

# Supplementary Information for “Is the Tea Party Libertarian, Authoritarian, or Something Else?”

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## Additional information on Factor Analysis

We used an oblique rotation which allows for factors to be correlated. This is appropriate here because, while we argue that moral statism and anti-governmentalism are unique and distinct, they are likely to be correlated. We use maximum likelihood as the factoring method because it has a more formal statistical basis than other methods and is widely seen as one of the optimal methods. See Fabrigar et al. (1999). We estimate two factors, which a scree plot (below) suggests to be the optimal number.

For  $N$  equal to 5914, a chi-square test of the hypothesis that two factors is sufficient is equal to 900.727 with a p-value of 0, suggesting that two factors are not sufficient, as we would expect. That said, the root mean square of the residuals is 0.044 and the Tucker-Lewis Index for factor reliability score is 0.869, both of which are near the conventional cutoffs of .05 and .9, respectively.

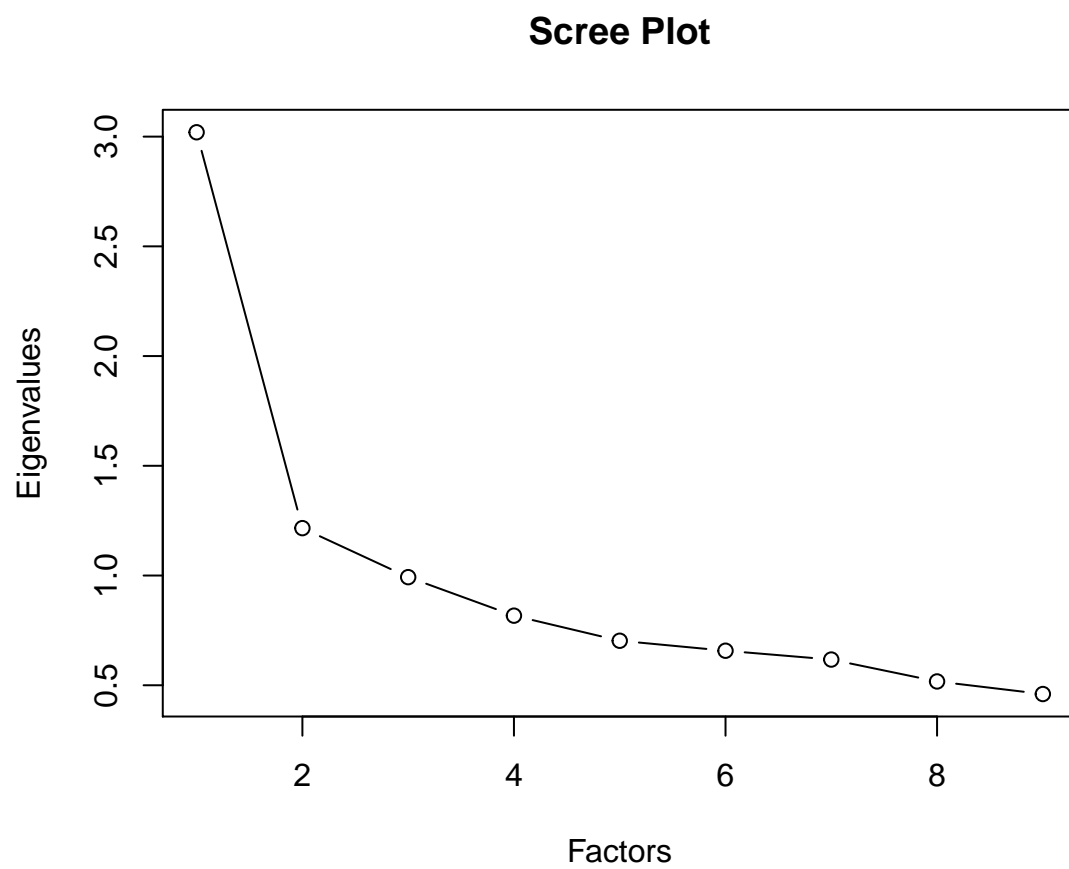


Figure 1: Scree plot shows elbow at two factors

	ML1	ML2
Family	0.03	0.59
Guns	0.40	-0.05
Intolerant	-0.12	0.44
Morals	-0.22	0.36
Wiretapping	0.21	0.35
Defense	0.04	0.49
Services	0.78	0.01
Immigration	-0.24	0.38
Jobs	0.61	-0.04

