Online Appendix
Rebel Victory and Constitutional Change

Sally Sharif   Ilia Murtazashvili   Jennifer Brick Murtazashvili

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A. Cases of Constitutional Change in Rebel Regimes (1946-2021)

Table 1 provides an overview of constitutional reforms in rebel regimes between 1946 and 2021. It includes information on the rebel regime, the group that led the rebellion, whether a constitutional change occurred, the type of constitutional change (new constitution, amendments, or interim constitution), and the date(s) corresponding to the change(s).

Table 1: Constitutional changes in rebel regimes (1946-2021)

Rebel Regimes	Group	Const. Change	Type	Date
Afghanistan (1992-96)	The Mujahideen	No	-	-
Afghanistan (1996-2001)	The Taliban	No	-	-
Argentina (1955-1983)	Military Junta & Peronist Forces	Yes	Amend Amend Interim Amend	1956 1957 1966 1970
Azerbaijan (1993-2021)	Forces of Suret Husseinov	Yes	New	1995
Bangladesh (1971-1991)	Awami League	Yes	New	1972
Bolivia (1946-1964)	Military Junta of Gualberto Villarroel	Yes	New	1947
Burkina Faso (1987-2014)	Forces of Blaise Compaoré	Yes	New	1988
Cambodia (1975-1991)	Khmer Rouge (Communist Party of Kampuchea)	Yes	New	1976
Central African Republic (2003-2012)	Forces of François Bozizé	Yes	New	2004
Central African Republic (2013-2021)	The Séléka coalition	Yes	Interim New	2013 2016
Chad (1984-2021)	Forces of Hissène Habré	Yes	New	1989

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Rebel Regimes	Group	Const. Change	Type	Date
Chile (1973-1990)	Forces of Augusto Pinochet	Yes	Multi Amends New	Multi Years 1980
China (1950-2021)	Communist Party of China (CPC)	Yes	New	1954
Comoros (1989-98)	The Presidential Guard	Yes	New	1992
Comoros (1999-2021)	Forces of Azali Assoumani	Yes	New	2001
Congo, D.R. (1997-2018)	Alliance of Democratic Forces for the Liberation of Congo (AFDL)	Yes	New	1997
Congo, R. (1997-2021)	Cobra militia	Yes	New	2001
Costa Rica (1948-1949)	National Liberation Army	Yes	New	1949
Cuba (1958-2021)	26th of July Movement (led by Fidel Castro)	Yes	New	1959
Côte d'Ivoire (2011-21)	Forces of Alassane Ouattara	Yes	Amend New	2012 2016
Eritrea (1991-2021)	The Eritrean People's Liberation Front (EPLF)	Yes	New	1997
Ethiopia (1991-2018)	Ethiopian People's Revolutionary Democratic Front (EPRDF)	Yes	Interim New	1991 1994
Georgia (1992-2021)	National Guard and Mkhedrioni	Yes	New	1995
Ghana (1966-2000)	National Liberation Council	Yes	New	1969
Guatemala (1954-1966)	Forces of Carlos Castillo Armas	Yes	New	1956
Guinea-Bissau (1999-2012)	Military Junta for the Consolidation of Democracy, Peace and Justice	No	-	-
Haiti (1991-94)	Forces of Raol Cédras	No	-	-

Rebel Regimes	Group	Const. Change	Type	Date
Iran (1979-2021)	Islamic Revolutionary Council	Yes	New	1979
Laos (1953-2021)	Pathet Lao (Lao People's Revolutionary Party)	Yes	Multi Amends New	Multi Years 1991
Liberia (1980-2003)	Forces of Samuel Doe	Yes	New	1986
Nicaragua (1979-1990)	Sandinista National Liberation Front (FSLN)	Yes	New	1987
Nigeria (1966-1979)	Supreme Military Council (Gowon Regime)	Yes	New	1975
Panama (1989-1994)	Panama Separatist Movement	Yes	Amend	1993
Paraguay (1954-2008)	Forces of Alfredo Stroessner	Yes	New	1967
Paraguay (1989-2008)	Forces of Andres Rodriguez	Yes	New	1992
Romania (1989-2021)	National Salvation Front (NSF)	Yes	New	1991
Rwanda (1994-2021)	Rwandan Patriotic Front (RPF)	Yes	New	1995
Somalia (1991-2000)	United Somali Congress (USC)	No	-	-
South Sudan (2011-2021)	Sudan People's Liberation Army (SPLA)	Yes	Interim Amend	2011 2013
Syria (1966-2921)	Ba'ath Party (Military Committee)	Yes	Interim Amend New	1969 1971 1973
Uganda (1986-2021)	National Resistance Movement (NRM)	Yes	Amend New	1986 1995
Vietnam (1975-2021)	Communist Party of Vietnam	Yes	New	1980

