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The Treadmill of Destruction in Comparative Perspective:
A Panel Study of Military Spending and Carbon Emissions, 1960-2014

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Abstract

This article analyzes a unique panel data set to assess the effect of militarism on per capita carbon dioxide emissions. We extend previous research examining the effects of military expenditures on carbon emissions by including in our analyses over 30 years of additional data. In addition, we compare our preliminary results to those obtained from other estimation procedures. Specifically, we report and visually illustrate the results of 54 cross-sectional models (one for each year) and 36 unique panel regression models on both balanced and unbalanced panels. We assess how this relationship has changed over time by testing for interactions between military spending and time and by systematically re-analyzing our data across 180 panel regressions with varying time frames. A strong and enduring association between military spending and per capita carbon emissions is indicated in cross-sectional comparisons. Our panel analyses reveal a much weaker and varying relationship that has become stronger in recent decades. Moreover, we find that the effect of military spending on per capita carbon emissions is moderated by countries' level of economic development, with military spending of more wealthy countries having relatively larger net effects on carbon emissions. We partially confirm previous findings on the temporal stability of the environmental impacts of militarism. Our analyses show, however, that this temporal stability has emerged relatively recently, and that the relationship between military expenditures and carbon emissions is weaker prior to the 1990s.

Keywords: Militarism, Militarization, Carbon emissions, Treadmill of destruction, Treadmill of production

Human reliance upon nonrenewable, carbon-based energy has generated unprecedented atmospheric concentrations of carbon dioxide, leading to global warming (Intergovernmental Panel on Climate Change 2013). Because the existing capitalist world system has historically been predicated upon an exponential growth in the use and depletion of scarce ecosystem resources, the eminent constraints imposed upon growth by nature permanently threaten the health of the global economy while decimating poor populations and degrading ecosystems (Schnaiberg 1980; Schnaiberg and Gould 1994). In addition, looming “peak oil” and other resource shortages render more likely an increase in the frequency, intensity, and duration of military conflicts fought over the control of these resources.

In response to these and related issues, a growing number of scholars have begun to examine the connections between militarism and the environment. These scholars have brought attention to the harmful pollutants that are generated from the manufacture of military weaponry as well as the massive quantities of resources that are depleted in order to sustain militaries’ permanent preparedness for war (e.g. Clark and Jorgenson 2012; Hooks and Smith 2005, 2012; Jorgenson, Clark, and Kentor 2010; Jorgenson and Clark 2009, 2016; Smith, Hooks, and Lengefeld 2014). Politicians and international organizations in the past decade have expressed increasing concern over resource scarcity and the related possibility of armed conflict (Theisen 2008). Moreover, key indicators suggest that the increasing scarcity of key resources relative to global demand renders more likely an increase in the frequency, intensity, and duration of military conflicts over their control (Homer-Dixon 1999; Parenti 2011).

This study analyzes cross-sectional time series data to examine a prominent political economy approach to studying the environmental impacts of militarism: the Treadmill of Destruction. More specifically, we examine how military expenditures affect per capita emissions of carbon dioxide. The most recent published study (to our knowledge) to also examine the effects of military expenditures on carbon emissions uses as its dependent variable total consumption-based CO2 emissions (Jorgenson and Clark 2016). We extend this research in three important ways: first, we focus on how military expenditures affect the *intensity* of carbon emissions (i.e. CO2 per capita), rather than on total emissions; second, we use as our dependent variable territorial emissions data rather than CO2 emissions embodied in trade (i.e. consumption-based estimates); and finally, we analyze a much longer period of time.

In the following sections, we first review the specific theories of relevance for our panel analysis. We then describe our estimation procedures and methods before turning to the results of our analysis. And finally, we conclude by summarizing our main findings and explaining their theoretical relevance.

Treadmill of Destruction

A burgeoning literature within the environmental social sciences explores the underlying logic of warmaking and its harmful effects to societies and the natural environment. Hooks and Smith (2004, 2005, 2012) refer to the unique environmental impacts of militarism and war as the "Treadmill of Destruction," in order to distinguish these effects from those produced by economic forces such as the pursuit of profit and the expansion of capital.

Militaries generate massive withdrawals of energy and resources. Increases in military spending and armed conflicts cause environmental degradation, reducing the biological capacity available to human populations (Bradford and Stoner 2014). In the United States, the military is the largest consumer of fossil fuels (Santana 2002). Militaries generate massive amounts of carbon dioxide waste (Dycus 1996) as well as toxic waste (LaDuke 1999; Shulman 1992). According to Hooks and Smith (2005), militaries exert negative environmental effects even when they are not actively engaged in warfare. Moreover, the environmental effects of militarism and warfare cannot be explained solely in terms of economic motives (Hooks and Smith 2005: 21). Military decision-making regarding actions that can (and do) have devastating social and biophysical consequences, such as the use of nuclear weapons amid geopolitical competition, or the recent spike in "drone" (unmanned aerial vehicles) strikes, cannot be reduced to the logic of profitability, even though these decisions as well as their socio-ecological consequences, may indeed be interconnected with the economic imperatives of capital.