Table 1: Factor Loadings

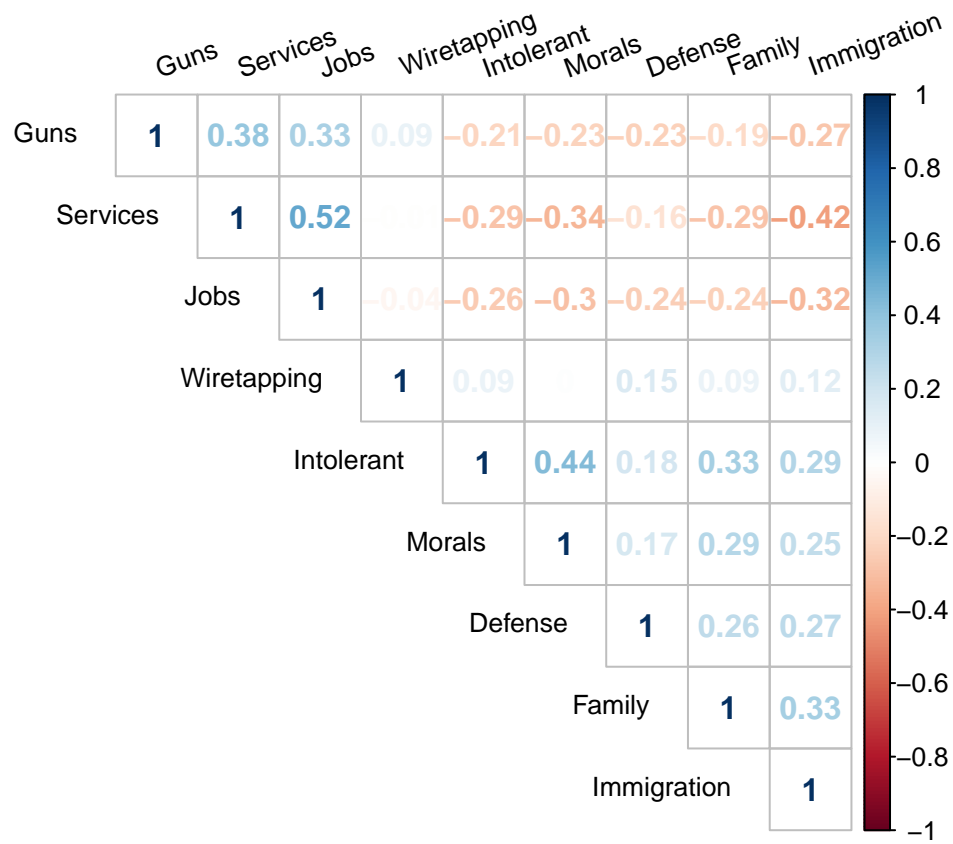


Figure 2: Correlation plot for different dimensions of right-wing attitudes

Table 2: Alternative Dependent Variables for Model 2

	<i>Dependent variable:</i>	
	PartyID (Republican)	Conservatism
	(1)	(2)
Gender (Male)	-0.006 (0.013)	0.008 (0.014)
Income	0.032** (0.015)	-0.003 (0.016)
Age	-0.057*** (0.014)	0.025 (0.016)
Race (White)	0.076*** (0.015)	-0.058*** (0.017)
Education	0.044*** (0.015)	-0.024 (0.017)
Obama	-0.545*** (0.020)	-0.103*** (0.025)
Authoritarianism	-0.029** (0.015)	0.039** (0.016)
BornAgain	0.016 (0.014)	0.030* (0.015)
Religion	0.001 (0.015)	0.038** (0.017)
PartyID (Republican)		0.321*** (0.022)
FoxNews	0.039** (0.015)	0.059*** (0.017)
Conservatism	0.256*** (0.018)	
MoralStatism	-0.001 (0.024)	0.259*** (0.026)
Government	-0.103*** (0.023)	-0.100*** (0.026)
MoralStatism*Government	0.025 (0.026)	0.044 (0.029)
Constant	-0.051*** (0.019)	-0.009 (0.022)
Observations	2,406	2,406
R <sup>2</sup>	0.674	0.523
Adjusted R <sup>2</sup>	0.673	0.521
Residual Std. Error (df = 2391)	0.305	0.342
F Statistic (df = 14; 2391)	354.000***	187.000***

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Individuals characterized by the highest observed levels of moral statism also in the 90th percentile of anti-governmentalism (below a value of -.7 on the governmentalism factor) have a probability of supporting the Tea Party around 40%. To be more precise, moving from minimum to maximum moral statism while in the 10th percentile of governmentalism increases the probability of supporting the Tea Party by .39 (sd=.07) more than it would in the 90th percentile of governmentalism, from .01 (sd=.00) to .42, (sd=.07) rather than .05 (sd=.02) to

Table 3: Including ideology in factor model and removing from regression model

	<i>Dependent variable:</i>
	Tea Party Support
Gender (Male)	0.116 (0.128)
Income	−0.301** (0.148)
Age	−0.343** (0.144)
Race (White)	−0.404** (0.169)
Education	0.066 (0.158)
Obama	−1.250*** (0.222)
Authoritarianism	0.035 (0.148)
BornAgain	0.298** (0.135)
Religion	−0.013 (0.155)
PartyID (Republican)	0.512** (0.199)
FoxNews	0.707*** (0.133)
MoralStatism	−0.556** (0.261)
Government	0.923*** (0.276)
MoralStatism*Government	1.380*** (0.268)
Constant	−2.700*** (0.214)
Observations	2,406
Log Likelihood	−830.000
Akaike Inf. Crit.	1,690.000
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

.03 (sd=.02).

