Mad CoW: A Reply to Gibler and Miller

RESPONSE

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In Divided Armies, I argue that inequality within armies ("military inequality") has shaped their battlefield performance in conventional wars since 1800. Gibler and Miller (2022) are unpersuaded. They raise a flurry of concerns about the crossnational evidence and one statistical analysis in the book's Chapter 4. In particular, they maintain that Project Mars, the book's dataset, offers nothing new compared to the Correlates of War (CoW). I find their criticisms misplaced. I use their own statistical models for reanalyzing Project Mars to demonstrate that military inequality is an important driver of battlefield performance across six different measures in all types of CoW wars over the past 200 years. We should build, not bury, a research program that further explores the relationship between inequality and political violence.

En Divided Armies, sostengo que la desigualdad dentro de los ejércitos ("desigualdad militar") ha moldeado su desempeño en el campo de batalla en las guerras convencionales desde 1800. Gibler y Miller (2022) no están convencidos. Ellos manifiestan una oleada de inquietudes acerca de las pruebas transnacionales y un análisis estadístico en el capítulo 4 del libro. En concreto, sostienen que el Project Mars, el conjunto de datos del libro, no ofrece nada nuevo en comparación con el proyecto Correlates of War (CoW). Considero que sus críticas son erróneas. Utilizo sus propios modelos estadísticos para volver a analizar el Project Mars y demostrar que la desigualdad militar es un importante impulsor del desempeño en el campo de batalla en seis medidas diferentes en todos los tipos de guerras del CoW en los últimos 200 años. Debemos crear, y no ocultar, un programa de investigación que explore más la relación entre la desigualdad y la violencia política.

Dans l'ouvrage Divided Armies, je démontre que l'inégalité au sein des armées (l'≪ inégalité militaire≫) a influencé leur efficacité sur le champ de bataille lors les guerres conventionnelles depuis 1800. Gibler et Miller (2022) restent sceptiques. Ils émettent certaines réserves concernant les preuves transnationales et l'analyse statistique dans le chapitre 4 du livre. Ils soutiennent plus précisément que le Projet Mars, la base de données du livre, n'apporte rien de nouveau par rapport aux Corrélats de guerre (CoW). Je considère leurs critiques injustifiées. Je me sers de leurs propres modèles statistiques pour réanalyser le projet Mars afin de démontrer que l'inégalité militaire est un facteur déterminant de réussite sur le champ de bataille pour six différentes mesures dans tous les types de guerre de CoW lors des 200 dernières années. Nous devrions soutenir, et non pas mettre de côté, un programme de recherche pour approfondir l'étude de la relation entre l'inégalité et la violence politique.

Introduction

Divided Armies argues that we have overlooked a key determinant of battlefield performance in conventional wars since 1800: inequality (Lyall 2020a). Specifically, prewar ethnic inequalities within armies help shape wartime performance by undercutting combat motivation, sowing seeds of distrust within units, and forcing commanders to adopt repressive countermeasures that further erode combat power. The argument is tested using a mixed-methods research design that incorporates a natural experiment, cross-national evidence from 250 wars (1800-2011), and three paired historical comparisons spanning 150 years. A micro-level study

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Author's note. For helpful feedback, I thank Jeff Friedman, Kosuke Imai, Ben Valentino, Yang-Yang Zhou, and Yuri Zhukov. The latest version of Project Mars (v.1.1), codebook (Lyall 2020b), replication files, and supporting documentation for these analyses have been archived on the Project Mars Dataverse site: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ DUO7IE. The data underlying this article are also available on the ISQ Dataverse, at https://dataverse.harvard.edu/dataverse/isq. A longer version of this reply can be found on my website (www.jasonlyall.com).

of four Soviet Rifle Divisions on the Eastern Front in 1941 drawn from declassified archival and personnel records rounds out the evidence. Military inequality, it turns out, sabotages battlefield performance. As inequality rises, so too does the likelihood of experiencing lopsided casualties, mass desertion and defection, and the use of violence to force one's own soldiers to fight.

