The Informative Power of Treaty Commitment: Using the Spatial Model to Address Selection Effects Supporting Information

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1 Treaty Data

Figures 1 through 4 present the trends in certain summary statistics of the treaty data set. As is well known, the number of multilateral treaties has increased significantly over recent decades. It is not surprising, therefore, that the average number of ratified treaties has increased consistently since 1950, as Figure 1 shows. The only significant drops observed in Figure 1 occur in two years, 1960 and 1991, when many new states entered the system. A more striking result is depicted in Figure 2, which shows that, accounting for the increase in the total number of treaties in force, the average percentage of treaties ratified by each state has nonetheless increased over time, particularly since the end of the Cold War (with predictable significant drops in 1960 and 1991). Figures 3 and 4 describe the numbers of states that have ratified given ranges of sums of treaties and percentages of treaties as of 2007. Most states have ratified between 50 and 150 treaties, although a fair number have ratified significantly more. Likewise, most states have ratified between 20% and 50% of the treaties.

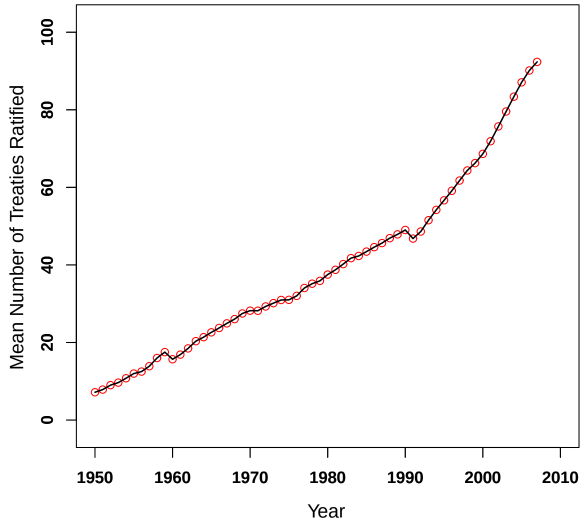

Figure 1: Mean Number of Treaties Ratified

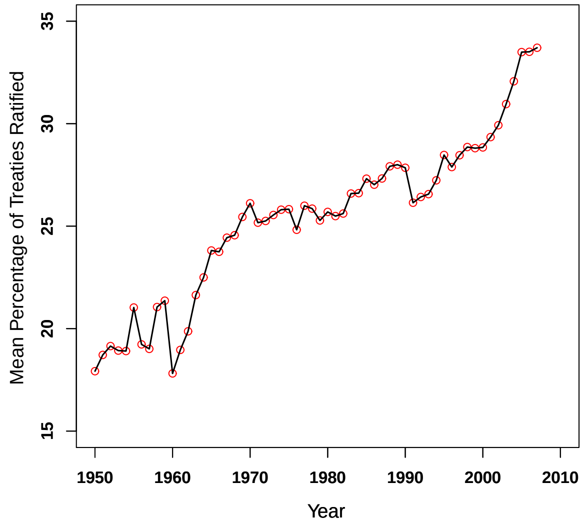

Figure 2: Mean Percentage of Treaties Ratified

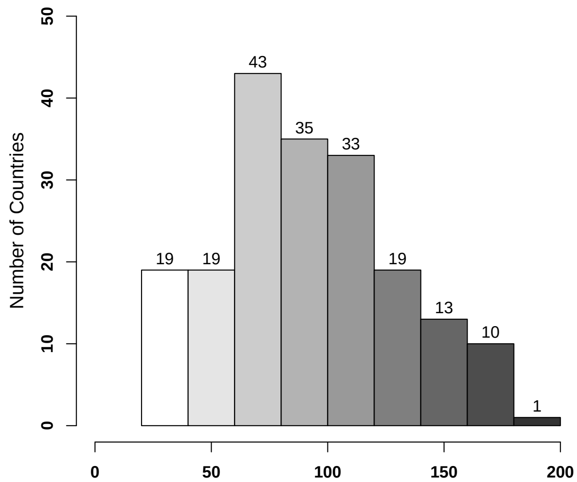

Figure 3: Number of Treaties Ratified as of 2007

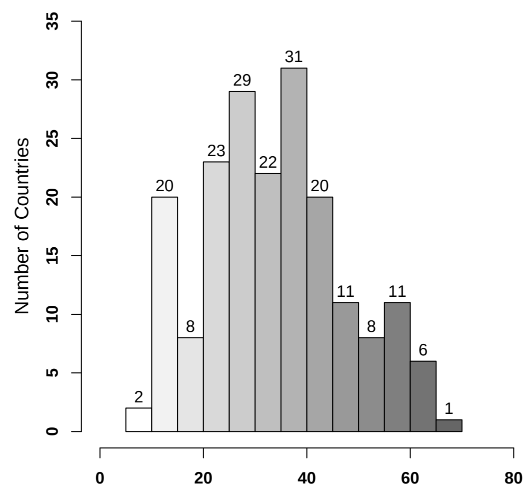

Figure 4: Percentage of Treaties Ratified as of 2007

2 Matching Results

This section supplements Tables 1 and 2 of the main text of the paper by providing additional information regarding the matched country-year samples. Figures 5, 6 and 7 indicate which countries are included in the matched samples. Countries shaded in darker gray appear in the sample during more years. Figure 8 indicates the frequencies of country appearances in the data. With respect to the ICCPR and CEDAW, the maximum number of years a country is included in the matched sample is 27, while this figure is 21 with respect to the CAT.

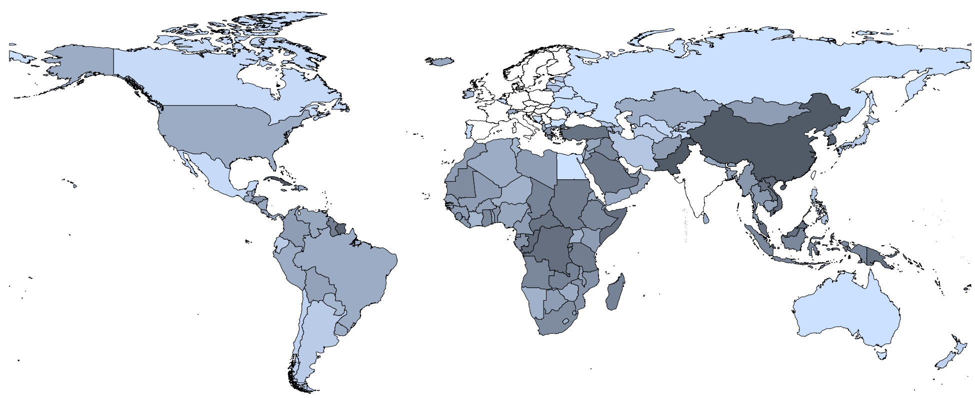

Figure 5: Countries included in the ICCPR matched sample. Countries shaded in darker gray appear in the sample during more years.

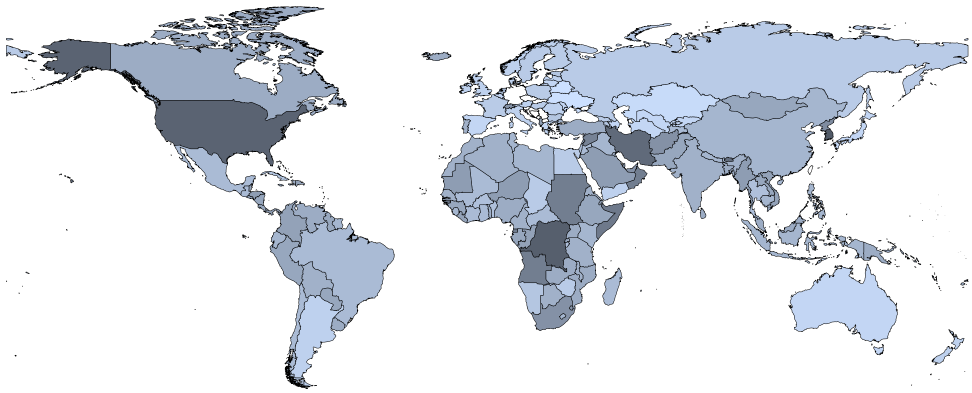

Figure 6: Countries included in the CEDAW matched sample. Countries shaded in darker gray appear in the sample during more years.