## Bayesian Model Averaging

regression results such as those presented above are sometimes sensitive to minor differences in model specification, such as including or excluding one variable. One risk is publication bias, if researchers prefer models that confirm their hypotheses. Another is loss of efficiency if too many unnecessary variables are included. Finally, an *ad hoc* approach leads to incomplete representations of model uncertainty (J. M. Montgomery and Nyhan 2010, 4).

In particular, a version of the R package *BMA* modified by Montgomery and Nyhan was used to search over the entire model space of Model 2.<sup>1</sup> The analysis uses uniform priors for all independent variables and the only restriction is that the interaction term and its two component variables are required to enter or not enter models together.<sup>2</sup> In the end, 8,192 models were selected.

The results show that the misarchist terms are highly robust to model selection, with a posterior probability of inclusion equal to 100% (one minus the cumulative posterior probability of all models excluding them). The expected value of the coefficient for *MoralStatism* is .78 (sd=.29), for *Governmentalism* it is -.71 (sd=.26), and for the interaction term it is -1.43 (sd=.31). *Obama* and *FoxNews* also had probabilities of inclusion equal to 100% with expected values not dissimilar to those estimated in Model 2. *Age* and *Race* had probabilities of inclusion greater than 50% but with unstable signs, as indicated by expected values hardly distinguishable from zero. All other variables had probabilities of inclusion less than 50%. More detailed graphical information is reported in Supplementary Information.

In the main models reported above, we have consciously chosen to include a large number of control variables because we are presently most concerned with testing our hypotheses and ruling out rival hypotheses. BMA provides further evidence that the models presented above likely contain superfluous independent variables. Though we believe it is best to rely primarily on the conservative estimates reported above, we briefly report how our coefficients of interest would change under different specifications suggested by the BMA. In a model with just those variables found to be the most robust to model selection (*Fox News*, *Obama*, *MoralStatism*, and *Governmentalism*), moving from 10th percentile of *MoralStatism* to 90th within the 90th of *Governmentalism*, is associated with the probability of supporting the Tea Party increasing from .01 (sd=.00) to .50 (sd=.06). Thus, the results from Bayesian Model Averaging suggest the main results reported above are highly robust and, if anything, conservative estimates of the partial correlation between misarchism and Tea Party support.

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<sup>1</sup>The analysis was conducted using the *bic.glmMN()* function, which is a version of the *bic.glm()* function in the R package *BMA*. See (Raftery et al. 2015) and (J. M. Montgomery and Nyhan 2010)

<sup>2</sup>Options were set to be least restrictive. No Occam's Window was used to narrow the models selected by the initial leap algorithm run over the entire model space and, following Montgomery and Nyhan (pp. 21), the number of best models of each size returned by the leaps algorithm was set to 100,000



