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Bayesian Analysis of Military Coups

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Abstract. Why are some coups succesfull but not others? Using multilevel Bayesian logistic modeling via Monte Carlo simulations, this paper investigates three hypotheses on the potential determinants of military coup success; namely plotter ranking, civillian disobedience, and incumbents' counterbalancing forces. I then run logistic regression with imputed data to see if missingness in the data significantly affects the results. I find that (i) coups led by higher-ranking officers have higher chances of success compared to mid-ranking officer led plots, (ii) public discontent, as measured by the incumbent seats' share in the parliament and number of riots, do not play a significant role in coup success, and (iii) coup violence is negatively correlated with coup success odds in statistically reliable levels. This study contributes to the literature on military coups and provides further guidance on future research.

Keywords: bayesian, statistics, military coups.

This is a working paper.

1 Research Question and Hypotheses

On the late-night of 15th of July in 2016, the news broke out that the army in Turkey was blocking the Bosphorus bridge in the largest city of the country, Istanbul, and fighter jets were flying low over the parliament in capital Ankara. Soon after masses filled in the streets to resist against the coup plot. Thousands of people, including both pro-government and opposition, fought back against the military (Esen and Gumuscu 2017; Grewal 2018). Having faced severe resistance and recieved no support from the media, opposition, or other factions within the military; the coup failed after 8 hours of fighting, leaving 251 civilians dead. The country previously had several coups (1960, 1971, 1980, and 1997) but none of them had seen such dramatic failure. Why was the last coup attempt failed, while almost all previous ones succeeded? This paper, hence, investigates the determinants of coup failures. Drawing on the literature on military coups, I test three hypotheses in the following paragraphs.

The first hypothesis is from (Singh 2014) and about the military ranking. Higher-ranking military officers have several advantages over mid-ranking officers when it comes to plotting coups. They can easily coordinate a plot without attracting unnecessary attention as they work closely with each other with regular meetings, unlike mid-ranking officers. They are better equipped to estimate costs and risks associated with a failure

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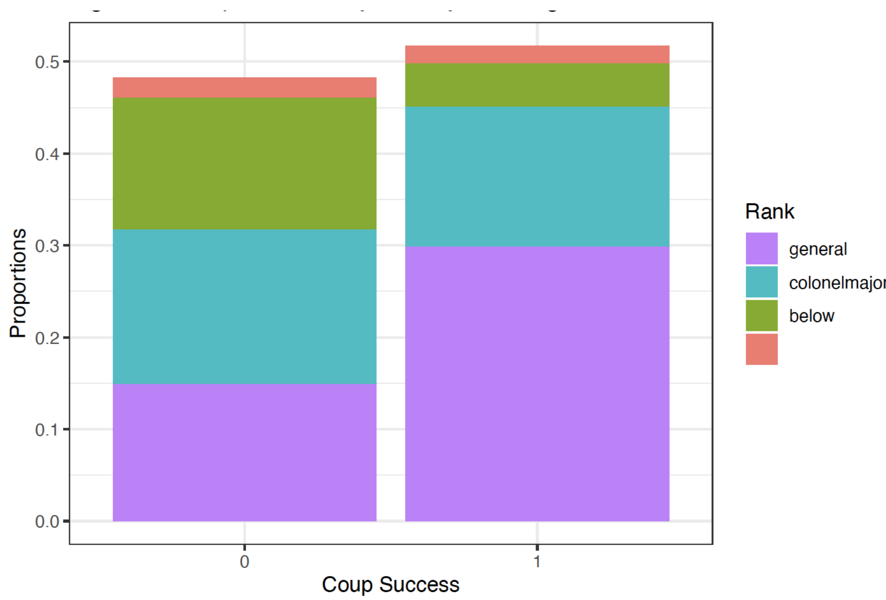

Figure 1: Coup Success by Military Ranking

beforehand. They have greater soft power in the military which allows them to convince other branches of the armed forces to join the plot because generals are more trusted in the military with their skills, experience, and networks. The Figure 1 shows the proportions of failed and successful coups by plotter rankings. It is clear that attempts by generals have been more successful than plots led by other ranked officers.