Rebel Regimes	Group	Const. Change	Type	Date
Yemen Arab Rep. (1948-1962)	Royalist Imamate Forces	No	-	-
Yemen People's Rep. (1986-1990)	Yemeni Socialist Party	No	-	-
Zimbabwe (1980-2021)	Zimbabwe African National Union – Patriotic Front (ZANU-PF)	Yes	Multi Amends New	Multi Years 2013

B.   Descriptive Statistics

Table 2 presents descriptive statistics for key variables. `rebel regime` is a binary variable indicating the presence (1) or absence (0) of a rebel regime. `Private property rights` is a categorical variable with values of 1 (protected), 0 (not protected), 90 (explicitly left to ordinary legislation), 96 (other, with accompanying comments), and missing values. `Expropriation for GPP` indicates whether expropriation is permitted for public purposes (1), not permitted (0), or not applicable (99). `Expropriation payment` and `Expropriation legal` are also binary variables, with 99 indicating that the question was not applicable. These codes reflect the specific coding scheme used in the dataset, where 90 denotes topics left to ordinary legislation, 96 signifies "other" responses with detailed comments, and 99 indicates a question was not applicable due to the response to a previous question.

Table 3 presents descriptive statistics for the control variables. `Population` and `GDP per capita` are presented in log form. `GDP growth` exhibits a mean of 3.65% with a standard deviation of 6.66%. `Oil (%GDP)` has a mean of 3.92%, ranging from 0% to 87.1%. `Ethnic fractionalization` and `Religious fractionalization` have means of 0.467 and 0.423, respectively. The average number of coups per country is 0.0478. Finally, 47.5% of countries are classified as non-democratic in the time period of the study.

Table 4 shows the correlations among the main variables. The primary explanatory variable has statistically significant correlations with all outcome variables. Among the control variables, `Oil % GDP` is moderately negatively correlated with `democracy` ($r = -0.31^{***}$). In the manuscript, models include `Oil % GDP` as a key control, while models with `democracy` are included in the appendix. Overall, the table indicates that multicollinearity is unlikely to significantly affect the main results.

Table 2: Descriptive Statistics for Explanatory and Outcome Variables

Variable	Statistic	Value
Rebel regime	0	10782 (90.2%)
	1	1175 (9.8%)
Private property rights	1	7907 (66.1%)
	0	1710 (14.3%)
	90	96 (0.8%)
	96	605 (5.1%)
	Missing	1639 (13.7%)
Expropriation for GPP	0	1928 (16.1%)
	1	6840 (57.2%)
	99	1549 (13.0%)
	Missing	1640 (13.7%)
Expropriation payment	0	5360 (44.8%)
	1	2612 (21.8%)
	99	1549 (13.0%)
	Missing	2436 (20.4%)
Expropriation legal	0	4083 (34.1%)
	1	3889 (32.5%)
	99	1549 (13.0%)
	Missing	2436 (20.4%)

Table 3: Descriptive Statistics for Control Variables

Variable	Statistic	Value
Population (log)	Mean (SD)	15.4 (2.17)
	Median [Min, Max]	15.6 [8.75, 21.1]
	Missing	1423 (11.9%)
GDP per capita (log)	Mean (SD)	8.27 (1.52)
	Median [Min, Max]	8.18 [-6.06, 12.2]
	Missing	2271 (19.0%)
GDP growth (%)	Mean (SD)	3.65 (6.66)
	Median [Min, Max]	3.81 [-64.0, 150]
	Missing	2311 (19.3%)
Oil (% of GDP)	Mean (SD)	3.92 (9.93)
	Median [Min, Max]	0.0167 [0, 87.1]
	Missing	4060 (34.0%)
Ethnic fractionalization	Mean (SD)	0.467 (0.264)
	Median [Min, Max]	0.493 [0.00200, 1.00]
	Missing	2574 (21.5%)
Religious fractionalization	Mean (SD)	0.423 (0.236)
	Median [Min, Max]	0.432 [0.00275, 0.860]
	Missing	690 (5.8%)
Number of coups	Mean (SD)	0.0478 (0.232)
	Median [Min, Max]	0 [0, 3.00]
	Missing	1198 (10.0%)
Democracy	0	5684 (47.5%)
	1	5167 (43.2%)
	Missing	1106 (9.2%)