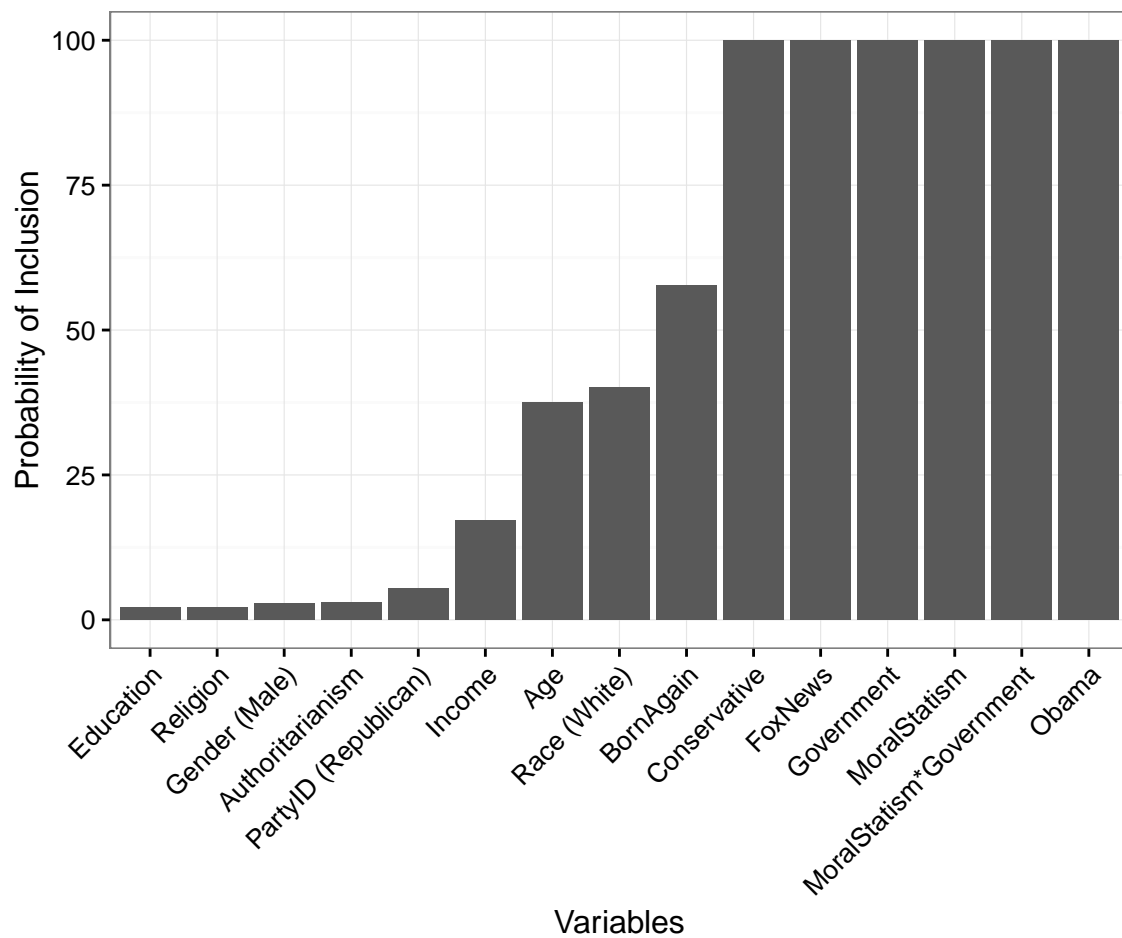


Figure 3: Inclusion Probabilites from Bayesian Model Averaging

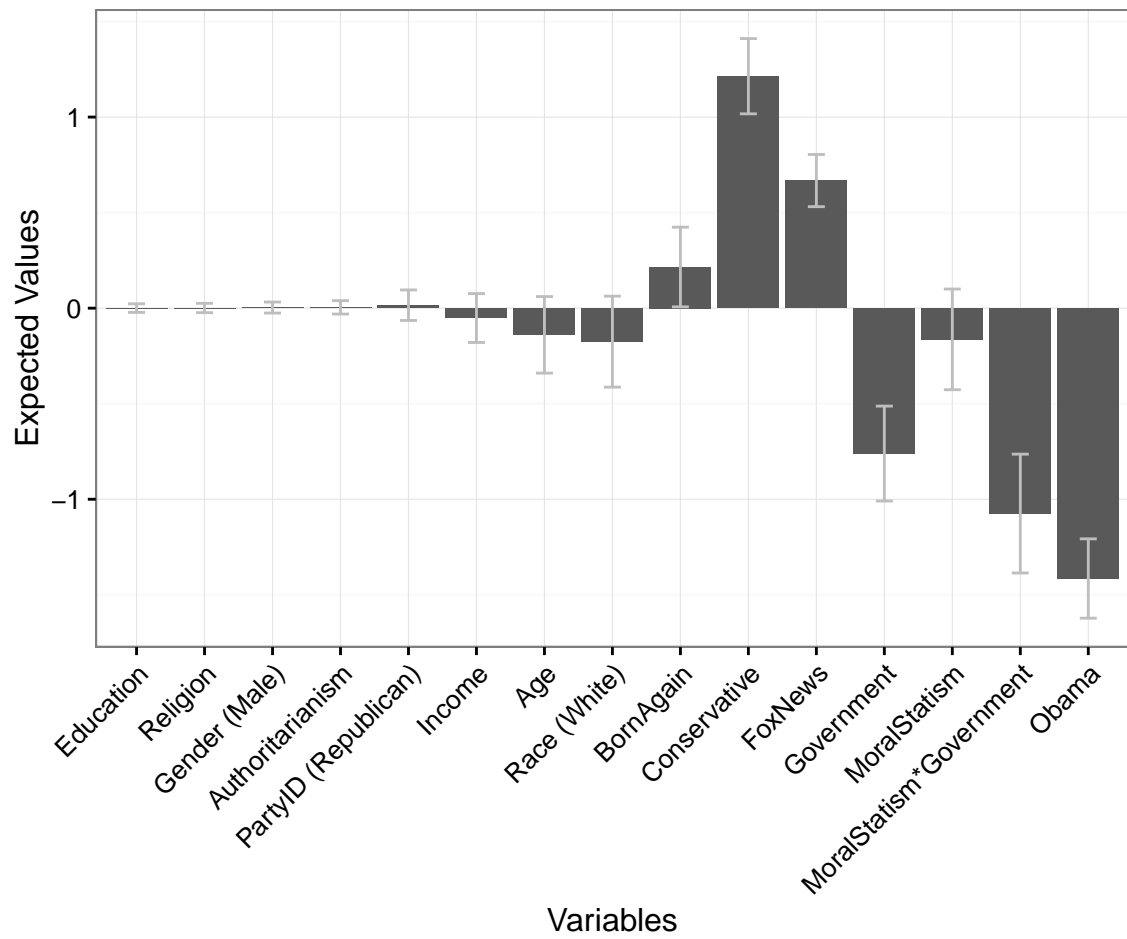


Figure 4: Expected Values from Bayesian Model Averaging

## Multiple Imputation

In particular, if relative misarchists were more (or less) likely to respond to certain questions than other respondents, we may have over-estimated (or under-estimated) the true partial correlation between our misarchist terms and Tea Party support. Multiple imputation refers to the process of using the information from observed variables to infer the most likely values for all missing cells. The process finishes by producing a set of new datasets each of which samples from the predictive distribution to assign most likely values to each missing cell. After multiple imputation, the models discussed above are re-estimated on each imputed dataset and the results are combined using “Rubin’s rules.” Specifically, we use the R package *Amelia* (Honaker, King, and Blackwell 2008) to generate 10 versions of the ANES dataset with missing values imputed and *Zelig* (Imai, King, and Lau 2009) to obtain pooled regression results. The multiple imputation algorithm only assumes that missing values are “missing at random,” not necessarily “missing completely at random.” In this context, “missing at random” only means that missingness is dependent on the observed variables.