The development of weapons of mass destruction (WMDs), including nuclear, chemical, and biological weapons, dramatically transformed war in the second half of the twentieth century. Today, the extent of environmental damage inflicted by militaries depends more on the technological sophistication of the weapons they employ than on the number of soldiers and other personnel that militaries possess (Hooks and Smith 2012; Kentor and Kick 2008). Whereas most wars fought throughout human history brought about environmental degradation indirectly, WMDs are intentionally designed to make ecosystems uninhabitable by humans (Hooks and Smith 2005). Jorgenson and Clark (2009), in their analysis of panel data for 53 developed and less-developed countries, find a positive association between per capita ecological footprints and military expenditures per soldier. They interpret this as evidence that more capital-intensive militaries place additional strains on the environment (Jorgenson and Clark 2009: 640). Downey, Bonds, and Clark (2010) find evidence of a significant positive relationship between resource extraction and armed violence, suggesting an intricate and complex web of industrial production and state power. Jorgenson et al. (2010) find that the ratio of military expenditures to the number of military personnel as well as the ratio of military personnel to the total population significantly effects total and per capita carbon dioxide (CO_2) emissions and Footprint per capita.

More recently, Jorgenson and Clark (2016) find that the environmental impacts of military expenditures and military personnel have been relatively stable between 1990 and 2010. Jorgenson and Clark (2016) estimate the net effects of militarism on total consumption-based CO2 emissions. Consumption-based CO2 emissions are "calculated as the territorial emissions minus the 'embedded' territorial emissions to produce exported products plus the emissions in other countries to produce imported products (consumption = territorial − exports + imports)" (Le Quéré et al. 2015: 357). In contrast, we estimate the effects of militarism on per capita territorial CO2 emissions (see below). Examining data both prior to 1990 and after 2010, our findings suggest that, with respect to territorial emissions, militaries have become significant and independent contributors *on average* only within the past 20 to 30 years. We suspect that the relationship between total *consumption-based* carbon emissions and military spending reported by Jorgenson and Clark (2016) has also emerged recently and would probably be weaker in earlier time periods, although we cannot at this time test our intuition directly because data for consumption-based estimates are not available prior to 1990.

Empirical Analyses: Data Set

We analyze both balanced and unbalanced panel data at 1-year increments. Our balanced panels include 40 observations each for 62 countries between 1975 and 2014. Our unbalanced panels include 162 countries between 1960 and 2014. Sample sizes for the unbalanced panels range from 47 countries in 1960 to a maximum of 154 in 2005. Data availability precludes us from including time points before 1960 and after 2014. Table 1 lists the countries included in our balanced and unbalanced panels and the number of observations per country.

To minimize skewness, our response and explanatory variables except Democracy (an ordinal measure) are transformed by taking the natural logarithms of one plus their respective values. Because our variables are log transformed, variable coefficients for all models indicate the average change in per capita carbon dioxide emissions over time when the explanatory variable increases by one unit. The units of change analyzed can therefore be interpreted as elasticity coefficients, or percentages (York, Rosa, and Dietz 2003, 2009). Table 2 provides descriptive statistics and bivariate pooled correlation coefficients for our response and explanatory variables for all cases.

Response Variable

Our response variable for all models is territorial carbon dioxide emissions measured in metric tons per person (CO2/population). We obtain our data from the Global Carbon Atlas (2016). For most countries and years (1959-2013), the Global Carbon Atlas obtains its CO2 estimates from

Table 1. Number of Observations per Country

Afghanistan 11	Djibouti 15	Latvia 20	***Rwanda** 42
Albania 35	***Dominican Republic** 55	Lebanon 26	Saudi Arabia 43
***Algeria** 52	***Ecuador** 55	Lesotho 25	Senegal 36
Angola 30	***Egypt** 50	Liberia 39	Serbia 19
***Argentina** 55	***El Salvador** 50	Libya 12	Seychelles 30
Armenia 22	Equatorial Guinea 6	Lithuania 20	Sierra Leone 52
***Australia** 55	Eritrea 10	***Luxembourg** 55	***Singapore** 45
***Austria** 55	Estonia 20	Madagascar 52	Slovakia 22
Azerbaijan 23	Ethiopia 34	***Malawi** 50	Slovenia 20
Bahrain 35	***Fiji** 45	***Malaysia** 55	***South Africa** 55
***Bangladesh** 42	***Finland** 55	Mali 46	***Spain** 55
Belarus 23	France 55	Malta 29	***Sri Lanka** 54
***Belgium** 55	Gabon 31	Mauritania 27	Sudan 46
Belize 29	Gambia 30	Mauritius 39	Swaziland 38
Benin 43	Georgia 19	***Mexico** 55	***Sweden** 55
***Bolivia** 50	***Germany** 45	Mongolia 28	Switzerland 35
Bosnia and Herzegovina 13	***Ghana** 54	Montenegro 10	Tajikistan 19
Botswana 38	***Greece** 54	***Morocco** 49	***Thailand** 55
***Brazil** 55	***Guatemala** 55	Mozambique 35	Macedonia 19
Brunei Darussalam 31	Guinea 15	Namibia 24	Timor-Leste 10
Bulgaria 26	Guinea Bissau 23	***Nepal** 45	Togo 45
***Burkina Faso** 55	Guyana 39	***Netherlands** 55	Trinidad and Tobago 30
Burundi 49	Haiti 17	New Zealand 38	***Tunisia** 40
Cabo Verde 28	Honduras 48	Nicaragua 38	***Turkey** 55
Cambodia 22	Hungary 24	Niger 30	Turkmenistan 6
***Cameroon** 45	Iceland 4	***Nigeria** 55	Uganda 33
***Canada** 55	***India** 55	***Norway** 55	Ukraine 22
Central African Rep. 14	***Indonesia** 41	Oman 44	United Arab Emirates 18
Chad 30	***Iran** 55	***Pakistan** 55	***United Kingdom** 55
***Chile** 55	Iraq 25	Panama 28	Tanzania 27
China 26	***Ireland** 45	Papua New Guinea 37	***United States** 55
***Colombia** 55	***Israel** 55	***Paraguay** 55	***Uruguay** 43
Congo 29	Italy 55	***Peru** 55	Uzbekistan 9
***Costa Rica** 55	Jamaica 36	Philippines 55	***Venezuela** 55
Côte D'Ivoire 47	***Japan** 55	Poland 25	Viet Nam 20
Croatia 20	Jordan 40	***Portugal** 55	Yemen 24
Cuba 5	Kazakhstan 22	Qatar 9	Zambia 26
Cyprus 30	***Kenya** 52	***Rep. of Korea** 55	Zimbabwe 47
Czech Rep. 22	Kuwait 20	Rep. of Moldova 22	-
DR Congo 32	Kyrgyzstan 23	Romania 25	-
***Denmark** 55	Laos 22	Russia 23	-