Table 4: Correlation Table

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Rebel regime	1												
2. Private property	0.05***	1											
3. Exprop GPP	0.04***	0.10***	1										
4. Exprop pay	-0.06***	0.03**	0.22***	1									
5. Exprop legal	-0.15***	-0.01	0.10***	0.27***	1								
6. Population	0.15***	0.07***	-0.01	-0.09***	0.02	1							
7. GDP per cap	-0.15***	-0.03**	0.07***	-0.13***	0.09***	-0.05***	1						
8. GDP growth	0.01	0	0	-0.03*	-0.03**	0.05***	-0.03*	1					
9. Oil % GDP	0.07***	0.06***	0.01	-0.10***	-0.06***	-0.03**	0.14***	0.09***	1				
10. Ethnic frac.	0.04***	0.04**	0.10***	0.12***	0.02	-0.02	-0.28***	0	0.14***	1			
11. Religious frac.	0.08***	-0.15***	-0.08***	0.08***	-0.05***	0.05***	-0.06***	-0.05***	-0.08***	0.26***	1		
12. Coups	0.07***	0.02	0.02	0.01	0	-0.03*	-0.09***	-0.05***	-0.01	0.07***	-0.04***	1	
13. Democracy	-0.25***	-0.04***	0.03**	0.07***	0.04***	0.01	0.30***	-0.07***	-0.31***	-0.23***	0.02*	-0.13***	1

C. Robustness Tests

We first check for multicollinearity using the Variance Inflation Factor (VIF) (Fox and Monette 1992). Table 5 shows VIF values for the four full models in the manuscript (Models 2 and 5). The VIF measures the extent to which a predictor can be linearly predicted by other predictors in the model. A VIF greater than 5 or 10 is typically considered problematic for coefficient estimation. Across all models, VIF values are well below conventional thresholds, ranging from 1.017 to 1.564.

Table 6 provides logistic estimates for private property rights and expropriation for general public purposes (GPP) under alternative model specifications. The models replace the variable `Oil (% GDP)` with `Democracy`. The results show that the presence of a rebel regime consistently increases the likelihood of recognizing private property rights (e.g., 0.554 in Model 1 and 0.935 in Model 3, both significant at $p < 0.001$). For expropriation for GPP, rebel regimes also positively influence the odds across specifications (e.g., 0.372 in Model 4 and 1.060 in Model 6, $p < 0.001$). Controls such as `ethnic fractionalization` (e.g., 1.425 for private property rights in Model 2) and `religious fractionalization` (e.g., -3.159 in the same model) remain significant predictors.

Table 7 shows the results for expropriation requiring payment and a legal process. Rebel regimes decrease the odds of expropriation requiring payment (-0.429 in Model 1, significant at $p < 0.001$) and a legal process (-1.074 in Model 4, also $p < 0.001$). `Population` and `GDP per capita` have mixed effects depending on the specification, while variables such as fractionalization show statistical significance in explaining the variance in these outcomes. These models confirm the robustness of the findings, as the direction and magnitude of coefficients align closely with those in the main manuscript.

Finally, we compared rebel regime-years with non-rebel regime-years within the same country, thus excluding any country that did not experience a rebel victory. We expect rebel regimes years within the same country to be associated with less inclusive governance strategies (Sharif and Joshi 2023). Table 8 examines the effect of rebel regimes on private property rights and expropriation for general public purposes (GPP) in countries with a history of rebel victory. For private property rights, the coefficients for `rebel regime` are consistently negative, ranging from -0.527 in Model 1 to -3.177 in Model 3 (all $p < 0.001$). This suggests that rebel regimes are significantly less likely to protect private property rights, with the magnitude of the effect increasing when controlling for additional covariates or including year fixed effects. By contrast, the results for expropriation for GPP show a positive relationship, with `rebel regime` coefficients ranging from 0.591 in Model 4 to 1.700 in Model 6 (all $p < 0.001$).

Table 9 reports the results for expropriation requiring payment and a legal process, also limited to countries with a history of rebel victory. For expropriation requiring payment, `rebel regime` has consistently negative coefficients, ranging from -0.636 in Model 1 to -1.512 in Model 3 (all $p < 0.001$). Similarly, for expropriation requiring a legal process, the coefficients are even more strongly negative, ranging from -1.346 in Model 4 to -2.099 in Model 6 (all $p < 0.001$). These findings indicate that rebel regimes are less likely to ensure compensatory or legal safeguards in expropriation processes. Across both tables, the

inclusion of additional controls such as `population`, `GDP per capita`, and fractionalization variables does not substantially alter the magnitude or direction of the key coefficients.