Hypothesis 1: *Coups led by generals are more likely to be successful than coups led by mid-rank officers.*

The second hypothesis is about civilian disobedience. Luttwak (1968) argues that civilian obedience is a requirement for military coups to succeed. If there is a large civilian resistance against a coup, then that coup is more likely to fail. Singh (2014) modifies this: Civilian protests or resistance does not matter by itself, but it can potentially change the other military officers' decision to join or not to join the coup. I argue that if there is popular discontent for the government, people would not have a strong objection against a coup. Thus, other military officer would not hesitate to join the plot, increasing the odds of coup success. If the incumbents have large public support, however, the military would have a lower chance of capturing power because the plotters will be facing civilian resistance, also leaving other military officers undecided to join or not to join the plot. The army technically can easily suppress any civilian resistance, but this would potentially lead to a split within the army, creating the worst case scenario, a civil war.

Hypothesis 2 *Popular discontent will decrease coups' probability of success.*

Finally, the third hypothesis is about counterbalancing, which is the creation of new security forces, usually against possible coup attempts (De Bruin 2018). They are independent of the traditional military branches, and can take the form of civilian militias as in Bolivia, republican guards as in Saddam's Iraq, militarized police as in Russia, or presidential guards as in Ghana. The very reason for their existence is to protect incumbents against coups, therefore we can expect that they must be effective against coup plots.

Hypothesis 3 *Counterbalancing reduces the probability of coup success.*

2 Data and Methodology

I compiled the dataset from several sources. The unif analysis is coup plots. The dependent dichotomous variable, *(coup success)*, as well as military officer rankings *(ranking)* are drawn from Powell and Thyne's (2017) data set of coup attempts (v11.28.2017). I then cross-referenced the reported coup events with UCDP/PRIO Armed Conflict Dataset v 17.2 (Gleditsch et al. 2002). There are 313 coup attempts in the final dataset; among them, 49% are failed attempts while 51% are successful coups. The cases in the dataset are fairly recent ranging from 1950 to 2017. The measure for the second hypothesis, popular disobedience, is retrieved from Banks and Wilson's (2019) Cross-National Time-Series Data Archive. I used three different proxies to test whether its effect is consistent, including an index of seats held by the largest party (incumbent seat), number of government crises *(gov crises)*, and number of riots *(riots)*. Finally, the measure for the last hypothesis, counterbalancing, is drawn from the State Security Forces dataset (De Bruin 2017; De Bruin 2018). Again, different measures of counterbalancing are used in different models to see if varying measures lead to different conclusions. These are (i) a dummy variable for the existence of presidential guards *(pguard)*, (ii) logged number of counterbalancing forces that were created by the incumbents *(affiliated forces (log))*, and (iii) another dichotomous variable for the creation of a new counterbalancing force in the previous year *(new cb force)*. I also control for several potential determinants of coup success and other explanatory variables, including GDP growth, population, military size, the violence degree of coup plots, and the incumbent regime type. Descriptive statistics for the variables can be found in Table 1.

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In terms of missing data, the dependent variable success, naturally, has no missing values. However, as it can be seen in Table 1, the predictors for counterbalancing have many missing values. Thus, in Table 2, I check the correlation between other variables and the missingness in counterbalancing variables. The table shows that missingness in counterbalancing is negatively correlated with population and military personnel. This makes sense, since it is difficult to code/know smaller countries' counterbalancing efforts. On the other hand, the Figure 2 demonstrates that there are no clear patterns in the data, and the missigness ratios are low. However, because the missingness is correlated with other variables (counterbalancing correlation with population), I then