Countries included in balanced panels are flagged by asterisks. Balanced panels include 40 obs. per country.

the U.S. Department of Energy's (2017) Carbon Dioxide Information Analysis Center (CDIAC).[1] For 40 countries (1990-2014), official national estimates reported to the United Nations (UNFCCC 2017) Framework Convention on Climate Change are used instead. We cross-validated the data obtained from the Global Carbon Atlas with that of the CDIAC.[2]

Table 2. Summary Statistics and Correlation Coefficients

	Mean	Std. dev.	Median	Min.	Max.	Skew	Kurtosis	Missing
tCO2 per person	1.23	0.954	1.055	-0.01	4.613	0.51	-0.686	1647
GDP per capita	8.21	1.511	8.117	4.757	11.886	0.131	-0.947	3996
Urban Pop (%)	3.764	0.645	3.911	1.124	4.615	-0.964	0.648	393
Pop. ages 15-64 (%)	4.083	0.116	4.07	3.835	4.465	0.135	-1.111	1567
Weighted Export Index	9.226	1.052	9.544	1.6	11.233	-0.898	0.28	3971
Exports (% of GDP)	3.396	0.686	3.427	0	5.444	-0.399	0.946	4254
Military (% of GDP)	1.176	0.557	1.109	0	4.774	0.816	1.588	5781
Democracy	4.248	4.126	3	0	10	0.22	-1.667	4295
	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
tCO2 per person	1							
GDP per capita	0.881	1						
Urban Pop (%)	0.669	0.751	1					
Pop ages 15-64 (%)	0.702	0.72	0.58	1				
Weighted Export Index	0.234	0.217	0.282	0.376	1			
Exports (% of GDP)	0.385	0.417	0.341	0.331	0.335	1		
Military (% of GDP)	0.16	0.076	0.102	-0.08	-0.248	-0.066	1	
Democracy	0.381	0.544	0.394	0.462	0.254	0.138	-0.275	1

All variables except *Democracy* are in natural logarithm form (base *e*).

[1] Available online http://cdiac.ornl.gov/.

[2] We found, for example, what appears to be a reporting error in the Global Carbon Atlas data. Carbon dioxide emissions are reported to be zero for Vietnam in 2014, which is otherwise inexplicable. We used instead the CDIAC estimates.

Territorial emissions data attribute carbon dioxide emissions to the country in which the emissions physically occur (i.e. are distinct from 'emissions embodied in trade' or consumption-based estimates). Emissions estimates include emissions from the oxidation of coal, oil, and gas; gas flaring arising from the combustion of vented gas in the oil and gas industry; and the manufacture of cement (see Le Quéré et al. 2015).

Predictor Variables

Military expenditures (% of GDP). Military expenditures data are obtained from the Stockholm International Peace Research Institute's (SIPRI 2017) Military Expenditures Database. Pre-1988 military expenditure data are obtained from the 'beta' version of the dataset obtained via email from SIPRI. Military expenditures data are measured in current local currency units (LCU). We then divide these estimates by estimates of each country's Gross Domestic Product, measured in current local currency units for the appropriate year. The coefficient for Military Spending indicates the average percent change in per capita CO2 emissions that occur when military spending increases by one percent of a country's total gross domestic product.

Included in this measure are expenditures on armed forces, peace-keeping forces, defense ministries and other government agencies engaged in defense projects; paramilitary forces trained and equipped for military operations; military operations in space; military research and development; military aid (of donor countries); wages, pensions and social services for current military personnel. Excluded from these data are veterans' benefits, destruction of weapons, and all other current expenditures for previous military activities.