After pooling the results, the estimates remain substantially the same. *MoralStatism*, *Governmentalism*, and the interaction term remain signed as in Model 2 with high statistical significance (.98,  $p < .00$ ; -.68,  $p < .00$ ; -1.35,  $p < .00$ , respectively). *FoxNews* and *BornAgain* also remain substantially the same. Graphical diagnostics for overimputation, dispersion, and comparing pre- and post-imputation densities for our main variables suggest no problems or anomalies in the imputation procedures.

	Value	Std. Error	t-stat	p-value
(Intercept)	-2.07	0.11	-18.21	0.00
Gender (Female)	-0.10	0.09	-1.21	0.23
Income	-0.27	0.11	-2.54	0.01
Age	-0.22	0.10	-2.27	0.02
Race (White)	-0.29	0.11	-2.77	0.01
Education	-0.02	0.11	-0.21	0.83
Obama	-0.95	0.14	-6.92	0.00
Authoritarianism	0.10	0.10	0.97	0.33
BornAgain	-0.26	0.09	-2.76	0.01
Religion	0.03	0.10	0.32	0.75
PartyID (Republican)	0.21	0.13	1.61	0.11
FoxNews	0.71	0.10	7.40	0.00
Conservatism	0.98	0.13	7.46	0.00
MoralStatism	0.07	0.20	0.35	0.73
Governmentalism	-0.86	0.18	-4.70	0.00
MoralStatism*Governmentalism	-0.85	0.21	-3.96	0.00

