Mad COW: A Reply to Gibler and Miller
Supplemental Information (SI)

Jason Lyall*

September 11, 2021

This supplemental appendix provides additional details on the statistical analyses conducted in Lyall 2021. Specifically, it (1) compares Project Mars to 11 different data sources; (2) details errors made by Gibler and Miller in assigning CoW codes to Project Mars wars; (3) rebuts their claims that the military inequality coefficient (MIC) is flawed; (4) provides the complete statistical tables for the average marginal effect plots used in Figure 2 to demonstrate the link between military inequality and five measures of battlefield performance; (5) conducts a robustness check using *Divided Armies*' alternative measure of military inequality (*Bands of inequality*); and (6) re-runs these tests using only wars found in Clodfelter (2008). Unless otherwise noted, these tests reflect Gibler and Miller's (2021) preferred statistical models, periodization, and data partitioning by CoW war typology. Together, these tests once again confirm that military inequality is an important determinant of battlefield performance in conventional wars since 1800.

*James Wright Chair in Transnational Studies and Associate Professor of Government, Dartmouth College. Email: jason.lyall@dartmouth.edu, URL: `www.jasonlyall.com`

1 Project Mars "Cross-Walk" With 11 Existing Datasets and War Lists

Project Mars (v.1.1) is a new dataset of 252 conventional wars (1800-2011). Table A1 details the degree of overlap between Project Mars and 11 different data sources. Note that the Inter-State War dataset only contains about one-third of all relevant observations of conventional war.[1]

Table A1: Project Mars Cross-Walk With 11 Existing Datasets and War Lists

Source	N in Project Mars	% of Project Mars
COW Datasets		
Inter-State War (v.4.0)	115	34.9%
Extra-State War (v.4.0)	62	18.8%
Intra-State War (v.4.0)	58	17.6%
Non-State War (v.4.0)	24	7.3%
Not in COW	70	21.3%
Additional Datasets		
Clodfelter (2008)	263	79.9%
Wimmer and Min (2009)	208	63.2%
Interstate War Data (v.1.1)	111	33.7%
Reiter and Stam (2002)	77	23.4%
CDB90	48	14.6%
Post-1945 Wars Only		
UCDP/PRIO Armed Conflict Dataset (v.20.1)	58	17.6%
Kalyvas and Balcells (2010)	29	8.8%

Note: There are 329 wars/campaigns and 825 belligerent observations in Project Mars (v.1.1).

[1] *Divided Armies* used Version 1.0 of Project Mars, which had 250 wars but the same number of observations (n=825). See Lyall 2020. The increase to 252 wars in Version 1.1 is due to the revision of two war codes, not to the addition of new data.

2 Coding Errors in Assigning CoW war ids to Project Mars wars

Gibler and Miller attempt to assign CoW war ids to each war in Project Mars. Space does not permit a war-by-war discussion of their efforts. Instead, I have archived our "cross-walk" document, which cross-references every Project Mars war with 11 different datasets (including CoW), on our Dataverse page.[2]

Here I simply provide a few examples of different errors made. These are important for both the historical record and for assessing the reliability of their war type coding used in the "reanalysis" of Project Mars.

First, they recycle the same CoW war id to cover separate war/conflicts. For example, they apply CoW war id 576 ("Tungan Rebellion of 1862-1873") to five separate conflicts in Project Mars despite the fact that these wars are separated by years and involved different actors than provided in Sarkees and Wayman (2010). They apply war id 1531 ("First Haiti-Santo Domingo War of 1844-45") to three distinct wars, including the Third Dominican War which was fought in 1849. Similarly, they assign CoW war id 303 ("First Bolivar Expedition of 1817-19") to three separate Project Mars wars, all of which occurred between 1810 and 1815.

Second, they assign CoW war ids to the wrong Project Mars war. For example, they assign war id 359 ("Russian-Kokand War of 1864-65") to Project Mars war id 95, which involved a war between China and Kokand in 1865. Similarly, they assign CoW war id 550 ("Viennese Revolt of 1848") to Project Mars war id 63 ("Austro-Venetian War of 1849"), which covers the April-October 1849 encirclement, siege, and subsequent fall of the Republic of Venice. Third, Gibler and Miller assign 12 Militarized Interstate Dispute ids to Project Mars wars. This is an odd move if the point is to demonstrate that these wars are already in one of four CoW datasets. Fourth, they drop 29 wars/campaigns in the pre-1816 as outside CoW's domain. For Gibler and Miller, these cannot be considered "outside" CoW because of its 1816 start date, and are apparently dropped from their reanalysis. Confusingly, they also allow 7 pre-1816 wars to count as "in" one of the four CoW datasets. Finally, CoW still does not recognize the multi-front treatment of World Wars I and II (as first proposed by Reiter and Stam 1998). I therefore coded all World I and II campaigns and belligerents in Project Mars as also found in CoW even if they lacked a relevant belligerent observation.[3] This somewhat inflates the degree of overlap between Project Mars and CoW.