Gross domestic product (GDP) per capita. We obtain countries' per capita gross domestic products (GDP per capita) from the World Bank's (2017) World Development Indicators (WDI) online database as a measure of economic activity and affluence. These data are measured in constant 2010 U.S. dollars. GDP is commonly used as a proxy measure of standard of living. More accurately, GDP is a flow variable quantifying the total market value of final goods and services produced in a country at a given time. Although an increase in GDP is commonly referred to as "economic growth," it is important to remember that this is not the growth of a stock of material wealth, but rather, an increase in the intensity or rate of monetary exchanges.

Urban population (% of total). To test the hypotheses of urban political economy perspectives, we include as a predictor variable in our analyses the percentage of a country's total population living in urban areas (World Bank 2017). Urban political economy approaches generally predict positive associations between urbanization and carbon dioxide emissions (e.g., Molotch 1976; Dickens 2004; Jorgenson and Clark 2012; Roberts and Parks 2007). We infer from these studies that urbanization will be positively correlated with per capita CO2 emissions.

Population ages 15-64 (% of total). We include as a control the percentage of the population between the ages of 15 and 64 (World Bank 2017). This variable has been used in previous studies (e.g. Jorgenson and Clark 2016) and is used as a proxy for countries' non-dependent, adult population. As expected, the coefficient of this variable is positive and statistically significant across nearly all models.

Additional Political-Economic Covariates

Although we focus specifically in this study on the relationship between militarism and carbon emissions, we include for Models 2 and 7 in Table 4 three additional explanatory variables: two measures of export dependence and one measure of institutionalized democracy.[3]

Exports (% of GDP). We obtain from the World Bank's (2017) World Development Indicators estimates of the monetary value of countries' "Exports of goods and services" measured as a percentage of total GDP. Ecologically Unequal Exchange posits that countries with higher levels of export dependence consume fewer resources than countries with lower levels of export dependence because the former export away the resources they would have otherwise consumed. Previous studies indicate a positive association between exports and carbon dioxide emissions (Jorgenson, 2007). Using panel data, Jorgenson (2009) has also reported that among low-income countries, exports to high income countries negatively impact per capita ecological footprints.

Weighted Export Index. Our second measure of export dependence is a "Weighted Export Index" calculated from the International Monetary Fund's (IMF 2017) Direction of Trade Statistics, which captures the degree to which a country's exports are sent to wealthy nations. Similar indices have been used in prior studies to measure export-dependence (e.g. Jorgenson & Rice 2005). The weighted export index of an exporting country i is the average per capita GDP of all n of exporting country i's trading partners j weighted by the proportion of i's total exports received by j, or:

$$\boldsymbol{Export\ Index_i = \sum_{j=1}^{n} GDPpc_j * \frac{Exports_{i \to j}}{\sum Exports_i}}.$$

[3] Based on our preliminary Bayesian model comparisons, we excluded from further consideration two other World Bank measures of trade: "Foreign direct investment, net inflows (% of GDP)" and "Exports of goods and services (constant 2010 US$)."

Countries with relatively high proportions of exports to wealthier nations will have higher weighted export index scores than countries that send proportionally more of their exports to less wealthy nations, regardless how much they export or how large their economies are. Thus, countries that are less dependent on exports can potentially score lower on this index than countries that are more dependent on exports so long as the former export proportionally more of their exports to wealthier countries. When coupled with per capita GDP and exports as a percentage of total GDP as controls, coefficients for the weighted export index indicate the extent to which differences in average wealth of trading partners contributes to differences in per capita carbon emissions *among countries with similar volumes of total exports*.

Institutionalized Democracy. Finally, we include as an additional control a measure of Institutionalized Democracy obtained from the *POLITY™ IV PROJECT* dataset published by the Integrated Network for Societal Conflict Research (INSCR 2016). The "Institutionalized Democracy" variable is an ordinal scale from 0 to 10. It consists of three sub-components: "the competitiveness of political participation, the openness and competitiveness of executive recruitment, and constraints on the chief executive" (INSCR 2016:14). In a recent study, Lv (2017) finds that for 19 emerging countries from 1997 to 2010, democracy is associated with lower CO2 levels only for countries beyond a certain income level.

Analysis of Missing Data

We include only "complete case"— that is, we exclude cases that contain any missing values for variables included in the model. We do not impute missing data. Figure 1 depicts the number of available (non-missing) observations per variable per year. We analyze whether there is any pattern to missing data in Figure 2. We performed separate bivariate regressions of all variables on dummy versions of all other variables, with zero (reference) values indicating cases with missing data (for the independent variable). The coefficients of Figure 2 represent differences in the group means of the response variables (indicated on the rows) between observations for which data are missing on the independent variables (indicated by the columns) compared to observations for which independent variable data are not missing. For example, the first column of Figure 2 indicates that the average per capita GDP, export index, and democracy index are smaller for cases which reported CO2 emissions data compared to cases for which CO2 data are missing. In contrast, the average percent of GDP allocated to military expenditures is larger for cases that reported CO2 data compared to cases for which CO2 data are missing.