Table 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Success	321	0.517	0.500	0	0	1	1
Ranking:General	309	0.469	0.500	0.000	0.000	1.000	1.000
Ranking:Colonel/Major	309	0.333	0.472	0.000	0.000	1.000	1.000
Ranking:Below	309	0.197	0.399	0.000	0.000	0.000	1.000
Incumbent Seats	309	110.298	109.914	0.000	0.000	181.000	633.000
Government Crises	313	0.476	0.906	0.000	0.000	1.000	7.000
Riots	313	0.840	2.068	0.000	0.000	1.000	17.000
Presendtial Guard	197	0.086	0.282	0.000	0.000	0.000	1.000
Affiliated Forces (log)	197	0.266	0.444	0.000	0.000	0.693	1.609
New CB Force	255	0.047	0.212	0.000	0.000	0.000	1.000
GDP Growth	311	6.530	0.896	4.353	5.966	7.075	8.901
Population (log)	311	8.916	1.272	4.533	8.156	9.740	11.834
Military Personnel (log)	301	3.281	1.452	0.000	2.197	4.407	6.548
Coup Violence	299	1.441	0.497	1.000	1.000	2.000	2.000
Regime Type:Military	297	1.246	0.431	1.000	1.000	1.000	2.000

apply multivariate imputation by chained equations (MICE). For the purposes of comparison, I first build a pooled logistic regression model in Table 3 with imputed values. The coups led by generals particularly have much higher success probabilities. I will be interpreting the log-odds of these estimates together with MCMC outputs in the following paragraphs.

	term	estimate	std.error	statistic	df	p.value
1	(Intercept)	5.8531115	2.6220728	2.2322460	176.54590	0.0268562
2	Ranking:General	2.3259442	0.5453267	4.2652305	140.27539	0.0000365
3	Ranking:Colonel/Major	1.1636866	0.5219009	2.2297078	164.01047	0.0271246
5	Incumbent Seats	0.0019996	0.0018422	1.0854467	157.38667	0.2793836
6	Presendtial Guard	-0.5553039	0.6355130	-0.8737883	178.12194	0.3834101
7	GDP Growth	-0.7376818	0.2238004	-3.2961596	173.05791	0.0011892
8	Population (log)	-0.0542665	0.2447216	-0.2217477	182.17424	0.8247587
9	Military Personnel (log)	-0.0970276	0.2030509	-0.4778487	182.73735	0.6333290
10	Coup Violence	-0.8967388	0.3767890	-2.3799492	88.24236	0.0194685
11	Regime Type:Military	-0.2875467	0.3990331	-0.7206087	171.03249	0.4721341