[2] `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DUO7IE`

[3] There are 33 belligerent observations over 9 different campaigns in WWI. A further 61 belligerent observations in 20 campaigns comprise Project Mars' coding of WWII.

3 Military Inequality as an Independent Variable

Since Gibler and Miller's two-sentence summary of the military inequality coefficient (MIC) contains multiple errors, it makes sense to restate how it was constructed. Briefly, the MIC calculates an army's level of inequality across its constituent ethnic groups. It consists of two components. First, I calculated the relative share that each group represented of an army's prewar personnel. Second, I assigned each ethnic group a numeric value based on its prewar treatment by the state. Specifically, I recorded whether the group enjoyed full citizenship (a "0"), faced state-organized discrimination (a "0.5"), or suffered state-orchestrated repression (a "1"). These two components are then combined to generate a value between 0 (perfect equality) and 1 (perfect inequality). Formally, we have:

$$MI = \sum_{i=1}^{n} pt_i$$

Here, p is the proportion of a belligerent's army that an ethnic group represents, t is the nature of the state's prewar treatment of that ethnic group, and n is the total number of ethnic groups in the army. The military inequality coefficient has several desirable properties. It is easily interpreted; higher values indicate greater inequality within the army. Both components are measured before war commences — not during battle, as Gibler and Miller claim — helping to avoid confounding with wartime processes. Finally, it is flexible; scholars can apply it to entire armies, specific divisions, or even small detachments. In Chapter 4, I simply calculated one prewar MIC per belligerent per war using the mean of high and low estimates.

Gibler and Miller remain unimpressed by the MIC variable, however, and submit a barrage of complaints about its measurement. It is data-greedy, they contend, requiring granular data on armies that "are not usually feasible to collect." This is an odd charge. Data collection difficulties do not justify excluding potentially important explanatory variables. To be sure, our coders spent years collecting high and low MIC estimates for each belligerent; this was easily the most time-consuming aspect of Project Mars. Yet to suggest that this task is infeasible is to ignore the recent explosion of similar efforts to collect crossnational, time-series, data on the ethnic composition of armies and security forces.[4] Similarly, multiple large-N datasets record the state's treatment of ethnic minorities over time, whether in terms of mass violence, physical security, or political rights.[5] Scholars harnessing the power of record linkage have now constructed panel data on the ethnic and racial composition of armed formations from millions of personnel records in conflicts as diverse as the American Civil War, the British Commonwealth armies in the Second World

[4] E.g., Harkness 2018; Johnson and Thurber 2020; De Bruin 2020; Carey, Mitchell and Paula 2022.
[5] E.g., Gurr 1993; Wucherpfennig et al. 2011; Eck and Hultman 2007.

War, and the Korean War.[6] In one notable case, 100 million personnel records were used to construct a *monthly* panel-dataset on the ethnic composition of 609 Soviet Rifle Divisions on the Eastern Front.[7] Gibler and Miller have simply missed the sea-change in sources and methods available to scholars interested in these questions.

There's no doubt that the quality and quantity of evidence available for estimating MIC values varied across conflicts, time, and belligerents. That's precisely why we created quality codes for our assessments; made them publicly available in Project Mars; and reestimated our results dropping observations with low confidence codes. Gibler and Miller, however, contend that these quality assessments are problematic. After scraping the online 1,200-page Project Mars bibliography, they conclude that "systematic bias" exists in the MIC value because our quality codes are inversely correlated with the number of sources per war. For Gibler and Miller, the quality of information should increase with the number of citations; here, however, the opposite appears true.

Unfortunately, there are two basic problems with their approach. First, the public Project Mars bibliography was designed as a starting guide for new coders to familiarize themselves with the wars; it is literally called the "starter kit" in the codebook (p.2). It is not a comprehensive accounting of the sources used to code MIC values (or, indeed, other variables). As noted in the book (p.154), the codebook (pp14-16), and in all of the historical cases (e.g., pp.208,210,262,265), the MIC was derived from diverse sources, including military tables of organization, large-N datasets, wartime correspondents, war diaries, censuses, official histories, and regimental narratives. The Project Mars bibliography reflects general histories, not these more specialized sources, which were recorded in a separate database. Second, the number of sources per war is simply not a credible measure for their quality. A single citation might indicate the absence of a robust historiography; it might also indicate the presence of a statistical encyclopedia with a wealth of information. Similarly, five sources might indicate a high volume of information, sharp disagreement over its true nature, or fragmentary data scattered over multiple sources. Given that they scraped the wrong sources and their own measure of quality makes little sense, their claim of systematic bias is unwarranted.