Ignoring five of six empirical chapters, Gibler and Miller issue a scattershot review of the book's cross-national evidence in Chapter 4 (Gibler and Miller 2022). They contend that Project Mars, the book's new dataset of conventional wars, adds little that is not already in the CoW universe; that Project Mars misses an additional 355-450 conventional wars in CoW; that the book's independent variable, the military inequality coefficient (MIC), is flawed; and that MIC explains fractional loss-exchange ratios (FLERs)—a measure I do not actually use—in only two of four CoW war types. They advocate discarding inequality in favor of more traditional explanations of military effectiveness like regime

These criticisms are misguided and, to an alarming degree, littered with factual errors. In this short reply, I demonstrate that they have mischaracterized Project Mars' intent, construction, and contributions. Hundreds of relevant wars are not missing from Project Mars. Given tight word limits, I make extensive use of an Online Appendix to set the record straight, including to rebut their incorrect claims about my independent variable, military inequality. Most importantly, I use the same statistical models, data partition, and periodization from their own reanalysis of Project Mars to demonstrate that military inequality outperforms traditional variables when explaining six different aspects of battlefield performance in all four types of CoW wars since 1800.

Project Mars and its Contributions

To test my claims about military inequality, I first needed a dataset of conventional wars. Unfortunately, no off-theshelf solution existed. For decades, nearly every quantitative study of military effectiveness (and war) has relied on CoW's Inter-State War dataset (see, e.g., Singer and Small 1972; Stam 1996; Reiter and Stam 2002; Biddle 2004; Downes 2008; Weeks 2014; Lehmann and Zhukov 2019; Min 2021). It is not, however, an exhaustive list of conventional wars. Indeed, CoW's own coding rules excluded dozens of relevant belligerents—mostly non-Western—and their wars from the Inter-State War dataset. As a result, we were forced to construct a new dataset to capture these missing belligerents and wars. We consulted a wide range of war lists, datasets, and specialized histories to construct our new sample. These datasets included: the CoW Inter-, Intra-, Extra-, and Non-State War datasets; Clodfelter's Warfare and Armed Conflicts (2008); Wimmer and Min's war list (2009); Reiter and Stam's (2002) modification to the CoW Inter-State War dataset; the CDB90 list of battles; the UCDP/PRIO Armed Conflict Dataset; and Kalyvas and Balcells (2010) list of civil wars. Table A1 in the Supplementary Information summarizes how many wars from each source are found in Project Mars. Our "cross-walk" spreadsheet, created in June 2010, details the source(s) for every single Project Mars war; it is archived on Dataverse.1

Built by the tireless efforts of 134 coders, Project Mars represents a new dataset of conventional wars fought between 1800 and 2011. Nowhere do I claim that Project Mars is a "completely new" dataset of 250 undiscovered wars, as Gibler and Miller charge. Tellingly, they do not provide a single quote from the book making this claim. Yet they devote one-third of their review to a quixotic quest to reverseengineer Project Mars to show that is "passing off" CoW wars "as its own discoveries." This is, frankly speaking, bizarre. In addition to the "cross-walk," *Divided Armies* took pains to acknowledge the importance of the CoW universe and, in particular, the dominant Inter-State War dataset. To cite just a few examples, the book's introduction (pp. 23-26) and codebook (pp. 4-12, "How does Project Mars compare with CoW?") discuss coding differences between the two datasets. All statistical models in Chapter 4 include indicators for CoW "non-states," civil wars (drawn mostly from the Intra-State War dataset), CoW Great Powers, and CoW country codes. Appendices detail which wars are included in the Inter-State War dataset and the 124 belligerents in Project Mars that are not considered states by CoW. Robustness checks reestimate all models using CoW-only belligerents and Inter-State War-only subsets. Even their own quote from my codebook —"Project Mars considerably expands our coverage of wars and combatants compared to COW's Inter-State 4.0 dataset"—accurately reflects its contribution.