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 250
##    Unobserved stochastic nodes: 77
##    Total graph size: 4040
```

Table 2: Correlation with Missingness

	Pres. Guard Miss.	Aff. Forces (log) Miss.	New CB Miss.
success	-0.0143994	-0.0143994	-0.0174439
general	0.0224772	0.0224772	0.1274997
colonelmajor	-0.0845154	-0.0845154	-0.1411731
below	0.0719104	0.0719104	0.0073369
incumbent.seat	0.1183581	0.1183581	0.0431773
gov.crises	-0.0880827	-0.0880827	0.0308916
riots	0.0260022	0.0260022	0.1898914
lgdpgrowth	-0.1397634	-0.1397634	-0.3208453
lpop	-0.2939264	-0.2939264	-0.0159812
lmilper	-0.2236667	-0.2236667	-0.0456387
violent	-0.0383378	-0.0383378	-0.0489672
gwf_military	-0.0950076	-0.0950076	0.0298248

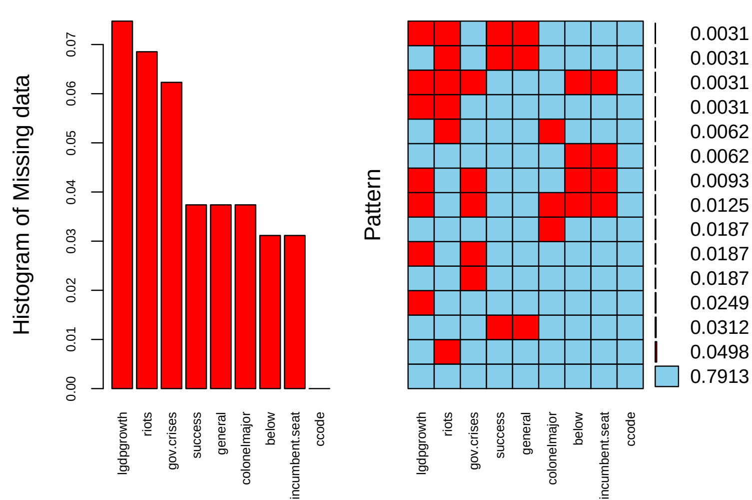

Figure 2: Missing Data Examination

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##
## Initializing model
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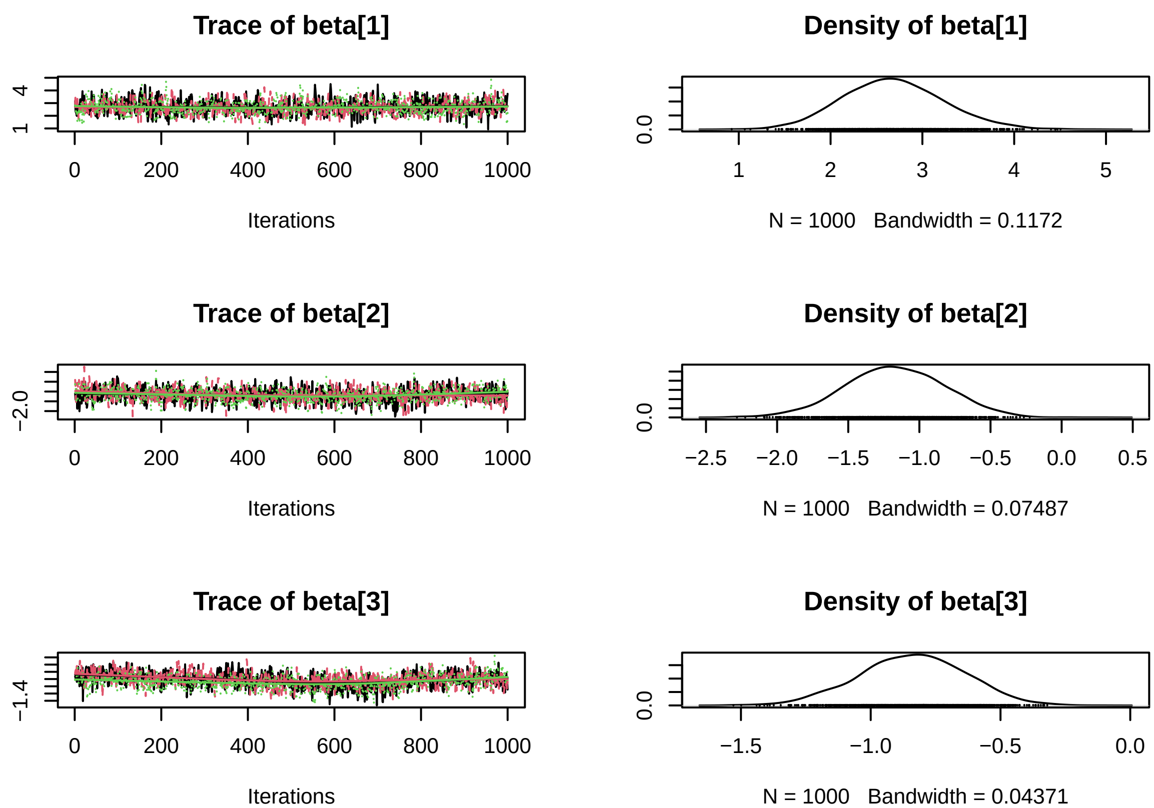
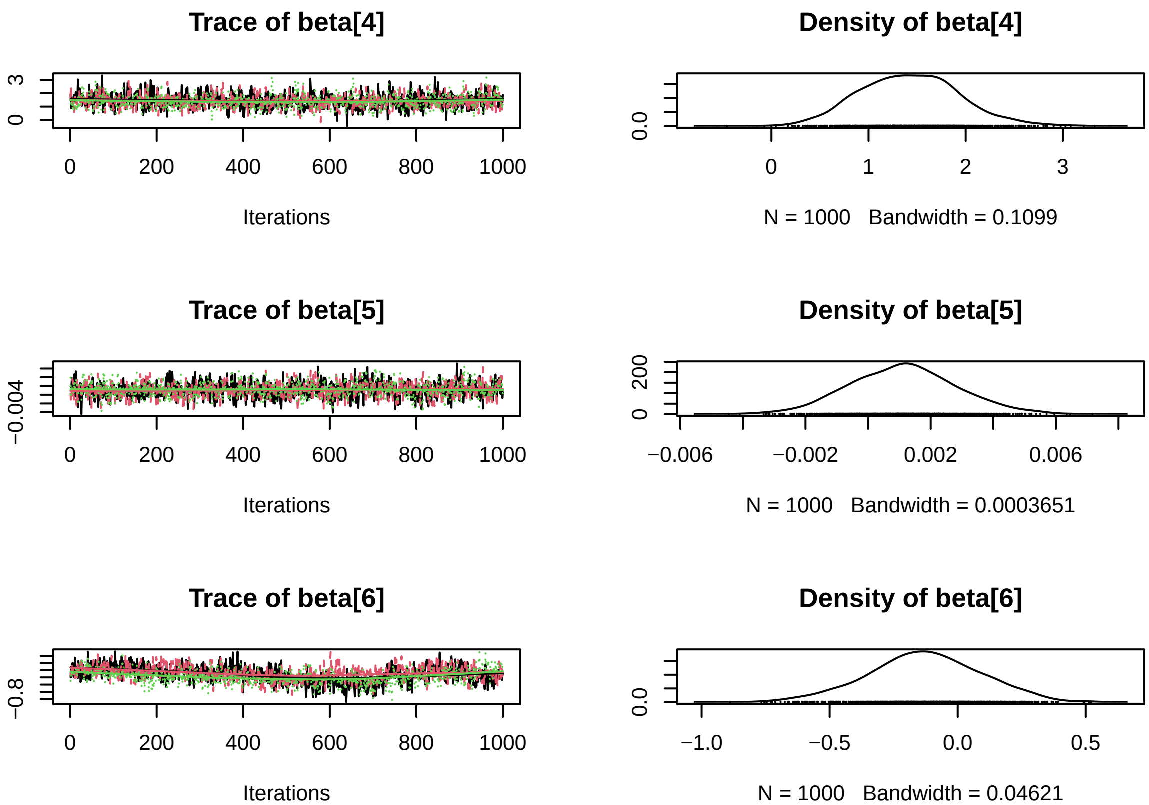
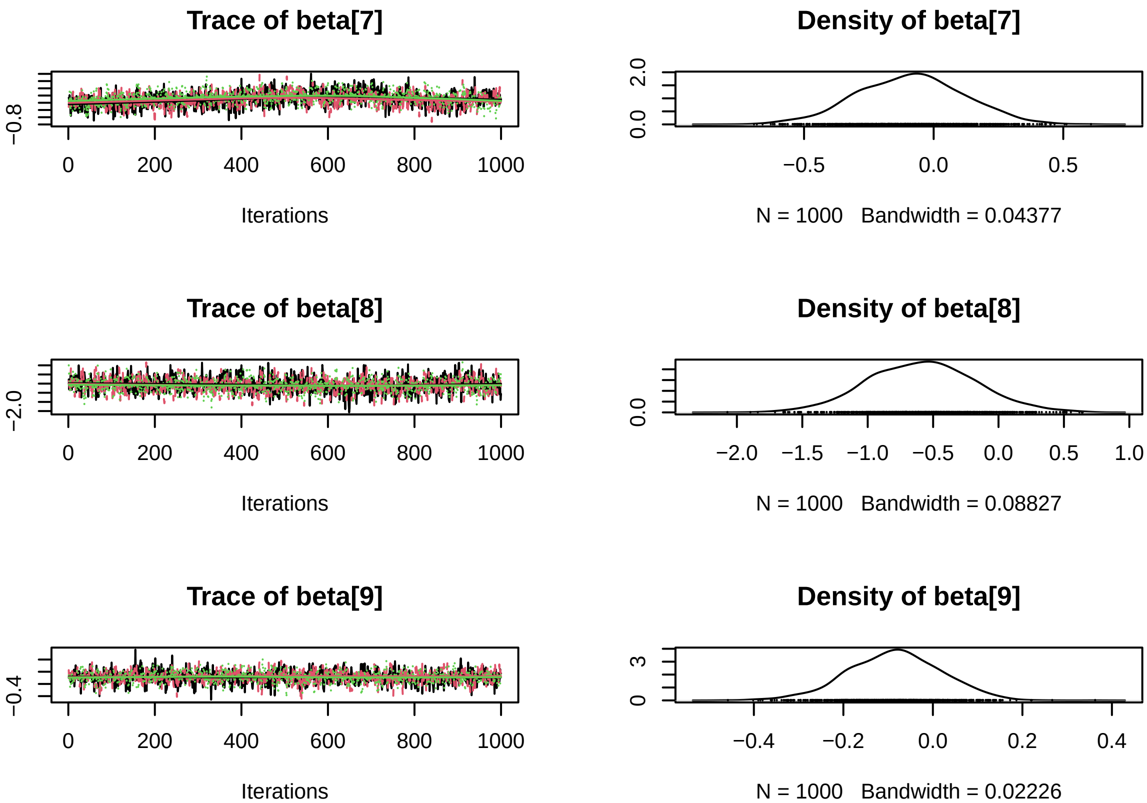
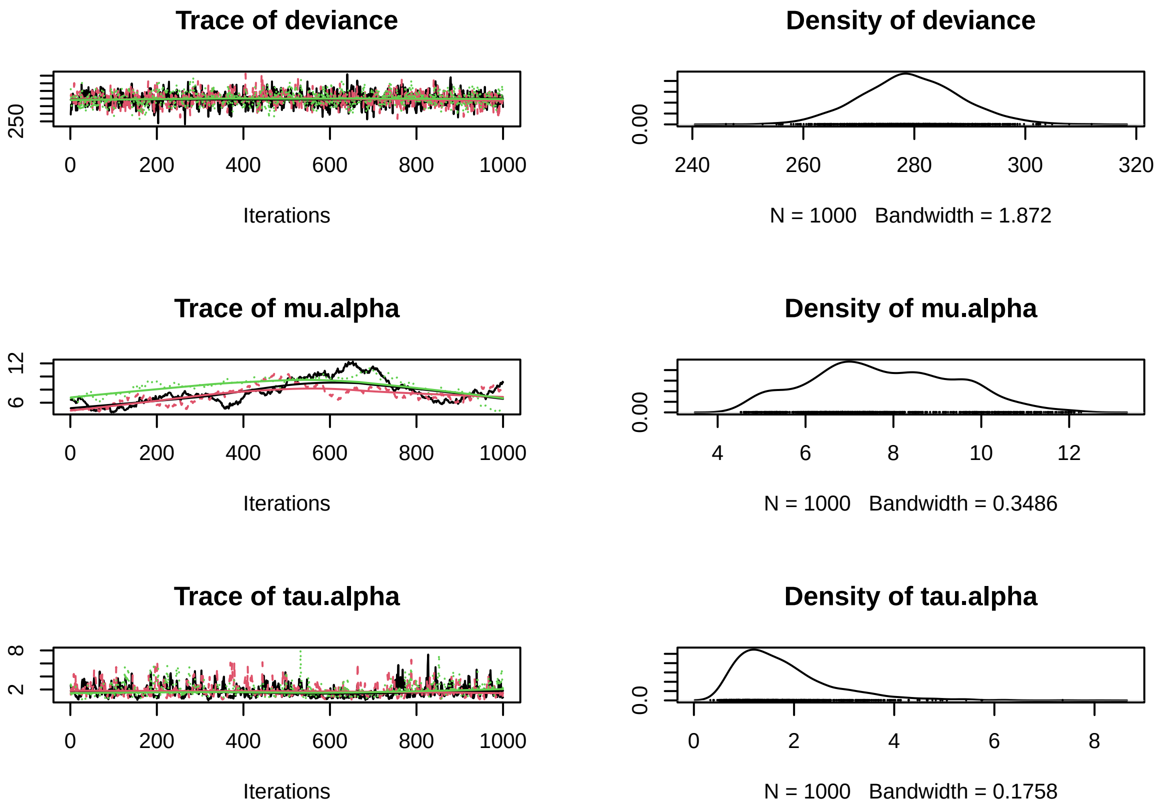
	mean	sd	2.5%	97.5%	Rhat	n.eff
Ranking:General	2.6852813	0.5483774	1.6752781	3.8197593	1.001153	3000
Coup Violence	-1.1730693	0.3502764	-1.8755078	-0.4977244	1.001042	3000