Next, Gibler and Miller claim that the MIC isn't especially useful. Armies, they contend, don't appear to be that divided; the mean MIC for belligerents is "only" 0.205. Yet this is a *high* value: it signifies that 20.5% of an army is comprised of soldiers from violently repressed ethnic groups or 41% from groups experiencing state discrimination. They also suggest that there are few high and medium inequality belligerents. This, too, is incorrect. Project Mars records 142 belligerent observations at high/extreme levels of inequality and a further 216 at medium levels. Six of the book's case studies involve bel-

[6]Dippel and Heblich 2021; Fennell 2019; Huff and Schub 2021.

[7]Rozenas, Talibova and Zhukov 2020. See also Talibova 2021.

ligerents with MIC values at these levels. They suggest something is amiss by noting that MIC's "effective range" only extends to 0.75. Yet, as I noted in the book (p.7), the MIC has a ceiling because it is impossible for armies to be fielded without some core of reliable soldiers.[8] The MIC performs exactly like its cousin, the Gini coefficient: while perfect inequality is theoretically possible, it is typically not achieved in reality. Both measures top out around 0.80.[9] Finally, they argue that MIC is "meaningless" because some values for some belligerents straddle the entire continuum of possible values. But there are no such belligerents in Project Mars.

[8]It is possible for some individual units to exceed 0.80 (see Chapter 8).
[9]Scheidel 2017, 445-448.

4 Military Inequality and Loss-Exchange Ratios, by CoW War Types

Table A2 details the relationship between military inequality and loss-exchange ratios for each type of CoW war. These estimates were derived from Gibler and Miller's preferred statistical models, which heavily modify the original models used in *Divided Armies*. These changes include dropping six variables (including many associated with CoW's own data), abandoning my periodization into early (1800-1917) and modern (1918–) wars, and partitioning Project Mars into four different types of war. The models used here retain all Project Mars data; Gibler and Miller had discarded all coalitional wars (dropping 44% of Project Mars). I added a fifth category of war to capture conflicts not in CoW. These models were used to generate Figure 1 in Lyall 2021.

Table A2: Military Inequality and Loss-Exchange Ratios, by CoW War Types

	Inter-State War	Intra-State War	Extra-State War	Non-State War	Not in COW
Military Inequality	-3.884^{***}	-2.173^{*}	-4.330^{***}	$-2.538^{\dagger}$	-2.740^{***}
	(0.861)	(1.028)	(1.039)	(1.462)	(0.650)
Regime Type	0.020	0.074	0.101^{*}	0.163	0.092^{**}
	(0.026)	(0.050)	(0.042)	(0.131)	(0.028)
Regime Type*Initiator	0.033	−0.013	−0.010	−0.054	−0.010
	(0.038)	(0.050)	(0.042)	(0.143)	(0.038)
Democratic Opponent	-1.391^{***}	−0.147	$-1.022^{\dagger}$	−2.167	-2.030^{***}
	(0.288)	(0.495)	(0.609)	(3.159)	(0.458)
Initiator	0.117	−0.406	−0.156	−0.758	−0.075
	(0.261)	(0.381)	(0.238)	(1.092)	(0.303)
Distance to Battle	0.120	0.188^{**}	0.221	0.134	0.231^{**}
	(0.098)	(0.059)	(0.090)	(0.140)	(0.070)
Standing Army	0.938	0.258	0.969	−0.516	0.619
	(0.621)	(0.359)	(0.646)	(0.568)	(0.396)
Volunteer Army	0.134	0.127	0.173	0.076	0.386
	(0.354)	(0.256)	(0.360)	(0.589)	(0.280)
Composite Army	$-0.388^{\dagger}$	-0.870^{**}	$-0.845^{\dagger}$	0.384	0.341
	(0.228)	(0.293)	(0.477)	(0.509)	(0.291)
Relative Forces	0.197	−1.435	-2.364^{**}	$-2.020^{\dagger}$	0.895
	(0.693)	(0.891)	(0.802)	(1.074)	(0.799)
Constant	0.400	$1.568^{\dagger}$	1.177	$2.822^{\dagger}$	$-1.166^{\dagger}$
	(0.639)	(0.792)	(0.477)	(1.411)	(0.629)
F Score	9.923^{***}	3.53^{***}	18.39^{***}	1.319	8.812^{***}
r^2	0.220	0.265	0.492	0.272	0.378
N	329	154	133	56	153

Note: Robust standard errors clustered on individual belligerents. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$.