Table 4: Pooled Logistic Regression Results From 10 Multiple Imputations

## Observed and Imputed values of MoralStatism

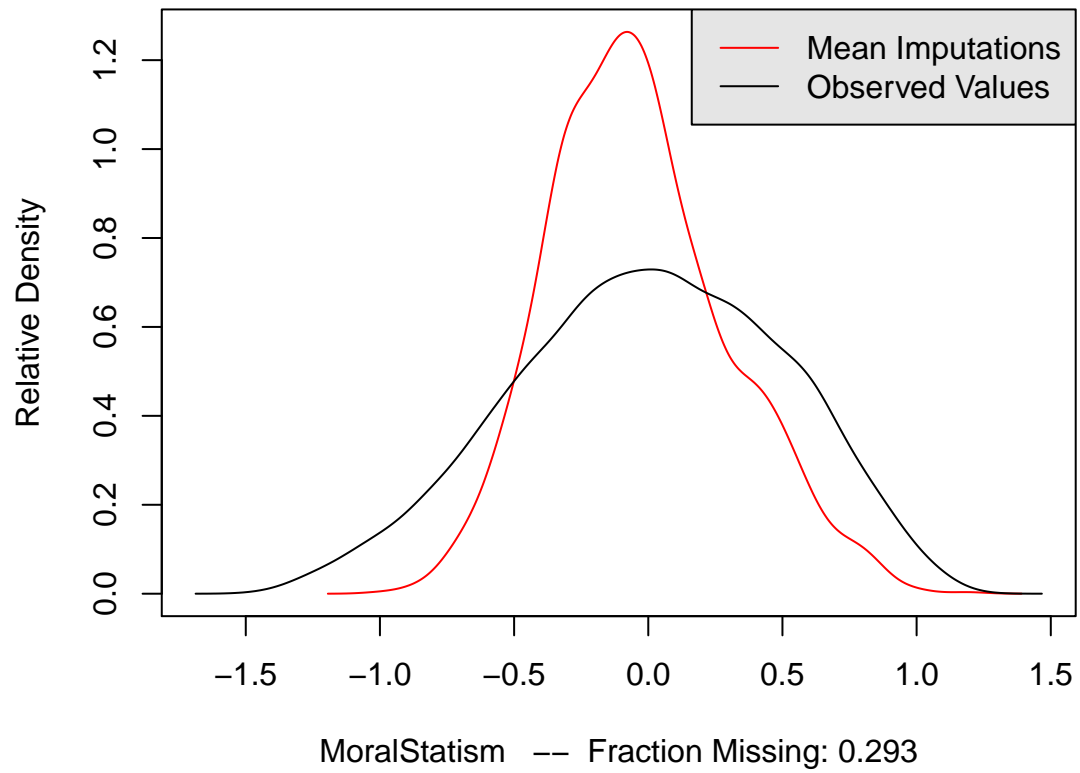


Figure 5: Distributions Before and After Multiple Imputation (1)

### Observed and Imputed values of Government

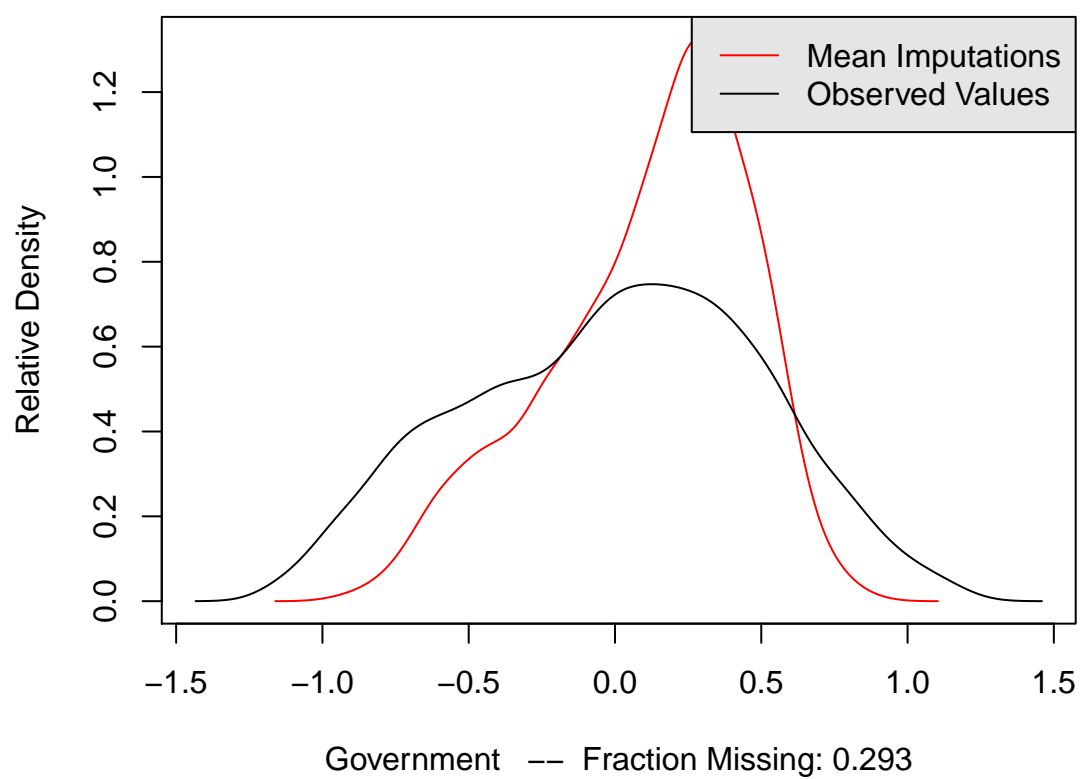


Figure 6: Distributions Before and After Multiple Imputation (2)