Worse, Gibler and Miller make serious mistakes when assigning CoW ids to wars in Project Mars. In particular, they overstate CoW's coverage of Project Mars by engaging in

questionable coding decisions. These include: (re) assigning the same CoW war id to multiple wars or wars not in CoW's own historical summaries; assigning war ids despite the fact that the belligerents involved are different in CoW and Project Mars wars; adding conflicts from the Militarized Interstate Dispute dataset; disregarding nearly all pre-1816 wars; and simply assigning CoW war ids to the wrong war.² In fact, Project Mars contains 70 wars without a close (or any) CoW match. Even apparent agreement between the two datasets masks important differences. For example, only 10 of 250 wars in Project Mars had the same start and end years as CoW. A full 75 wars had different start years between the two datasets; 84 had different end dates, with discrepancies in start/end years of ±5 years common.

They conclude that Project Mars is merely a pale shadow of CoW that "does not constitute data creation." Left unsaid, however, is anything about the data we collected for dozens of new variables. We built new measures for regime type, for army size and recruitment, for the distribution of forces deployed, distance to the battlefield, and at least ten aspects of battlefield performance. Their own "reanalysis" (see below) is impossible without these new data. By contrast, CoW's own Intra-, Extra-, and Non-State War datasets possess no information about the "non-state" belligerents that fought these wars. They are glorified lists of war unsuitable, and unused, for statistical analysis since they lack even basic data about belligerents' political systems, armies, or military power. Despite a 50-year head-start, CoW still has not even managed to assign unique ids to these non-states.³ A fair review would at least acknowledge how Project Mars represents a costly investment in data collection that greatly improves existing coverage of conventional wars.

Missing Wars?

After chastising Project Mars for borrowing too much from CoW, Gibler and Miller reverse course, arguing that Project Mars did not take enough. They conduct a random audit of 20 (unnamed) Intra-State Wars and conclude that 17, and possibly all 20, were conventional wars. Extrapolating from this estimate to the entire CoW universe, they maintain that Project Mars is missing a staggering 350–455 additional relevant wars. In effect, they argue that (nearly) *all* wars in CoW are conventional in nature.

This claim simply is not credible. CoW's own founders rejected organizing CoW by type of warfare (Sarkees and Wayman 2010, 67). As a result, the Intra-State War dataset, much like its Extra- and Non-State cousins, is a kaleidoscope of political violence. It contains conflicts as diverse as street violence (Sparticist Uprising, 1919), guerrilla wars (Ukrainian Partisans War of 1945-1947), coups (Overthrow of Abd el-Aziz, 1907–1908) and counter-coups (Young Turks Counter-Coup of 1908), one-sided government violence (the Janissary Revolt of 1826), revolutionary warfare (Cultural Revolution Phase I of 1967), peasant rebellion (Green Rebellion, 1920–1921), and low-tech "symmetrical non-conventional" (Kalyvas and Balcells 2010) wars (First Congo-Brazzaville War of 1997).

Unsurprisingly, we excluded 313 of the remaining 335 wars in the Intra-State War dataset (ver. 5.1) because these conflicts did not meet our definition of conventional war.⁴

¹I have updated it by adding the new Inter-State War dataset (v.1.1), which appeared after Project Mars was finished, Reiter, Stam, and Horowitz (2016). I have also brought the UCDP/PRIO ACD up to its latest version (ver.20.1).

² See Section A2 of the Supplementary Information for examples.

³All non-states are designated by a "-8" code.

⁴We identified six possible reasons for excluding a war; multiple reasons for exclusion are possible. Our original exclusion list was drawn from Version 4.0 of the Intra-State War dataset. I have updated it here to reflect the latest version.