5 Military Inequality and Five Measures of Battlefield Performance, By CoW War Type, 1800-2011

Tables A3-A7 detail the relationship between military inequality and five different measures of battlefield performance (as outlined in *Divided Armies*' Chapter 4) for each type of CoW war. These estimates were derived from Gibler and Miller's preferred statistical models, which heavily modify the original models used in *Divided Armies*. These changes include dropping six variables (including many associated with CoW's own data), abandoning my periodization into early (1800-1917) and modern (1918–) wars, and partitioning Project Mars into four different types of war. The models used here retain all Project Mars data; Gibler and Miller had discarded all coalitional wars (dropping 44% of Project Mars). I added a fifth category of war to capture conflicts not in CoW. These models were used to generate Figure 2 in Lyall 2021.

These tests confirm the importance of military inequality for explaining battlefield performance in modern war. *Military inequality* is statistically significant and negatively correlated with all measures of battlefield performance in 23 of 25 models. By contrast, traditional explanations — including regime type, as favored by Gibler and Miller — find little empirical support within or across war types.

Table A3: Military Inequality and Battlefield Performance in CoW Inter-State Wars, 1800-2011

	LER Below Parity	Mass Desertion	Mass Defection	Blocking Units	BP Index
Military Inequality	4.567***	4.951***	3.437**	3.750***	−0.734***
	(0.911)	(0.901)	(1.097)	(1.077)	(0.136)
Regime Type	−0.035	−0.037	−0.081†	−0.095*	0.007***
	(0.027)	(0.026)	(0.041)	(0.043)	(0.002)
Regime Type*Initiator	−0.015	−0.008	0.063	0.070	−0.003
	(0.041)	(0.040)	(0.055)	(0.062)	(0.002)
Democratic Opponent	1.332***	−0.490	−0.266	−0.687	−0.016
	(0.315)	(0.341)	(0.449)	(0.452)	(0.035)
Initiator	−0.325	−0.495†	0.210	−0.275	0.045*
	(0.297)	(0.291)	(0.405)	(0.444)	(0.021)
Distance to Battle	−0.119	0.030	0.086	0.175	−0.003
	(0.074)	(0.076)	(0.106)	(0.129)	(0.007)
Standing Army	−0.766	−0.389	−1.186	15.085	0.076
	(0.780)	(0.823)	(0.923)	(1127.265)	(0.077)
Volunteer Army	0.208	−0.140	0.155	−2.365*	0.028
	(0.346)	(0.347)	(0.474)	(1.045)	(0.026)
Composite Army	−0.091	0.018	0.470	0.094	−0.009
	(0.284)	(0.278)	(0.381)	(0.375)	(0.037)
Relative Forces	−0.870	−0.131	0.109	−1.088	0.065
	(0.726)	(0.716)	(0.958)	(0.971)	(0.076)
Constant	0.149	−1.229	−2.594*	−17.968	0.799***
	(0.893)	(0.935)	(1.144)	(1127.265)	(0.078)
Wald χ^2	70.65***	59.62***	38.58***	60.40***	
F Score					10.97***
(Pseudo) r^2	0.173	0.137	0.093	0.190	0.287
N	329	329	329	329	329

Note: Robust standard errors clustered on individual belligerents. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$.

Table A4: Military Inequality and Battlefield Performance in CoW Intra-State Wars, 1800-2011