Figure 1. Annual Observations per Variable

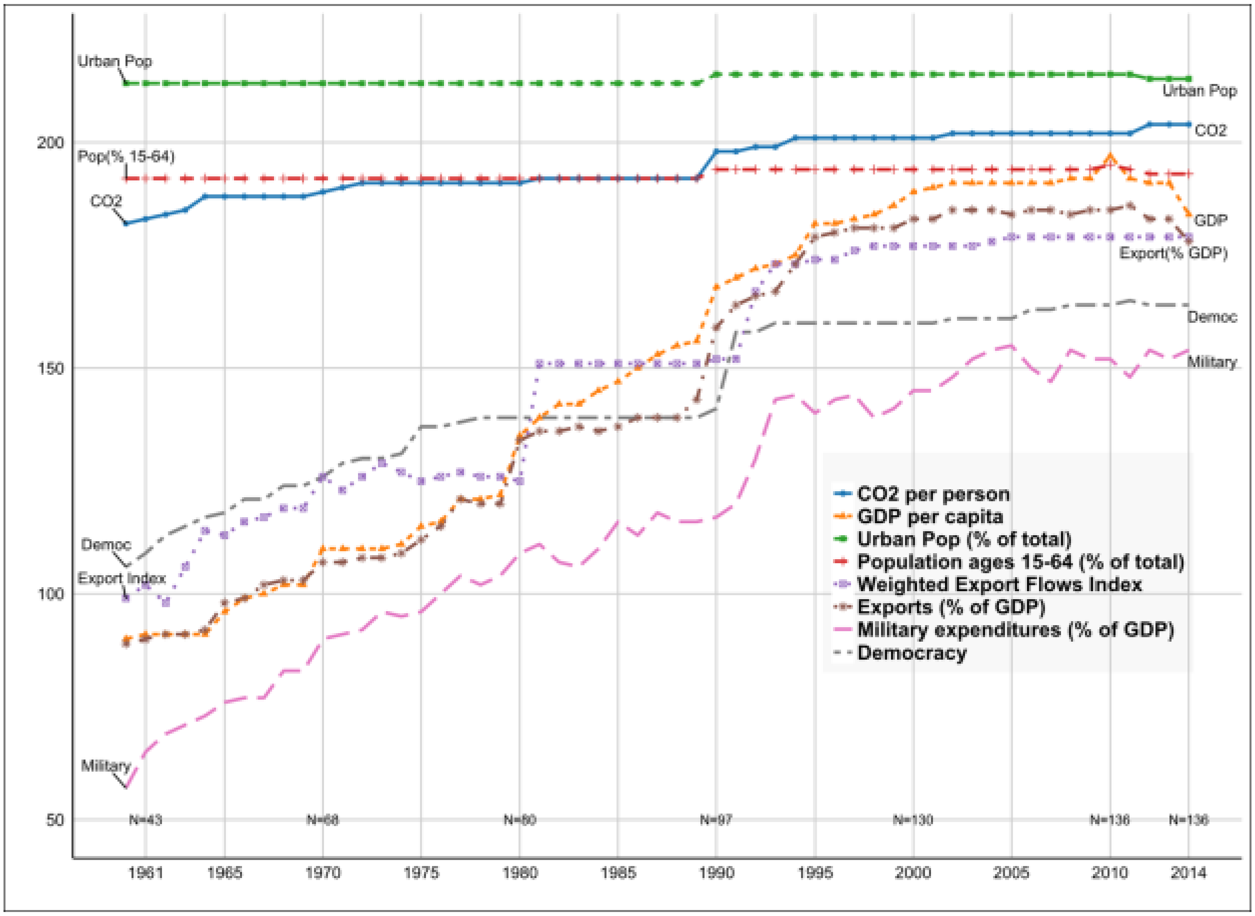
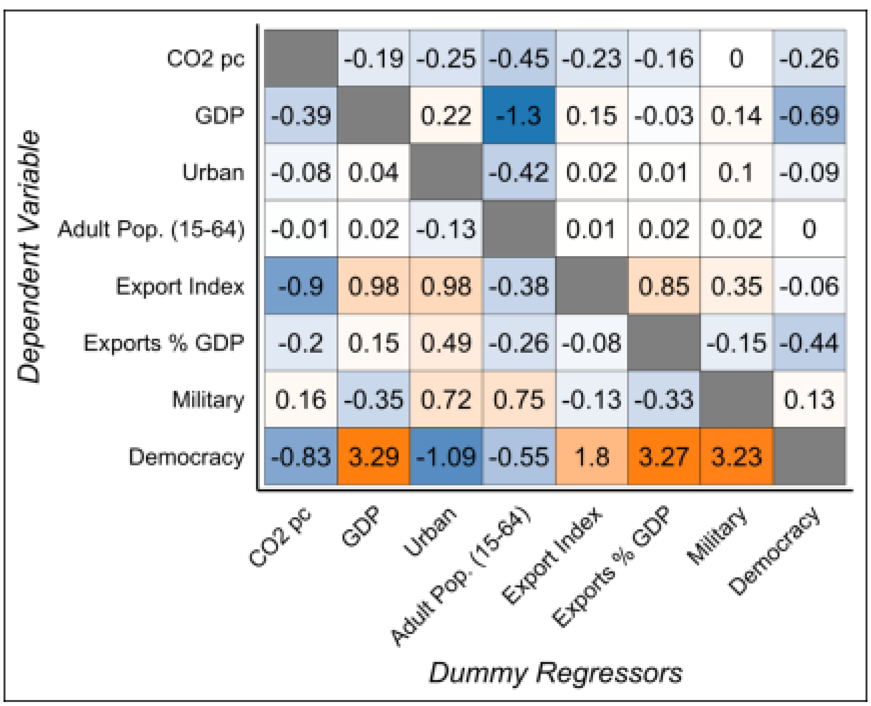