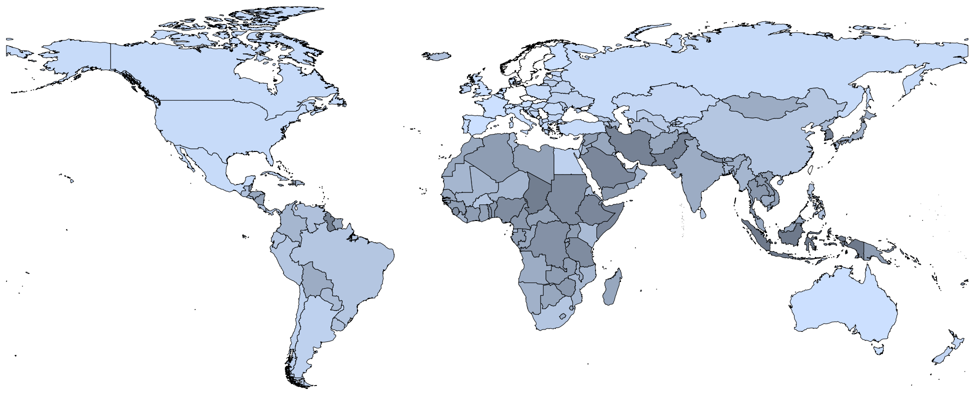

Figure 7: Countries included in CAT matched sample. Countries shaded in darker gray appear in the sample during more years.

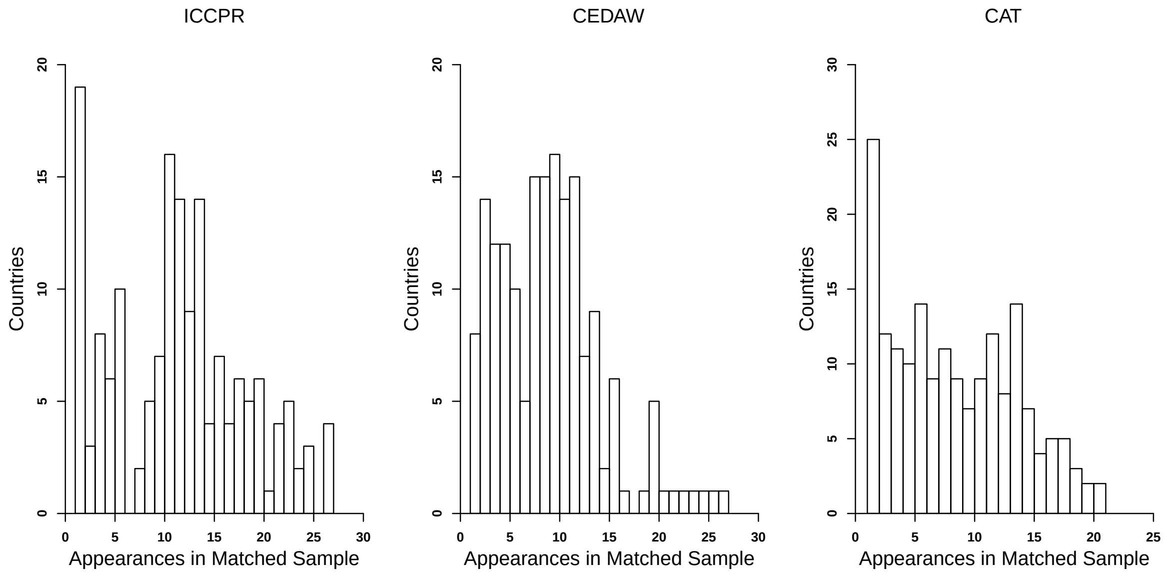

Figure 8: Frequencies of country appearances in the three matched samples.

3 Robustness Tests

This section sets forth the results of alternate specifications to the models presented in the main text. Tables 1 and 2 provide the balance statistics of the matched sample. Table 3 provides the results of ordered probit models used to estimate the effects of treaty commitment using the matched samples.