	LER Below Parity	Mass Desertion	Mass Defection	Blocking Units	BP Index
Military Inequality	1.878	4.092**	5.857***	6.367***	−0.829***
	(1.194)	(1.296)	(1.391)	(1.551)	(0.121)
Regime Type	0.002	0.094*	−0.063	0.029	−0.003
	(0.044)	(0.046)	(0.053)	(0.059)	(0.004)
Regime Type*Initiator	−0.096	−0.089	0.017	−0.095	0.010*
	(0.076)	(0.065)	(0.073)	(0.083)	(0.005)
Democratic Opponent	0.654	1.005	0.425	1.715**	−0.174***
	(0.537)	(0.614)	(0.588)	(0.636)	(0.046)
Initiator	−0.553	0.621	0.556	0.115	−0.040
	(0.550)	(0.476)	(0.541)	(0.613)	(0.043)
Distance to Battle	−0.162†	0.089	0.084	0.123	−0.004
	(0.089)	(0.088)	(0.096)	(0.109)	(0.007)
Standing Army	0.015	−1.296*	−0.302	−0.794	0.102†
	(0.593)	(0.579)	(0.618)	(0.681)	(0.053)
Volunteer Army	−0.164	−1.115**	0.702†	0.186	0.032
	(0.394)	(0.421)	(0.423)	(0.489)	(0.051)
Composite Army	0.645	1.051*	0.299	0.999*	−0.126***
	(0.406)	(0.414)	(0.419)	(0.509)	(0.036)
Relative Forces	1.891†	−0.132	−0.795	−1.088	−0.016
	(0.990)	(0.963)	(1.020)	(1.234)	(0.085)
Constant	−1.609†	−0.824	−2.967**	−3.293**	0.895***
	(0.890)	(0.861)	(0.995)	(1.164)	(0.080)
Wald χ^2	19.86*	30.28***	38.94***	38.97***	
F Score					11.24***
r^2	0.132	0.214	0.175	0.263	0.443
N	154	154	154	154	154

Note: Robust standard errors clustered on individual belligerents. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$.

Table A5: Military Inequality and Battlefield Performance in CoW Extra-State Wars, 1800-2011

	LER Below Parity	Mass Desertion	Mass Defection	Blocking Units	BP Index
Military Inequality	5.414**	9.519***	6.815***	6.746***	-1.012^{***}
	(1.793)	(1.924)	(1.898)	(1.772)	(0.085)
Regime Type	-0.153^{*}	0.047	0.157*	0.07	-0.001
	(0.068)	(0.054)	(0.068)	(0.061)	(0.003)
Regime Type*Initiator	-0.021	0.028	-0.106	0.085	0.000
	(0.089)	(0.075)	(0.103)	(0.090)	(0.004)
Democratic Opponent	1.226	-0.809	-0.759	-0.566	0.016
	(0.858)	(0.835)	(1.177)	(0.929)	(0.059)
Initiator	0.790	0.089	-0.754	-0.182	-0.007
	(0.566)	(0.491)	(0.667)	(0.572)	(0.025)
Distance to Battle	-0.113	$-0.185^{\dagger}$	-0.088	-0.068	0.017*
	(0.121)	(0.108)	(0.158)	(0.133)	(0.007)
Standing Army	0.245	0.358	-0.736	-1.460^{*}	0.038
	(0.760)	(0.746)	(1.006)	(0.819)	(0.050)
Volunteer Army	-0.277	-0.248	-0.184	-0.759	0.056†
	(0.535)	(0.501)	(0.661)	(0.6406)	(0.028)
Composite Army	0.739	-0.582	0.495	0.000	-0.017
	(0.626)	(0.584)	(0.804)	(0.715)	(0.032)
Relative Forces	4.619***	-1.172	0.365	-0.676	-0.094
	(1.216)	(0.912)	(1.155)	(1.100)	(0.060)
Constant	-4.568^{***}	-0.728	-2.564^{*}	-0.768^{***}	0.835***
	(1.364)	(1.072)	(1.265)	(1.142)	(0.096)
Wald χ^2	52.42***	38.97***	15.35	33.95***	
F Score					26.15***
r^2	0.430	0.287	0.226	0.228	0.598
N	133	133	133	133	133

Note: Robust standard errors clustered on individual belligerents. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$.

Table A6: Military Inequality and Battlefield Performance in CoW Non-State Wars, 1800-2011

	LER Below Parity	Mass Desertion	Mass Defection	Blocking Units	BP Index
MILITARY INEQUALITY	8.834**	8.212***	19.802*	8.459*	−1.066***
	(3.064)	(2.389)	(8.253)	(3.455)	(0.161)
REGIME TYPE	−0.276	−0.077	0.774†	−0.109	0.004
	(0.199)	(0.171)	(0.431)	(0.215)	(0.012)
REGIME TYPE*INITIATOR	0.181	0.032	−0.287	0.259	−0.010
	(0.209)	(0.192)	(0.302)	(0.240)	(0.013)
DEMOCRATIC OPPONENT	0.207	−0.102	−17.248	−19.025	0.220
	(4.034)	(1.858)	(2494.659)	(2453.817)	(0.187)
INITIATOR	1.233	−0.872	−4.288	0.355	0.034
	(1.627)	(1.461)	(2.965)	(1.723)	(0.097)
DISTANCE TO BATTLE	0.022	−0.308	−0.976†	0.188	0.018
	(0.213)	(0.219)	(0.508)	(0.283)	(0.015)
STANDING ARMY	−0.280	−0.539	−2.709	−2.803*	0.102
	(0.949)	(0.882)	(1.986)	(1.284)	(0.068)
VOLUNTEER ARMY	0.600	1.014	−2.104	−0.595	−0.054
	(0.868)	(0.834)	(1.621)	(0.909)	(0.071)
COMPOSITE ARMY	−1.573	−0.444	4.362†	1.758	−0.053
	(0.984)	(0.904)	(2.503)	(1.246)	(0.062)
RELATIVE FORCES	6.040**	−1.076	−4.087	2.456	−0.125
	(2.110)	(1.677)	(2.574)	(1.971)	(0.127)
Constant	−7.406*	−0.868	3.236	−5.968†	0.940***
	(2.881)	(2.005)	(3.343)	(3.274)	(0.123)
Wald χ^2	12.62	15.20	23.81**	34.17***	
F Score					8.93***
r^2	0.378	0.335	0.515	0.325	0.565
N	56	56	56	56	56