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Project Mars defines conventional wars as armed combat between the military organizations of two or more belligerents engaged in direct battle that caused >500 battlefield fatalities over the duration of hostilities. Armies fought using combined arms; wore uniforms; had functional specialization (infantry-artillery-cavalry or historical equivalent); and were under the central direction of the belligerent's political authorities. A belligerent is defined as a political entity that claims control over, and authority within, a definite territory and populace, and that can field a conventional army (pp. 23–26). We only included wars that were fought predominantly along conventional lines. By contrast, many of these excluded cases represent guerrilla wars. Again, this is unsurprising: leading datasets of irregular war build on the Intra-State War dataset precisely because it contains so many cases of insurgency (Fearon and Laitin 2003; Kalyvas and Balcells 2010). I have posted our Intra-State War exclusion list to Dataverse.

Similarly, 214 of these 335 conflicts involved a belligerent that did not meet our definition of a state. CoW's own historical summaries detail wars against bandits (China-Pai-Ling War of 1914), protestors (Romanian War, 1989), drug lords (Eighth Colombian War of 1989–present), political parties (Agrarian Uprising of 1923), cults (Third Brazil-Canudas War, 1896–1897), and miners (Spanish Miners War of 1934). As a whole, belligerents in the Intra-State War dataset run the gamut from "factions," "rebels," "Communists," "leftists," "guerrillas," "anti-imam coalitions," "warlords," and more (Dixon and Sarkees 2016). We excluded actors that did not have a territorial base, that lacked a political system, or that functioned as private militia acting on behalf of a political, tribal, or ideological faction. These non-state actors are simply outside Project Mars' original remit.

Of course, scholars might disagree over what constitutes a conventional war, just as they still do for civil wars. That's why we archived a subset of 111 wars that we excluded from Project Mars, along with our reasons, on Dataverse ("ExcludedCases"). This subset represents edge cases that other scholars had treated as conventional wars but that did not meet our stricter inclusion criteria. In some cases, we did not have the confidence in existing sources to code the independent or dependent variables. As the preceding discussion shows, these edge cases are merely a subset of the wars we considered, not the entire universe, as they mistakenly claim.

Inequality, Loss-Exchange Ratios, and Battlefield Performance Across CoW War Types

Gibler and Miller's cavalcade of criticism culminates in a final claim: that Project Mars "naively" pools the four types of CoW wars together. They insist on two interventions: (1) Project Mars must be partitioned by CoW war type to prevent exaggerating its explanatory effects on battlefield performance and (2) these tests should use their preferred measure of military effectiveness, not the ones actually used in *Divided Armies*.

To review briefly, I used four variables to test the association between military inequality and battlefield performance. These are (1) a binary indicator of whether the belligerent (or coalition) suffered higher casualties than its enemy (*LER below parity*); (2) an indicator of whether \geq 10 percent of a belligerent's army deserted (*Mass desertion*)

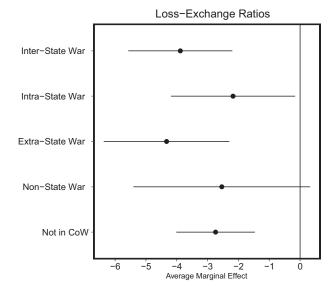


Figure 1. Average marginal effects of military inequality on loss-exchange ratios, by CoW war type, 1800-2011.

or (3) defected (*Mass defection*) during the war; and (4) whether the belligerent fielded specialized units authorized to kill one's own soldiers to enforce discipline (*Blocking units*). These measures were combined into a summary index to facilitate cross-national comparison (*BP Index*).⁶

Gibler and Miller ignore these new measures. Instead, they propose a return to the venerable loss-exchange ratio (LER) as the "clearest example" of battlefield performance. To be clear, Project Mars does contain the raw LERs used to construct *LER below parity*. But, they contend that I used an outmoded calculation (enemy killed in action/friendly KIA). Instead, they prefer a fractional approach (enemy casualties/enemy casualties + friendly casualties), which they claim reflects the prevailing standard in the literature. They also allege that errors were made when calculating LERs, noting that 36% of "low" LER estimates are actually higher than the supposed "high" estimates.