Table 1: Robustness Test Balance Statistics

	CEDAW		CAT		ICCPR	
	Full	Matched	Full	Matched	Full	Matched
Sample Size	4368	1592	3519	1552	4368	1870
Treatment Units (Treaty Members)	3139	796	2252	776	2947	935
Control Units (Non-Treaty Members)	1229	796	1267	776	1421	935
Mean Pr(Ratification) - Treatment Group	0.911	0.676	0.760	0.330	0.882	0.656
Mean Pr(Ratification) - Control Group	0.484	0.679	0.230	0.358	0.481	0.667
Percentage Improvement in Balance	94.92%		98.61%		97.33%	

Table 2: Robustness Test Balance Statistics - Controls. Mean values reported for treatment and control groups.

	CEDAW		CAT		ICCPR	
	Treatment	Control	Treatment	Control	Treatment	Control
Judicial Independence	1.13	1.14	0.97	1.03	1.00	1.06
Polity	-1.73	-0.72	0.07	0.65	-2.00	-0.56
Regime Durability	30.15	27.37	17.31	19.82	23.03	22.80
Civil War	0.26	0.21	0.22	0.20	0.22	0.19
External War	0.04	0.03	0.03	0.02	0.03	0.03
GDP Per Capita (logged)	7.63	7.54	7.03	7.20	7.27	7.28
Population (logged)	15.73	15.75	15.89	15.78	15.94	15.88
INGOs	467.48	547.12	403.51	507.88	413.08	521.37

Table 3: Robustness Test: Effects of Treaty Ratification - Ordered Probit Models

		CEDAW		CAT	ICCPR
	Pol. Rights	Econ. Rights	Soc. Rights	Torture	Personal Integrity
Treaty Ratification	0.274***	0.203**	0.272***	-0.098	0.010
	(0.074)	(0.065)	(0.070)	(0.079)	(0.062)
Judicial Independence	0.069	0.122*	-0.042	0.159*	0.171**
	(0.059)	(0.058)	(0.058)	(0.069)	(0.053)
Polity	0.016*	0.013*	0.027***	0.020**	0.030***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.005)
Regime Durability	-0.000	0.002	0.001	0.003	0.003**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Civil War	-0.038	-0.301***	-0.203**	-0.545**	-0.763***
	(0.084)	(0.075)	(0.078)	(0.103)	(0.089)
External War	0.200	-0.101	-0.204	-0.014	-0.011
	(0.227)	(0.131)	(0.174)	(0.308)	(0.150)
GDP Per Capita (logged)	-0.115***	0.026	-0.003	0.064	0.020
	(0.032)	(0.032)	(0.033)	(0.033)	(0.027)
Population (logged)	-0.043	-0.044	-0.045	-0.158***	-0.158***
	(0.029)	(0.027)	(0.027)	(0.031)	(0.028)
INGOs	0.000**	0.000**	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rights_{t-1}	1.088***	0.749***	0.834***	0.996***	0.505***
	(0.101)	(0.091)	(0.070)	(0.086)	(0.068)
Rights_{t-2}	0.609***	0.530***	0.607***	—	—
	(0.082)	(0.063)	(0.082)		
Fixed Effects for Year	Yes	Yes	Yes	Yes	Yes
n	1592	1592	1592	1552	1870

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Monte Carlo Simulations

I conduct the simulations according to the following procedure:

Step 1. Create a data set of 100 hypothetical countries and 100 hypothetical universal treaties.

Step 2. Create five random variables with standard normal distributions that determine treaty commitment decisions (X_1 through X_5). X_1, X_2, X_4 and X_5 are observable variables that can be measured without error or bias, while X_3 is unobservable (or unmeasurable). The decision Y of country i to ratify treaty j is given by the following equation:

$$Y_{ij} = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} \tag{1}$$

where I arbitrarily assign the following values to the coefficients: $\beta_1 = 1$, $\beta_2 = -1$, $\beta_4 = 1$, $\beta_5 = -1$. The value of β_3 is also fixed in a given simulation, but varies across simulations per Step 9.