GDP Growth	-0.8404039	0.2045093	-1.2437631	-0.4554114	1.027066	78
Ranking:Colonel/major	1.4245694	0.5142245	0.4607879	2.4778701	1.002373	1100
Incumbent Seats	0.0011279	0.0017082	-0.0021544	0.0045959	1.002306	1100
Population (log)	-0.1291572	0.2198462	-0.5777052	0.2890870	1.040041	55
Military Personnel (log)	-0.0889090	0.2047984	-0.4962194	0.3048222	1.015669	140
Regime Type:Military	-0.5845889	0.4129787	-1.3926221	0.2484372	1.003437	680
Riots	-0.0853417	0.1041593	-0.2997938	0.1158759	1.002163	1200
Deviance	279.3863034	8.9698317	262.0655134	297.5847119	1.001492	2000
Mu.alpha	7.7883882	1.6310179	4.8964524	10.9380160	1.130799	20
Tau.alpha	1.8007858	0.9726328	0.6084827	4.2949710	1.006716	320




Trace of beta[4]
Iterations
Density of beta[4]
N = 1000 Bandwidth = 0.1099
Trace of beta[5]
Iterations
Density of beta[5]
N = 1000 Bandwidth = 0.0003651
Trace of beta[6]
Iterations
Density of beta[6]
N = 1000 Bandwidth = 0.04621


Trace of beta[7]
−0.8
0
200
400
600
800
1000
Iterations
Density of beta[7]
0.0
2.0
−0.5
0.0
0.5
N = 1000 Bandwidth = 0.04377
Trace of beta[8]
−2.0
0
200
400
600
800
1000
Iterations
Density of beta[8]
0.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
N = 1000 Bandwidth = 0.08827
Trace of beta[9]
−0.4
0
200
400
600
800
1000
Iterations
Density of beta[9]
0
3