Figure 2. Missing Variable Coefficients



We analyze differences between our unbalanced and balanced panels in Table 3 by regressing our selected variables on a dummy variable indicating whether an observation is included in or excluded from our balanced panels. We restrict our analysis to cases beginning in 1975 and include year as a control. Compared to countries included only in our balanced panels, the additional cases utilized in our unbalanced panels have smaller average per capita carbon emissions; smaller average per capita GDPs; less urbanization; and smaller percentages of people with ages 15 to 64. Importantly, *there is no significant difference in the percentage of GDP allocated to military expenditures between cases in our balanced panels and those excluded from our balanced panels.* Figure 3 visually represents variable distributions of cases included in our balanced panels compared to those excluded from our balanced panels.

Table 3. OLS Regression Coefficients of Selected Variables on Balanced Panel Dummy

Dependent Variable (Y)	**Unbalanced Panels (X)** (Reference = Balanced)	**Year**	**Constant**	**Obs.**	**Adjusted R-Squared**
Year	4.37*** (.31)	--	1,995*** (.22)	4,970	.038
tCO2 per person	-.396*** (.027)	.012*** (.001)	-22.642*** (2.41)	4,819	.052
GDP per capita	-1.051*** (.043)	.023*** (.002)	-37.191*** (3.84)	4,819	.118
Urban Pop. (% of total)	-3.18*** (.016)	.012*** (.001)	-20.894*** (1.43)	4,819	.107
Pop. ages 15-64 (% of total)	-.052*** (.003)	.004*** (0)	-4.53*** (.28)	4,819	.181
Military (% of GDP)	-.002 (.015)	-.012*** (.001)	24.75*** (1.34)	4,819	.062

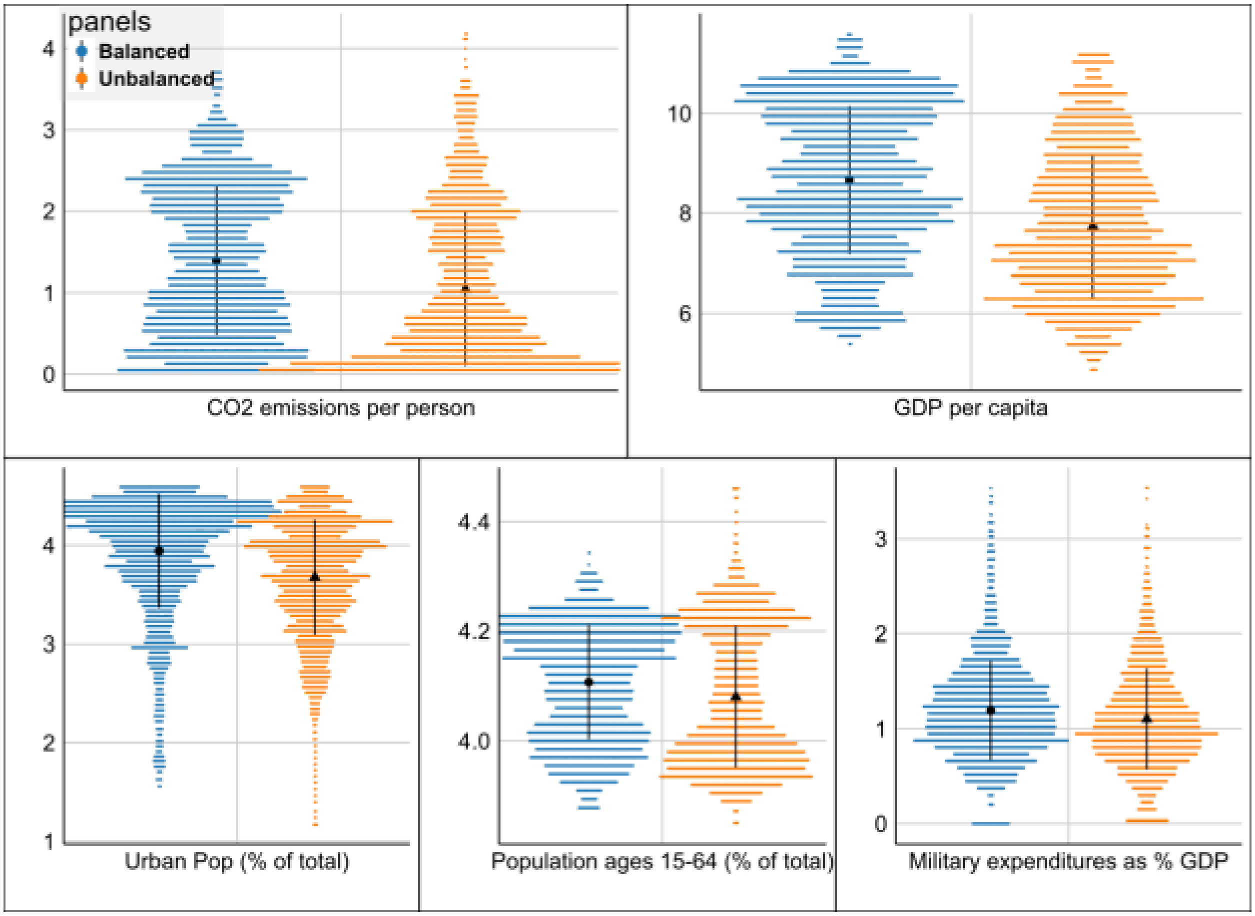
Bivariate Regressions restricted to cases after 1974. All dependent variables except 'Year' are in natural logarithm form (base e). *p<0.05; **p<0.01; ***p<0.001