Table 5: Variance Inflation Factors (VIF) for Models in the Manuscript

Variable	Property rights	Exprop. GPP	Exprop. pay	Exprop. legal
Rebel regime	1.149	1.160	1.148	1.110
Population (log)	1.046	1.035	1.028	1.022
GDP pc (log)	1.457	1.502	1.497	1.504
GDP Growth	1.017	1.028	1.020	1.018
Oil (% GDP)	1.200	1.164	1.153	1.185
Ethnic Fract.	1.564	1.518	1.488	1.516
Religious Fract.	1.246	1.142	1.152	1.137
Coups	1.023	1.028	1.027	1.027

Table 6: Logistic estimates of private property rights and expropriation for general public purposes with alternative controls

	DV: Private property rights			DV: Expropriation GPP		
	(1)	(2)	(3)	(4)	(5)	(6)
Rebel regime	0.554***	1.256***	0.935***	0.372***	0.935***	1.060***
	(0.106)	(0.149)	(0.153)	(0.095)	(0.117)	(0.119)
Population (log)		0.160***	0.140***		−0.259***	−0.258***
		(0.025)	(0.025)		(0.022)	(0.023)
GDP per cap (log)		0.036	−0.008		0.067*	0.084**
		(0.030)	(0.031)		(0.029)	(0.029)
GDP growth		−0.010	−0.003		0.005	0.002
		(0.006)	(0.006)		(0.006)	(0.007)
Democracy		0.209*	−0.011		0.648***	0.723***
		(0.082)	(0.086)		(0.078)	(0.079)
Ethnic frac.		1.425***	1.185***		1.379***	1.536***
		(0.159)	(0.161)		(0.142)	(0.146)
Religious frac.		−3.159***	−3.123***		−0.969***	−1.027***
		(0.179)	(0.178)		(0.146)	(0.148)
No. of coups		0.405	0.606**		0.144	0.065
		(0.217)	(0.220)		(0.165)	(0.169)
Constant	1.486***	−0.603	−0.502	1.233***	4.280***	4.614***
	(0.028)	(0.487)	(0.589)	(0.027)	(0.455)	(0.622)
Observations	9,617	6,196	6,196	8,768	5,592	5,592
Year FE	No	No	Yes	No	No	Yes
Log Likelihood	−4,486	−2,551	−2,457	−4,610	−2,809	−2,779
AIC	8,976	5,121	5,050	9,225	5,636	5,693

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 7: Logistic estimates of expropriation requiring payment and expropriation requiring a legal process with alternative controls

	DV: Expropriation payment			DV: Expropriation legal process		
	(1)	(2)	(3)	(4)	(5)	(6)
Rebel regime	−0.429***	−0.323**	−0.371***	−1.074***	−1.199***	−1.121***
	(0.084)	(0.099)	(0.102)	(0.082)	(0.100)	(0.102)
Population (log)		−0.001	−0.012		−0.021	−0.014
		(0.021)	(0.021)		(0.019)	(0.020)
GDP per cap (log)		−0.319***	−0.336***		0.057*	0.071**
		(0.027)	(0.028)		(0.024)	(0.024)
GDP growth		−0.011*	−0.010		−0.008	−0.014**
		(0.005)	(0.006)		(0.005)	(0.005)
Democracy		0.339***	0.281***		−0.212***	−0.172**
		(0.069)	(0.071)		(0.063)	(0.065)
Ethnic frac.		0.219	0.141		0.010	0.082
		(0.134)	(0.137)		(0.124)	(0.125)
Religious frac.		0.416**	0.399**		−0.194	−0.208
		(0.136)	(0.138)		(0.124)	(0.124)
No. of coups		0.008	0.088		0.076	0.006
		(0.142)	(0.147)		(0.136)	(0.139)
Constant	−0.677***	1.346**	1.856***	0.055*	0.029	0.174
	(0.025)	(0.438)	(0.544)	(0.024)	(0.401)	(0.501)
Observations	7,972	5,337	5,337	7,972	5,337	5,337
Year FE	No	No	Yes	No	No	Yes
Log Likelihood	−5,028	−3,141	−3,088	−5,428	−3,576	−3,549
AIC	10,061	6,299	6,311	10,859	7,170	7,235

