simulated partitions was 0.2960, with a standard deviation of 0.0083. At 0.4168, the observed modularity is significantly greater than the null distribution at p=0 (a one-sample t-test statistic of –462.82). In other words, the observed data present a significantly greater level of clustering than would be expected at random, even while constraining the data to adhere to respondents’ opinion distributions.

Next, we use the gap statistic to estimate the goodness of fit of our three-class partition. The gap statistic computes partition compactness, Wk, for a partition into k classes, which equals the normalized sum of distances between observations in each class. Formally:

$$W\_{k}=\sum\_{r=1}^{k}\frac{1}{2n\_{r}}D\_{r}$$

where k is the number of classes, nr is the size of class r, and Dr is the sum of pairwise distances between observations in r. We use one minus relationality as the distance between two observations. The gap statistic method compares the observed compactness to that obtained from the null reference distribution:

$$Gap\_{n}\left(k\right)=E\_{n}^{\*}\left\{log\left(W\_{k}\right)\right\}-log\left(W\_{k}\right)$$

 where $E\_{n}^{\*}$ denotes expectation under a sample size n. The optimal number of classes is the smallest k that satisfies:

$$Gap\left(k\right)\geq Gap\left(k+1\right)-s\_{k+1}$$

where $s\_{k+1}$ is the simulation standard error (see Tibshirani et al. [2001] for more details). As illustrated in Figure B1, this condition is satisfied only for k=3.

Figure B1: Gap statistic for number of clusters produced by RCA



Thus the gap statistic confirms the statistical validity of our substantively motivated decision that a three-class partition best fits the data.

**Appendix C: Multivariate Analyses of Relational Class Scales**

In this table we report three OLS models of the three pro-market scales in their respective classes on various sociodemographic predictors. These models correspond to the OLS model of the Homo Economicus scale (reported in Table 2) which is applied to the sample as a whole. The predictors are fixed across all models.

Table C1: Multivariate models of pro-market scales in their respective classes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Economism | Hostile Worlds | Progressive |  |
| Education | 0.159 | (1.79) | -0.000 | (-0.00) | 0.183\*\*\* | (4.24) |
| log(Income) | 0.206 | (0.83) | 0.355\*\* | (2.84) | 0.432\*\*\* | (3.48) |
| White-Collar | 0.696 | (1.46) | 0.191 | (0.85) |  -0.394 | (-1.75) |
| Church Attendance | -0.051 | (-0.61) | 0.111\*\* | (2.68) |  -0.043 | (-1.07) |
| Catholic | -1.146 | (-1.84) | -0.209 | (-0.81) |  -0.585\* | (-2.25) |
| Evangelical | -1.487\* | (-2.43) | -0.188 | (-0.70) |  -0.206 | (-0.80) |
| Jew/Other | -0.541 | (-0.78) | 0.250 | (0.61) |  -0.626 | (-1.65) |
| Female | -1.343\*\* | (-3.04) | -0.505\* | (-2.42) |  -0.026 | (-0.13) |
| Black | -1.145 | (-1.54) | -0.101 | (-0.29) | -1.303\*\*\* | (-3.62) |
| Age | -0.016 | (-1.20) | 0.014\* | (2.08) | -0.021\*\* | (-3.01) |
| Conservatism | -0.149 | (-0.89) | 0.099 | (1.28) | -0.217\*\* | (-2.73) |
| Republicanism | 0.282\* | (2.35) | 0.023 | (0.43) | 0.092 | (1.67) |
| log(Community Size) | 0.175 | (0.69) | -0.219 | (-1.82) | 0.006 | (0.05) |
| West | 1.151 | (1.89) | 0.664\* | (2.38) | -0.129 | (-0.47) |
| South | 0.783 | (1.46) | -0.010 | (-0.04) | -0.208 | (-0.82) |
| North East | 0.940 | (1.47) | -0.115 | (-0.37) | -0.087 | (-0.30) |
| Married | -0.442 | (-0.94) | -0.143 | (-0.64) | -0.055 | (-0.25) |
| Children | 0.041 | (0.31) | -0.043 | (-0.67) | -0.176\* | (-2.54) |
| Immigrant | -0.941 | (-1.27) | -0.153 | (-0.40) | -0.577 | (-1.39) |
| Constant | -1.712 | (-0.58) | -4.356\*\* | (-3.12) | -3.401\* | (-2.52) |
| N | 228 |  | 447 |  | 458 |  |
| R2 | 0.236 |  | 0.124 |  | 0.252 |  |

*t* statistics in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

1. For a fuller explanation of the difference between RCA and Latent Class Analysis, including comparison of results from parallel analyses, see Goldberg 2011, App. C (online at http://www.jstor.org/stable/full/10.1086/657976#apc). [↑](#footnote-ref-1)