Step 3. Assign the true probability P_{ij} of country i to ratify treaty j using the logistic function of Y_{ij}, as follows:

$$P_{ij} = \frac{1}{1 + \exp(-Y_{ij})} \tag{2}$$

The function used to calculate P_{ij} here need not be the logistic function so long as the function used here is the same as that used in Step 7.

Step 4. Use the true probabilities of treaty commitment to randomly generate the commitment decisions T_{ij} (where $T \in (0, 1)$) of all countries with respect to all treaties.

Step 5. Estimate the country-treaty ideal points using the W-NOMINATE algorithm on the simulated ratification matrix $\mathbf{T}$.[1] To be clear, none of the data on the X variables are used in the W-NOMINATE estimation. Using Equation 3 of the main text of this paper, estimate the probability of each country to ratify each treaty $\hat{P}_{ij_{wn}}$. These estimations were performed using the wnominate package in the R programming language (**?**).

Step. 6. For each treaty j, estimate a logit regression model that predicts the simulated

[1] I use a two-dimensional model for these simulations. With additional dimensions, the W-NOMINATE estimates perform better, although this also creates a risk of over-fitting.

ratifications using the observable, measurable variables, as follows:

$$T_j = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon \tag{3}$$

Step 7. For each country i, estimate the probability $\hat{P}_{ij_{ob}}$ of ratifying treaty j using the logistic function of the estimates generated by this model, as follows:

$$\hat{P}_{ij_{ob}} = \frac{1}{1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \hat{\beta}_4 X_{4i} + \hat{\beta}_5 X_{5i})} \tag{4}$$

Step 8. Repeat steps 2 through 7 for a given value of β_3 100 times.

Step 9. Repeat steps 2 through 8 for a range of values of β_3 from 0 to 5.

The results include two sets of estimated treaty commitment probabilities, and the question is which method results in better estimates of P_{ij} for each value of β_3. To determine which method estimates P_{ij} more efficiently, I calculated the root mean squared error (RMSE) of each set of estimated probabilities with respect to the true propensity scores P_{ij} for each simulation. This results in 100 values of the RMSE for each value of β_3 for each method. For each method, Figure 4 shows the means of the RMSEs for each value of β_3. To provide a sense of scale, the x-axis shows the value of β_3 divided by the sum of the absolute values of all the βs. The mean RMSEs for the W-NOMINATE estimates appear in blue, while those for the estimates based on observables appear in red.

Predictably, the model based on observable country characteristics performs very well when β_3 is small. When $\beta_3 = 0$, the regression model given by Equation 3 is estimating the true model given by Equation 1, subject to the stochastic component. Yet, as β_3 becomes larger, the mis-specification in the model given by Equation 3 grows in importance. As a result, as β_3 becomes larger, the error in the estimates grows significantly. In substantive terms, this means that as unobservable or unmeasurable variables become more important determinants of treaty ratification decisions, estimating probabilities of treaty commitment based on the observable variables becomes increasingly inefficient.

By contrast, the efficiency of the W-NOMINATE estimates is not made worse by the presence or importance of unobservable variables. Increasing the magnitude of β_3 does not reduce the extent to which $\hat{P}_{ij_{wn}}$ correctly estimates P_{ij}. This is ultimately because, regardless of the weight given to the unobservable variable, $\hat{P}_{ij_{wn}}$ is estimated based on the simulated treaty ratifications, rather than the other variables that predict treaty ratification. In this simulation, as β_3 becomes larger, the W-NOMINATE estimates actually become more efficient. This is likely the case because, when β_3 grows, its magnitude becomes larger than those of the other βs. When a particular underlying factor explains treaty ratifications more so than others, W-NOMINATE becomes a more efficient estimator specifically because it is designed to find the most important latent dimension. Thus, the improvements in W-NOMINATE estimate efficiency shown in Figure 4 as β_3 becomes larger may not occur for all real-world data. The more important point is that the W-NOMINATE estimates are not made worse by unobservable variables, and this should continue to be the case for real-world data.