Estimation Procedures

Our analyses were implemented primarily in R version 3.3.3. We use the *panelAR* package (Kashin 2014) to estimate our Prais-Winsten regression models and the *plm* package (Croissant and Millo 2008) to estimate our first-differences models. We cross-validated our PW regressions in Stata (ver. 12) using the *xtpcse* suite of commands.[4]

[4] In sensitivity tests, we also recalculate the panel-corrected standard errors in R using the package *pcse* (Bailey and Katz 2011). In Stata, we re-estimate the models using the *xtregar* command, an alternative method of conducting fixed-effects models with AR(1) correction. All model results are substantively similar to the ones presented here.

Figure 3. Comparison of Variable Distributions by Inclusion or Exclusion in Balanced Panels



The two-way fixed effects models reported in Tables 4, 5, and 6 are estimated by including dummy variables for each country and each year. This is commonly referred to as dummy variable regression (Wooldridge 2013: 490).[5] Country and time dummies estimate the unit (i.e. country) and period (i.e. year)-specific intercepts, respectively.

Including country dummies controls for all potentially omitted confounders that do not change within each respective country over time (e.g. geographical or cultural factors). The inclusion of dummies for each year, on the other hand, controls for any potentially omitted confounders that are universal or commonly experienced across all cases in each respective year. The inclusion of unit-specific and period-specific intercepts reflects that our primary interest is the

[5] Including unit dummies in an OLS regression generates coefficients that are identical to the so-called 'one-way fixed effects' model; whereas including both unit dummies and period dummies in an OLS regression generates coefficients that are identical to the so-called 'two-way fixed effects model.' Although the coefficient estimates of dummy variable and fixed effects models are identical, the term 'fixed effects' in econometrics is commonly reserved for estimation procedures that utilize the 'within transformation', which first removes the group (i.e. country or yearly) means.

extent to which our selected predictor variables account for the variance in per capita carbon dioxide emissions not attributable to factors invariant within countries across time or invariant within a given year across countries. Our one-way fixed effects models include country dummies but not dummies for each year.

Because PW regression has been used by several other studies of time-series cross-sectional CO2 data (e.g. Jorgenson and Clark 2012; Jorgenson and Clark 2016), and does not result in the loss of first observations, we utilize this estimation procedure to compare coefficients across models including different sets of regressors.[6]

Results: Cross-sectional Regressions

Cross-sectional analyses can provide an insightful contrast to the dynamic panel analyses that follow. We therefore begin by reporting in Figure 4 the coefficients, confidence intervals, and p-values of 54 cross-sectional robust MM Regressions of per capita CO2 emissions on military expenditures, including as controls per capita GDP, urban population (% of total), and the percentage of people ages 15 to 64.[7]

As depicted in Figure 4, in only 4 of 54 regressions is the positive coefficient for military expenditures not statistically significant. Moreover, from 1990 onwards, all coefficients are statistically significant, and 16 out of 25 are significant at $p < .001$. An important finding of these regressions is that for any given year, countries that allocate higher than average percentages of their GDP to the military also have higher than average per capita emissions even after controlling for potential economic and population confounders.