## Observed versus Imputed Values of MoralStatism

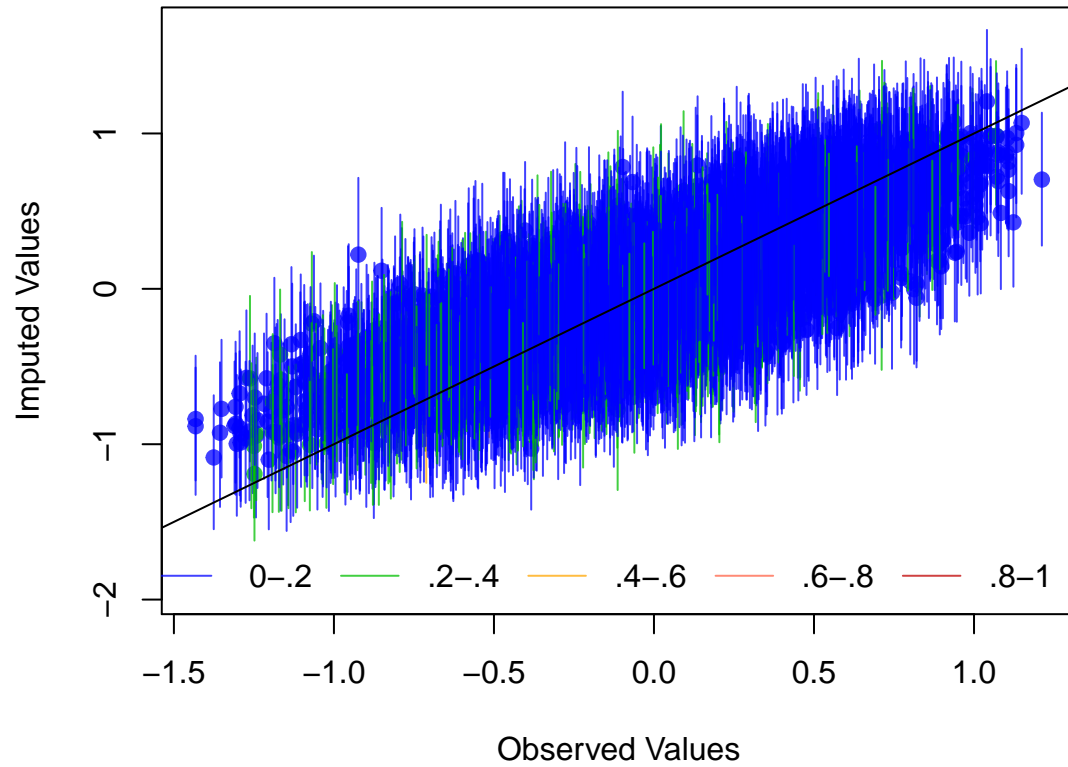


Figure 7: Diagnostic Plot for Overimputation (1)

### Observed versus Imputed Values of Government

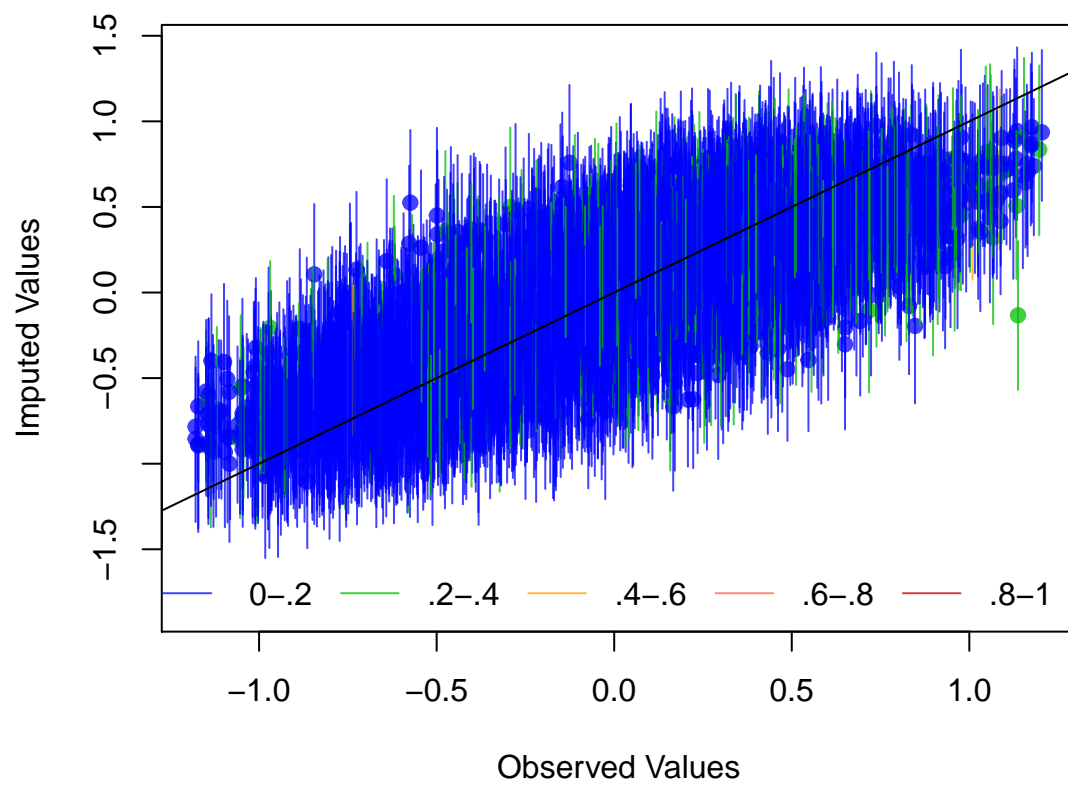


Figure 8: Diagnostic Plot for Overimputation (2)