This simulation, however, relies on the unrealistic assumption that a given country considers the same set of factors for each treaty commitment decision. It is more likely that countries take treaty-specific factors into account, such as the subject matter of the treaty (these are noted as O_2 in Equation 1 of the main text of this paper). Thus, I run a second simulation that introduces treaty-specific variables by changing Steps 2 and 6 from the above procedure as follows:

Step 2. Create 11 random variables with standard normal distributions that determine country treaty commitment decisions (X_1 through X_1). All but X_3 are observable variables that can be measured without error or bias. The decision Y of country i to ratify treaty j is given by the following equations:

$$Y_{ij} \mid j \in (0:25) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i}$$

$$Y_{ij} \mid j \in (26:50) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_6 X_{6i} + \beta_7 X_{7i}$$

$$Y_{ij} \mid j \in (51:75) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_8 X_{8i} + \beta_9 X_{9i}$$

$$Y_{ij} \mid j \in (76:100) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_{10} X_{10i} + \beta_{11} X_{11i}$$

where I arbitrarily assign the following values to the coefficients: $\beta_1 = 1$, $\beta_2 = -1$, $\beta_4 = 1$, $\beta_5 = -1$, $\beta_6 = 1$, $\beta_7 = -1$, $\beta_8 = 1$, $\beta_9 = -1$, $\beta_{10} = 1$, $\beta_{11} = -1$.

Step. 6. Estimate logit regression models that predict the simulated ratifications using the observable, measurable variables, as follows:

$$T_j \mid j \in (0:25) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon$$

$$T_j \mid j \in (25:50) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon$$

$$T_j \mid j \in (51:75) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_8 X_8 + \beta_9 X_9 + \varepsilon$$

$$T_j \mid j \in (76:100) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{10} X_{10} + \beta_{11} X_{11} + \varepsilon$$

Figure 4 shows the results of the second simulation. As above, the model based on the observable variables performs relatively well when β_3 is small, but the W-NOMINATE model is more efficient when β_3 is sufficiently large.

The simulations demonstrate that, under certain conditions, estimation of treaty commitment probabilities based only on observable variables known to affect those decisions is the more efficient method. One such situation is when we know and can measure all of the predictors of treaty commitment. A second is when the unobservable, unmeasurable or unknown predictors explain relatively little of the variance in those decisions. In the simulations reported above, when the magnitude of the unobservable factors reaches about 25% to 30% of the sum of coefficients, the probabilities estimated using the observable factors become less accurate than those estimated using spatial modeling. Importantly, these results assume we can measure the observables without error or bias.

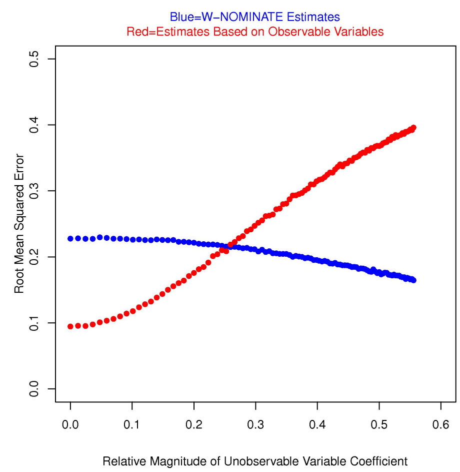

Figure 9: Comparison of Root Mean Squared Errors for parameters estimated using W-NOMINATE and parameters estimated based on observable variables.

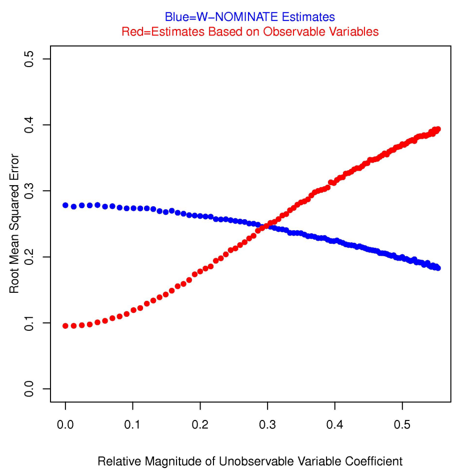

Figure 10: Second comparison of Root Mean Squared Errors for parameters estimated using W-NOMINATE and parameters estimated based on observable variables.