These issues can be dismissed quickly. It is true that the chapter did not directly test how military inequality affected the magnitude of relative casualties. I did, however, conduct robustness checks in the book's Supplemental Appendix (table A27) using actual LERs. These tests confirmed a negative association between military inequality and logged LER values; the higher the belligerent's prewar inequality, the worse its relative losses. Moreover, my calculation of LER follows leading quantitative (e.g., Biddle 2004; Pilster and Böhmelt 2011) and qualitative studies (e.g., Talmadge 2015; McNerney et al. 2018) of military effectiveness as well as warand battle-level datasets (e.g., Dupuy 1984; Cochran and Long 2017). As one recent study concluded, "dividing enemy casualties by friendly casualties is a standard measure of relative attrition" (Lehmann and Zhukov 2019, 145). Fractional LERs, by contrast, have received little attention in the literature. If we care about comparing our findings to earlier influential work, then we need to use the same LER calculation. Finally, there are no errors in my calculation of LER; they simply misread the codebook. "Low" estimates are simply the lowest credible estimate of soldiers killed for each side (low/low); "high" estimates are the highest credible assessments of soldiers killed on each side (high/high). It is

⁵ Unlike CoW, Project Mars did not require that a belligerent have diplomatic recognition by Great Britain or France or, later, the United Nations, to be included. Civil wars, if fought conventionally, are also included in Project Mars.

⁶The index runs from 0 to 1, where 0 indicates poor performance, 1 denotes excellent performance, and a 0.25 penalty to the belligerent's score is assigned for the presence of each of these four problems.

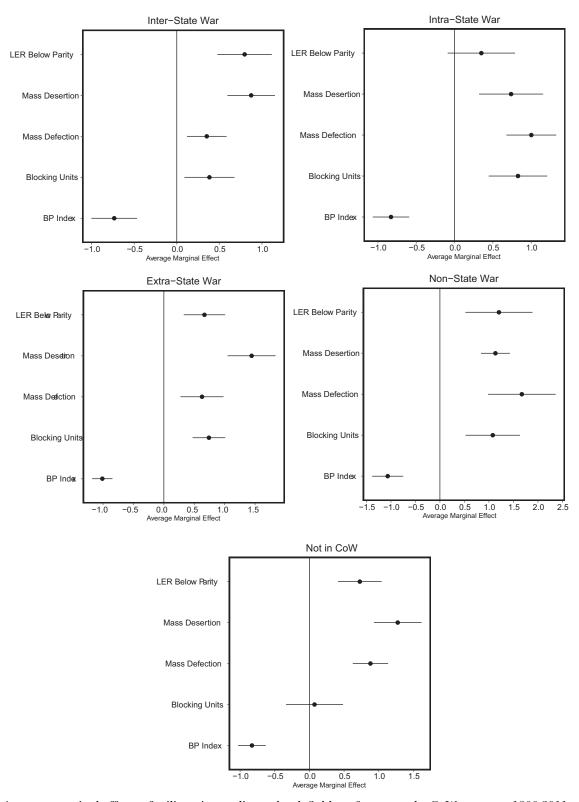


Figure 2. Average marginal effects of military inequality on battlefield performance, by CoW war type, 1800-2011.

therefore possible for "low" LER estimates to exceed "high" ones depending on the range of casualties recorded. This is precisely why I used the *mean* of LER estimates for *LER below parity* and associated robustness checks.