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 8: Logistic estimates of private property rights and expropriation for general public purposes for countries with a history of rebel victory

	DV: Private property rights			DV: Expropriation for GPP		
	(1)	(2)	(3)	(4)	(5)	(6)
Rebel regime	−0.527***	−1.514***	−3.177***	0.591***	1.572***	1.700***
	(0.150)	(0.414)	(0.681)	(0.112)	(0.167)	(0.173)
Population (log)		0.551***	1.037***		−0.334***	−0.323***
		(0.127)	(0.225)		(0.051)	(0.052)
GDP per cap (log)		0.497*	0.733*		0.733***	0.797***
		(0.226)	(0.349)		(0.077)	(0.081)
GDP growth		0.019	0.027		−0.010	−0.008
		(0.018)	(0.024)		(0.011)	(0.012)
Oil % of GDP		0.022	−0.010		−0.071***	−0.076***
		(0.026)	(0.032)		(0.007)	(0.008)
Ethnic frac.		4.697***	7.098***		2.609***	2.756***
		(0.871)	(1.546)		(0.295)	(0.305)
Religious frac.		−16.929***	−28.299***		0.598	0.646
		(1.913)	(3.828)		(0.368)	(0.382)
No. of coups		−0.817*	−0.552		−0.027	−0.260
		(0.394)	(0.606)		(0.268)	(0.295)
Constant	2.566***	−0.385	14.471	1.014***	−0.755	−0.721
	(0.110)	(2.935)	(10.519)	(0.065)	(1.102)	(1.775)
Observations	2,185	1,442	1,442	2,077	1,361	1,361
Year FE	No	No	Yes	No	No	Yes
Log Likelihood	−656	−155	−85	−1,092	−627	−611
AIC	1,315	328	291	2,189	1,272	1,342

Note: *p<0.05; **p<0.01; ***p<0.001.

Table 9: Logistic estimates of expropriation requiring payment and expropriation requiring a legal process for countries with a history of rebel victory

	DV: Expropriation payment			DV: Expropriation legal		
	(1)	(2)	(3)	(4)	(5)	(6)
Rebel regime	−0.636***	−1.413***	−1.512***	−1.346***	−2.094***	−2.099***
	(0.100)	(0.157)	(0.164)	(0.098)	(0.148)	(0.151)
Population (log)		0.268***	0.224***		−0.134*	−0.111*
		(0.054)	(0.057)		(0.053)	(0.054)
GDP per cap (log)		−0.172*	−0.259***		0.107	0.136
		(0.072)	(0.076)		(0.068)	(0.070)
GDP growth		−0.032**	−0.031**		−0.010	−0.014
		(0.011)	(0.012)		(0.010)	(0.010)
Oil % of GDP		−0.050***	−0.046***		−0.025***	−0.028***
		(0.010)	(0.010)		(0.006)	(0.007)
Ethnic frac.		2.012***	1.850***		−0.954***	−0.854**
		(0.293)	(0.302)		(0.289)	(0.296)
Religious frac.		2.532***	2.498***		2.937***	3.016***
		(0.393)	(0.407)		(0.387)	(0.392)
No. of coups		−0.573*	−0.391		−0.193	−0.352
		(0.266)	(0.285)		(0.253)	(0.267)
Constant	−0.470***	−4.904***	−17.438	0.327***	1.291	1.156
	(0.060)	(1.217)	(436.518)	(0.059)	(1.181)	(1.654)
Observations	2,024	1,327	1,327	2,024	1,327	1,327
Year FE	No	No	Yes	No	No	Yes
Log Likelihood	−1,261	−692	−669	−1,292	−748	−733
AIC	2,525	1,401	1,458	2,588	1,514	1,586

Note: *p<0.05; **p<0.01; ***p<0.001.

D. Missing Values and Multiple Imputations

The analysis in the manuscript employs listwise deletion to handle missing values. Missing data can introduce bias if the missingness is systematic. When missingness is completely random, unrelated to the outcome variables, or related only to observable covariates, listwise deletion does not create bias (Arel-Bundock and Pelc 2018). However, if missingness is not random and involves both explanatory and outcome variables, both listwise deletion and multiple imputation may result in biased estimates (Pepinsky 2018). Missing data also reduces sample size, potentially compromising the reliability of statistical inferences (Lall 2017).