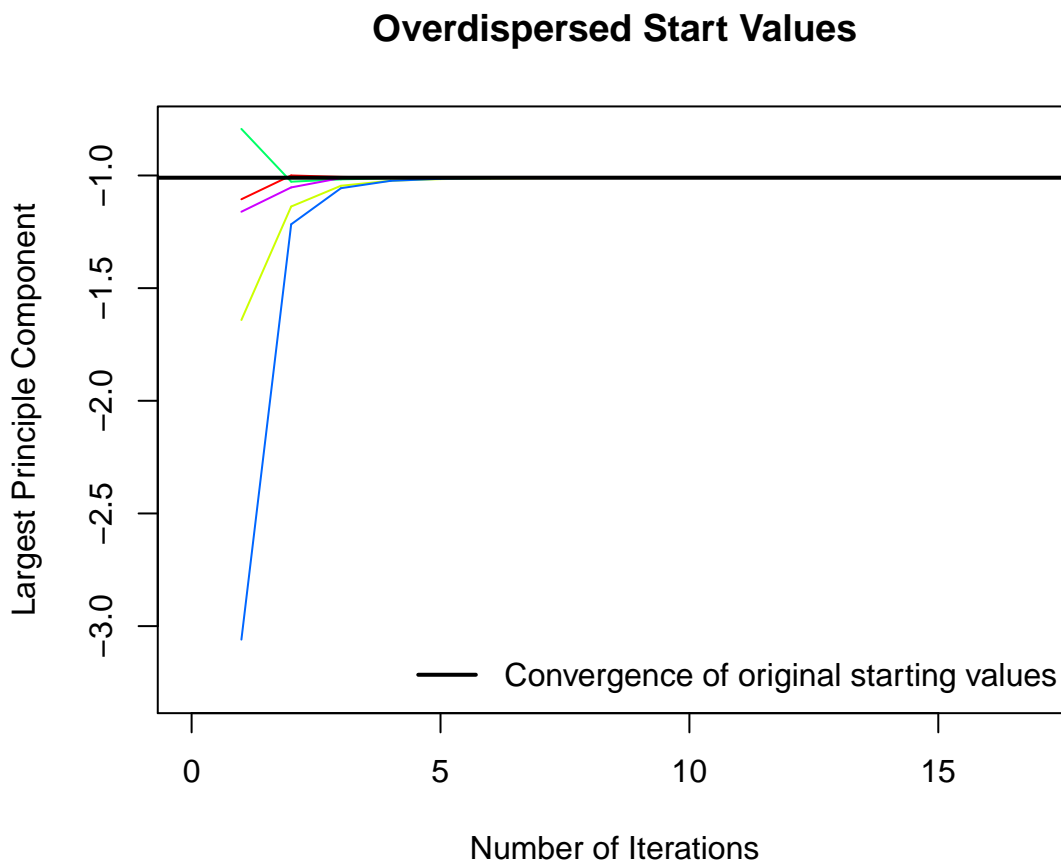


Figure 9: Diagnostic Plot for Dispersion

## Matching and Sensitivity

The algorithm obtains the matched pairs of those “treated” and not treated to governmentalism and moral statism which are otherwise optimally balanced in the propensity to be treated. The average treatment effect for the treated obtained from this subset will approximate that which we would obtain from a randomized experiment, unless some unobserved factor shapes the propensity to be treated. Although the possibility of omitted variables can never be ruled out, we can quantify the sensitivity of these matching estimates to some potential unobserved source of bias. Thus, we also report sensitivity bounds as developed by Rosenbaum (1988), using the R package *rbounds* (Keele 2014).

We generate matching estimates for the effect of governmentalism and the interaction term, one at a time, using one-to-one genetic matching with replacement (Sekhon 2011). We ignore moral statism because the main analyses suggest it does not have an independent effect. In each case, “treatment” is defined as having a value above the sample mean of the variable of interest. For each estimate, we balance on all covariates in Model 2 except the two components of the interaction term and including the treatment variable’s propensity scores with respect to those covariates. We do not balance on the components of the interaction term, or the interaction term itself, because this would remove the covariation of governmentalism and

moral statism the effect of which we wish to test, but we do include the components and the interaction term as covariates.

The average treatment effect on those “treated” with greater than the mean level of governmentalism is -0.025, with a standard error of 0.012 ( $p=.04$ ). The Rosenbaum bounds for this effect suggest that for it to become statistically insignificant at the 95% confidence level, the odds of differential assignment to treatment due to an unobserved factor would have to be about 1.45. The average treatment effect on those “treated” with greater than the mean level of the interaction term is -0.022, with a standard error of 0.01 and a ( $p=.03$ ). The Rosenbaum bounds for this effect suggest that for it to become statistically insignificant at the 95% confidence level, the odds of differential assignment to treatment due to an unobserved factor would have to be about 1.39. The direction and statistical significance of the key relationship in Model 2 (the interaction term), and one of its independent components (governmentalism), do not appear to be spurious artifacts of systematic assignment into treatment from any of the other main covariates making individuals more likely to be misarchist.

## References

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