Armed with their preferred measure of casualties, Gibler and Miller turn to a "reanalysis" of the relationship between military inequality and LER. In doing so, they drop all coalitional wars from Project Mars (44% of all observations); use a "corrected" version of MIC; drop six control variables from

my original models, including measures drawn from CoW itself; pool observations from the early (1800–1917) and modern (1918–) periods of combined arms rather than splitting the sample to reflect changes in military technology; and then partition the remaining observations by CoW war types, despite their serious mistakes (noted above) in assigning CoW wars to Project Mars.

Few would consider this a fair test. Yet despite dictating the relevant sample, model specification, dependent

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variable, and data subsets, Gibler and Miller nonetheless, conclude that military inequality is *still* associated with poor FLERs in the two most frequent forms of war, Inter- and Extra-State Wars. It also narrowly misses conventional significance for Non-State Wars. Military inequality outperforms all other explanations—even their favorite, regime type⁷—across multiple types of war while using an idiosyncratic dependent variable and scarcely half of the relevant observations. At worst, their findings suggest scope conditions for my argument, not its wholesale rejection.

But what happens if we use the standard LER measure (enemy/friendly KIA)? One empirical contribution of Project Mars is that we are able to conduct these crosswar type comparisons for the first time. I therefore use their preferred statistical model, periodization, and CoW typology to reestimate the relationship between military inequality and LER using the entire Project Mars sample. As table A1 in the Supplementary Information illustrates, rising military inequality is associated with increasingly poor LERs in *every* CoW war type, including wars not in CoW, though only at the p = 0.089 level for Non-State Wars (the least frequent category). I plot the average marginal effects of military inequality on LERs in figure 1 for ease of interpretation.

We can repeat this analysis for all five measures of battlefield performance actually used in the Divided Armies. In figure 2, I plot the average marginal effects of military inequality on each measure for each war type using their preferred models.8 Military inequality is associated with decreased battlefield performance in 23 of 25 models. As a robustness check, I reestimated these same models using my alternative measure of inequality (Bands of inequality, p. 157). Once again, military inequality is associated with poor battlefield performance in 23 of 25 models (figure A1 in the Supplementary Information). Put simply, military inequality is associated with a statistically significant and substantively large increase in relative casualties suffered, the likelihood of mass desertion and defection, the fielding of blocking detachments, and poor aggregate performance in every type of CoW war. Similar results are also obtained if we restrict our sample to wars found only in Clodfelter (2007) (table A8 and figure 8 in the Supplementary Information). By contrast, prevailing explanations, including regime type and force ratios, find little empirical support.

Conclusion

Taken together, Gibler and Miller misrepresent Project Mars; botch their discussion of the book's independent variable, and conduct a reanalysis that only confirms the disastrous effects of military inequality on battlefield performance across six different measures in four types of CoW wars over the past 200 years. Yet they conclude with a warning: "novel" theories like mine are dangerous because they lead us to "ignore other factors that could help militaries defend their countries." I disagree. The evidence amassed in Divided Armies and here suggest that we need more, not less, research on inequality and military effectiveness since many existing theories struggle to explain patterns of battlefield outcomes. Other inequalities—class, gender, income, reli-

gion, ideology—surely matter as well. We need additional theorizing about how these inequalities intersect to shape patterns of wartime and postwar violence for both armies and rebels alike. We also need to harness all our methodological tools to test, revise, and extend these theories. And we need to invest in data collection to reset our empirical work on a more global, less Western, foundation. Collaborative in spirit and execution, this research agenda promises to break new ground if we are willing to build on, and move beyond, a status quo that continues to dismiss inequality and its effects on violence.

Supplementary Information

Supplementary information is available at the *International Studies Quarterly* data archive.

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⁷Gibler and Miller are encouraged that *Regime Type* is significant in three of four war types. But regime type is not a standalone variable. Following standard practice, it was interacted with *Initiator* status to create a joint *RegimeType*Initiator* variable. We must calculate the joint significance of these three variables, not *Regime Type* alone. When we do so, regime type appears to have no effect on LERs in their own models.

⁸ See tables A2–A6 of the Supplementary Information.