To address this, we impute missing values using Multiple Imputation by Chained Equations (MICE), which estimates missing values based on regression models fitted to the observed data (Buuren and Groothuis-Oudshoorn 2011). The results are then compared to those obtained from listwise deletion to evaluate consistency. Figure 1 illustrates the missing data pattern for explanatory and outcome variables, with rows representing observations and columns representing variables. Blue cells denote observed values, while pink cells indicate missing data. Notably, the explanatory variable is fully observed, and 7,972 observations are complete across the explanatory and outcome variables.

Table 10 presents flux analysis and FICO scores, which quantify the efficiency gains from multiple imputation relative to listwise deletion. High FICO scores across most variables indicate substantial efficiency improvements. For example, variables with low `outflux`, such as `population` (0.073), are effective predictors for imputing missing data in other variables but gain little from imputation themselves. Conversely, variables with higher `influx`, like `expropriation payment` (0.249), rely heavily on other variables for their imputation.

We employ the Classification and Regression Tree (CART) method for imputations, a non-parametric technique that uses recursive partitioning to handle complex, non-linear relationships between variables. Figure 2 shows density plots of observed and imputed values. Blue lines represent observed data distributions, while red lines depict imputed values. Ideally, the red lines should closely align with the blue lines, indicating that the imputed values integrate plausibly with the observed data distribution.

Table 11 presents the results after imputation. The coefficients for key predictors remain stable in direction and magnitude compared to pre-imputation results, highlighting robustness. For private property rights, the coefficient for `rebel regime` remains positive (0.383, $p < 0.001$), indicating an 38% increase in the odds of recognizing private property rights in rebel-controlled areas. Similarly, for expropriation for general public purposes (GPP), `rebel regime` maintains a significant positive effect (0.428, $p < 0.001$), corresponding to a 42% increase in the odds. Across all models, control variables such as `population`, `GDP per capita`, `ethnic fractionalization`, and `religious fractionalization` exhibit consistent patterns of statistical significance and effect sizes.

Figure 1: Missing Data Pattern for Selected Variables

Table 10: Flux Analysis and FICO Scores for Missing Data Patterns

Variable	pobs	influx	outflux	ainb	aout	fico
Rebel regime	1.000	0.000	1.000	0.000	0.213	0.617
Private property	0.804	0.133	0.546	0.596	0.145	0.524
Exprop. GPP	0.733	0.185	0.397	0.609	0.115	0.478
Exprop. pay	0.667	0.242	0.292	0.639	0.093	0.426
Exprop. legal	0.667	0.242	0.292	0.639	0.093	0.426
Population	0.881	0.070	0.677	0.513	0.164	0.566
GDP per cap	0.810	0.118	0.514	0.546	0.135	0.527
GDP growth	0.807	0.120	0.504	0.544	0.133	0.526
Oil % GDP	0.660	0.256	0.318	0.663	0.102	0.420
Ethnic frac.	0.785	0.179	0.636	0.730	0.173	0.512
Religious frac.	0.942	0.033	0.842	0.508	0.190	0.594
Coups	0.900	0.055	0.712	0.478	0.169	0.575

Figure 2: Density Plots of Observed and Imputed Values Using CART

Table 11: Logistic Estimates After Imputation

	DV: Private Property	DV: Exprop. GPP	DV: Exprop. Pay	DV: Exprop. Legal
Rebel regime	0.383***	0.428***	−0.283***	−0.607***
	(0.106)	(0.094)	(0.083)	(0.079)
Population (log)	0.085***	−0.036***	−0.100***	−0.040***
	(0.012)	(0.012)	(0.011)	(0.011)
GDP per cap (log)	0.001	0.105***	−0.078***	0.076***
	(0.021)	(0.019)	(0.017)	(0.017)
GDP growth	−0.004	0.001	−0.004	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Oil (% GDP)	0.005	−0.003	−0.008**	−0.006*
	(0.003)	(0.003)	(0.003)	(0.002)
Ethnic frac.	0.480***	0.809***	0.349***	0.291**
	(0.113)	(0.107)	(0.098)	(0.091)
Religious frac.	−1.424***	−0.779***	0.370***	−0.299**
	(0.118)	(0.118)	(0.101)	(0.092)
Coups	0.034	0.085	0.032	0.088
	(0.142)	(0.122)	(0.111)	(0.095)
Constant	0.600*	0.891***	1.189***	0.026
	(0.288)	(0.277)	(0.252)	(0.246)
Observations	9,617	9,617	7,972	7,972
Year FE	No	No	No	No
Log Likelihood	−4,486	−4,486	−4,486	−4,486
AIC	8,976	8,976	8,976	8,976

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

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