Note: Robust standard errors clustered on individual belligerents. Note that DEMOCRATIC OPPONENT returns large standard errors in several specifications due to the relative sparsity of observations of democratic opponents and the small number of overall conflict observations. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$.

Table A7: Military Inequality and Battlefield Performance in Non-CoW Wars, 1800-2011

	LER Below Parity	Mass Desertion	Mass Defection	Blocking Units	BP Index
Military Inequality	$3.746^{\star\star}$	$7.359^{\star\star\star}$	$8.436^{\star\star\star}$	0.669	$-0.829^{\star\star\star}$
	(1.185)	(1.407)	(1.841)	(1.505)	(0.101)
Regime Type	$-0.101^{\dagger}$	0.023	0.065	0.096	0.001
	(0.059)	(0.054)	(0.096)	(0.062)	(0.003)
Regime Type*Initiator	0.087	−0.016	−0.047	0.031	−0.003
	(0.072)	(0.072)	(0.119)	(0.080)	(0.006)
Democratic Opponent	$1.613^{\star}$	−0.769	−0.333	−0.132	−0.031
	(0.735)	(0.750)	(0.901)	(0.914)	(0.037)
Initiator	0.895	−0.123	−0.467	0.782	−0.043
	(0.579)	(0.554)	(0.921)	(0.616)	(0.049)
Distance to Battle	$-0.275^{\star\star}$	$0.095^{\dagger}$	$0.263^{\dagger}$	−0.160	0.008
	(0.103)	(0.096)	(0.145)	(0.116)	(0.006)
Standing Army	0.000	−1.249	−0.689	−0.267	$0.099^{\dagger}$
	(0.652)	(0.753)	(0.792)	(0.851)	(0.059)
Volunteer Army	−0.671	$0.520^{\dagger}$	$1.120^{\dagger}$	−0.909	−0.000
	(0.446)	(0.465)	(0.601)	(0.630)	(0.039)
Composite Army	−0.271	−0.034	0.784	0.626	−0.018
	(0.396)	(0.429)	(0.600)	(0.577)	(0.037)
Relative Forces	$-1.593^{\dagger}$	−0.286	−0.016	0.925	0.058
	(0.911)	(0.915)	(1.148)	(1.146)	(0.083)
Constant	0.766	$-5.946^{\star\star\star}$	$-5.946^{\star\star\star}$	−1.300	$0.757^{\star\star\star}$
	(1.008)	(1.746)	(1.746)	(1.170)	(0.081)
Wald χ^2	$34.08^{\star\star\star}$	$24.66^{\star\star}$	$39.19^{\star\star\star}$	$28.85^{\star\star}$	
F Score					$11.16^{\star\star\star}$
r^2	0.168	0.223	0.302	0.102	0.383
N	153	153	153	153	153

Note: Robust standard errors clustered on individual belligerents. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ † $p < 0.10$.

6 Robustness Check: *Bands of Inequality* and Five Measures of Battlefield Performance, by CoW War Type, 1800-2011

As an additional robustness check, I reestimated the models above with an alternative measure of military inequality, *bands of inequality*, which was also used in *Divided Armies* (pp.179-83). *Bands* assigns belligerents to one of four "bands" based on their military inequality coefficients. These bands are: Low (0-0.20), Medium (0.21-0.40), High (0.41-0.60) and Extreme ($\geq$0.61). These bands help reduce sensitivity to measurement error while also providing a grammar for speaking about the magnitude of inequality across belligerents.