−0.4
−0.2
0.0
0.2
0.4
N = 1000 Bandwidth = 0.02226



3 Discussion of Results

Model diagnostics above show that our estimates are only fairly strong, some of them failing in several criteria. Due to the limited sample size, and the infrequency of military coups around the world, these results are somehow expected. When it comes to interpretating coefficients, we see consistent results from the Bayesian logit model with the previous GLM model, although I used non-informative priors. In terms of individual predictors, according to both models, coup plots led by generals have clearly higher chances of succeeding coups compared to mid-ranking officers. This result is consistent with the first hyptothesis. Secondly, as proxies for public discontent, I used two variables: an index variable showing the incumbent seats' share in the partliament and number of riots. Neither the incumbent seats nor riots seem to affect odds of success of military coup plots. Finally, among the control variables, coup violence is negatively correlated with coup success odds in statistically reliable levels. This is also consistent with the fact that generals make plots more succesfull: They calculate the risks and opportunites associated with a plot. Thus, higher-ranking plotters are less likely to engage in coup attempts where there is high risk, and high death toll possibility.

4 Conclusion

Throughout the paper, I tested three potential determinants of military coups' success: plotter ranking, civillian disobedience, and incumbents' counterbalancing forces. I then run logistic regression with imputed data, using glm function. I also run Bayesian logistic regression via Manto Carlov simulations. The results are consistent with each other. There are, however, a few caveats. First is that more informative priors could have been selected for counterbalancing forces from the literature, but due to the time constraints, I was not unable to do so. Second, riots and seat percentages are not exactly good proxies of civillian disobedience as they belong to the year when coup plot happened. These riots could have happened in favor or in opposition of the incumbent government as we do not know the exact time: They may have happened before or after the coup plot. Despite the caveats, however, results tell us clearly that plots led by generals have much higher chances of success. Also, bloody coups are less likely to succeed.

Supplementary Material

Data and Replication Materials. Please contact the author to access the data and the code for this article.