Figure A1 plots the average marginal effects of *Bands* across five measures of battlefield performance for each type of CoW war. As above, a fifth category of non-CoW wars is included. Once again, Gibler and Miller's own preferred specification and data partitioning illustrate the importance of military inequality for explaining battlefield performance. In short, 23 of 25 models return favorable results for this alternative measure of inequality, increasing our confidence in the association between inequality and a wide range of battlefield outcomes.

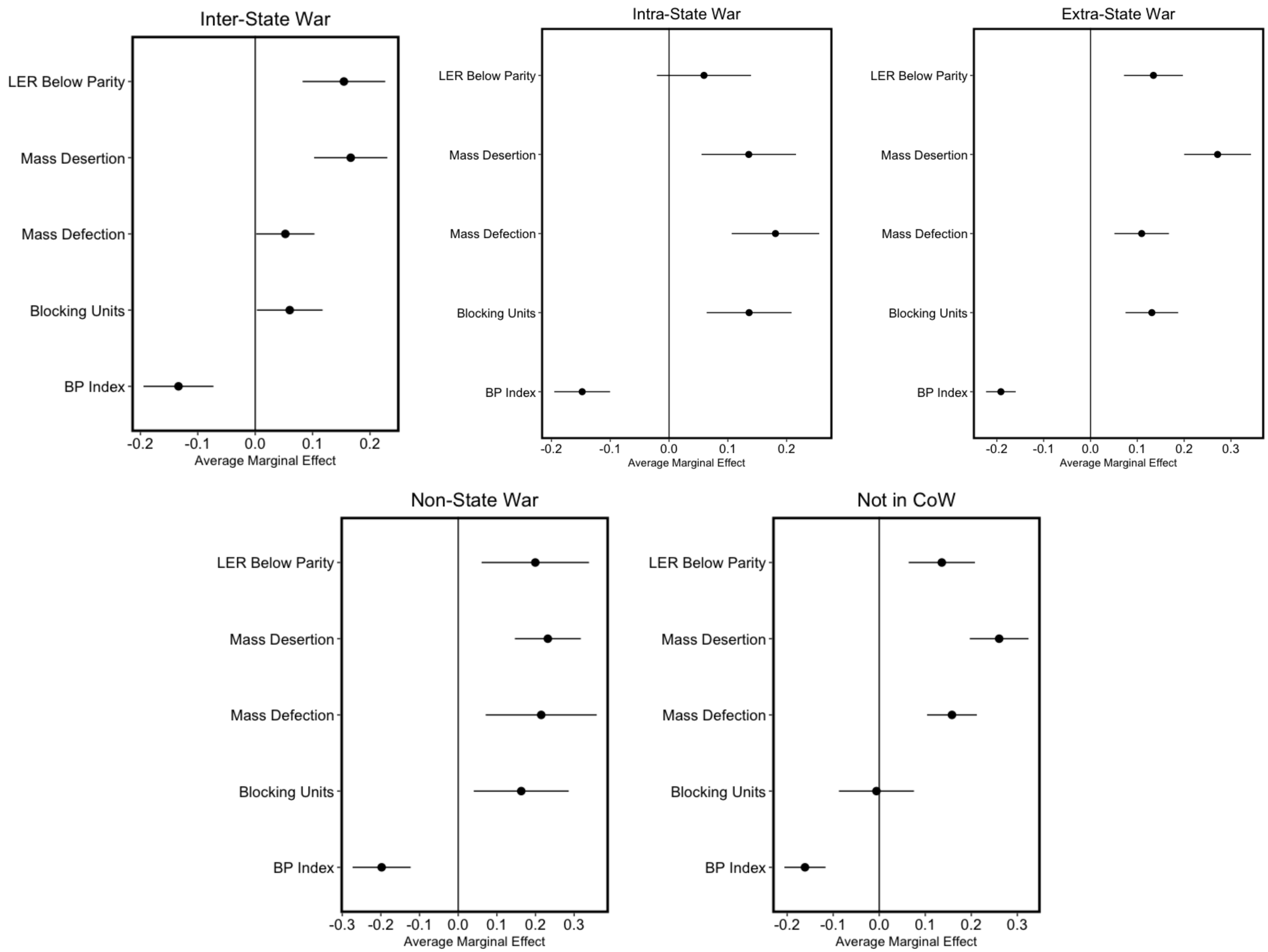

Figure A1: Average Marginal Effects of Military Inequality on Battlefield Performance, by CoW War Typology, 1800-2011, Using *Bands*

7 Additional Robustness Check: Reestimating Models Using Clodfelter (2008)-only Wars

I reestimate Gibler and Miller's preferred models using only the wars recorded in Clodfelter (2008) to examine how military inequality performs in a non-CoW sample. Our confidence in the military inequality argument should increase if MIC performs consistently across the full Project Mars dataset, the CoW-partitioned subsets, and an influential non-CoW sample. As expected, MIC is again associated with diminished battlefield performance across all measures (Figure A2).

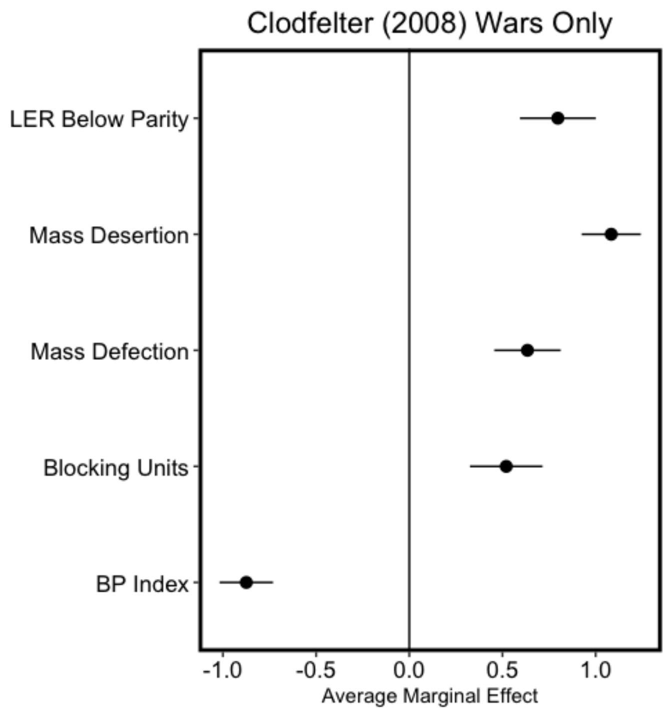

Figure A2: Average Marginal Effects of Military Inequality on Battlefield Performance, Clodfelter (2008)-only Wars, 1800-2011

References

Carey, Sabine, Neil Mitchell and Katrin Paula. 2022. "The Life, Death, and Diversity of Pro-Government Militias: The Fully Revised Pro-Government Militia Database Version 2.0." *Research and Politics* 9(1).

Clodfelter, Michael. 2008. *Warfare and Armed Conflicts: A Statistical Reference to Casualty and Other Figures, 1494-2007*. New York: McFarland and Company, Inc. Third Edition.

De Bruin, Erica. 2020. "Mapping Coercive Institutions: A New Data Set of State Security Forces, 1960-2010." *Journal of Peace Research* 58(2):315–325.

Dippel, Christian and Stephan Heblich. 2021. "Leadership in Social Movements: Evidence from the "Forty-Eighters" in the Civil War." *American Economic Review* 111(2):472–505.

Eck, Kristine and Lisa Hultman. 2007. "One-Sided Violence against Civilians in War: Insights from New Fatality Data." *Journal of Peace Research* 44(2):233–246.

Fennell, Jonathan. 2019. *Fighting the People's War: The British and Commonwealth Armies and the Second World War*. Cambridge: Cambridge University Press.

Gurr, Ted. 1993. *Minorities at Risk: A Global View of Ethnopolitical Conflict*. Washington, D.C.: United States Institute of Peace Press.

Harkness, Kristen. 2018. *When Soldiers Rebel: Ethnic Armies and Political Instability in Africa*. Cambridge: Cambridge University Press.

Huff, Connor and Robert Schub. 2021. "Segregation, Integration, and Death: Evidence from the Korean War." *International Organization* 75(3):858–79.

Johnson, Paul and Ches Thurber. 2020. "The Security-Force Ethnicity (SFE) Project: Introducing a new dataset." *Conflict Management and Peace Science* 37(1):106–129.

Lyall, Jason. 2020. *Divided Armies: Inequality and Battlefield Performance in Modern War*. Princeton, NJ: Princeton University Press.

Rozenas, Arturas, Roya Talibova and Yuri Zhukov. 2020. "Fighting for Tyranny: How State Repression Affects Military Performance." Working Paper.

Scheidel, Walter. 2017. *The Great Leveler: Violence and the History of Inequality from the Stone Age to the Twenty-First Century*. Princeton, NJ: Princeton University Press.

Talibova, Roya. 2021. "Repression, Military Service, and Insurrection." *Working Paper* .

Wucherpfennig, Julian, Nils Weidmann, Luc Girardin, Lars-Erik Cederman and Andreas Wimmer. 2011. "Politically Relevant Ethnic Groups across Space and Time: Introducing the GeoEPR Dataset." *Conflict Management and Peace Science* 28(5):423–437.