Panel Regressions

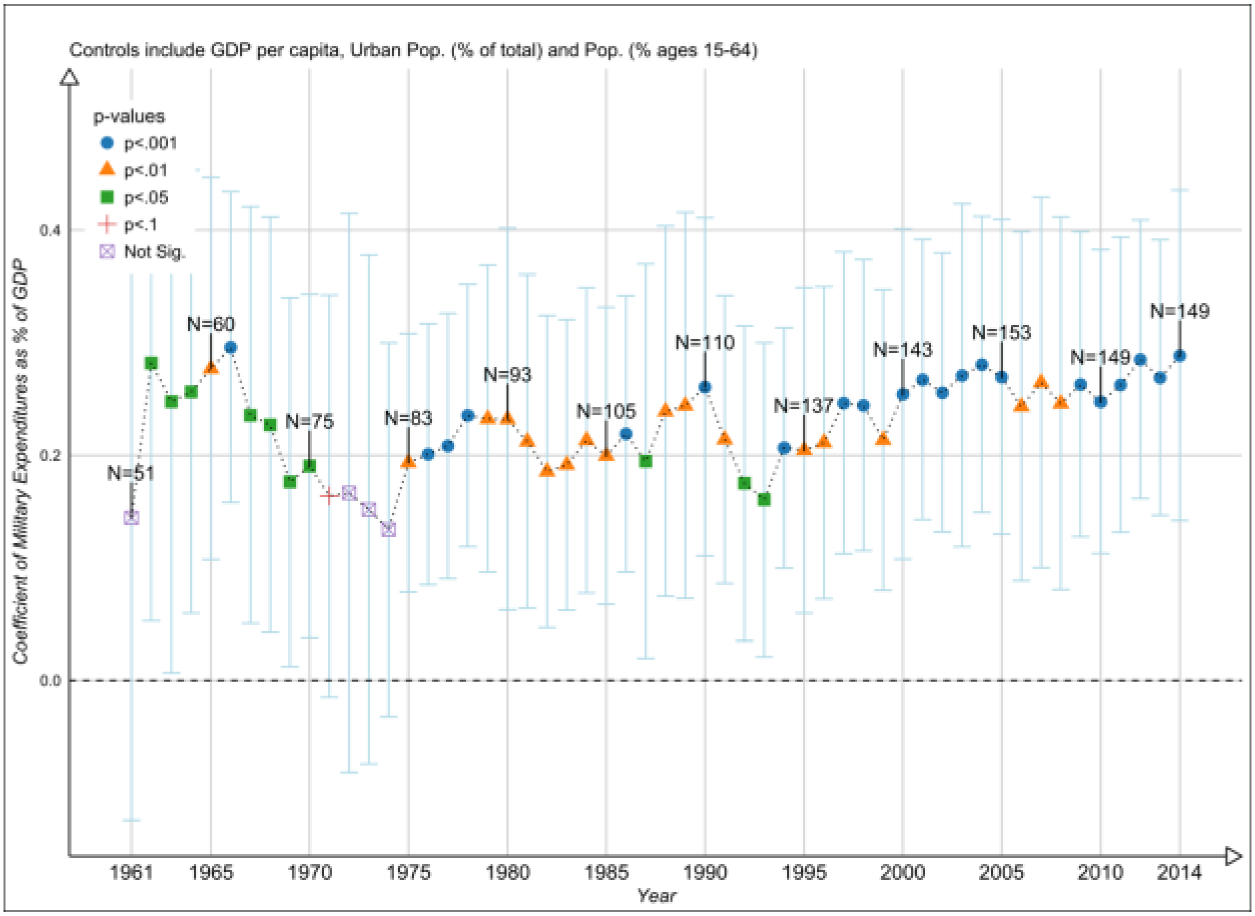
We report in Table 4 a total of ten two-way fixed effects regressions incorporating the Prais-Winsten AR1 correction and Panel Corrected Standard Errors (PCSE) for both unbalanced (models 1-5) and balanced (models 6-10) panels.[8] The PCSE estimates are robust both to unit heteroskedasticity as well as contemporaneous correlation across units, both of which are common in panel data (Bailey and Katz 2011: 2).

[6] The Prais and Winsten (1954) correction for first-order serial correlation is a generalized least squares (GLS) estimator that improves upon the Cochrane and Orcutt (1949) method by preserving the first observation in the series.

[7] We use the *robustbase* R package to perform robust MM regression (Susanti et al. 2014).

[8] The Hausman test statistic (significant at $p<.001$) indicates that a random-effects (RE) estimator would yield inconsistent results, and thus the FE model is preferable. In addition, we conduct an augmented Dickey-Fuller test for unit roots. We reject the null hypothesis that the series has a unit root (i.e. is non-stationary) at a significance level of $p < .001$.

Figure 4. Cross-Sectional Robust MM Regression Coefficients & Confidence Intervals for Military Expenditures



We restrict our attention here to military expenditures, our two measures of export dependence, and institutional democracy. The latter three all have small, statistically insignificant coefficients in both the unbalanced panel model 2 and the balanced panel model 7. Military expenditures in model 1 is positive and statistically significant at $p < .05$. For the countries included in model 1, a one percent increase in GDP allocated to the military is associated with a .015 percent increase in per capita carbon emissions. In model 2, the coefficient for military spending is also positive but too small relative to its standard error to achieve statistical significance. Moreover, the coefficient becomes negative in Models 6 and 7 which utilize balanced panels. The relationship between changes in military expenditures and carbon emissions is not uniform across nations or across time. The average direction of the effect, moreover, changes depending on which counties are included or excluded from analysis.

The results of our panel analyses are in stark contrast to most of our cross-sectional regressions for which military spending coefficients are 10 to 30 times larger than those reported in Table 4. Although Models 1 and 6 in Table 4 include the same reported covariates as those in the cross-sectional analyses, the former also include country and year dummy variables.

Table 4. Two-Way Fixed Effects Regression of Territorial Per Capita Carbon Dioxide Emissions, with Panel-Corrected Standard Errors and Prais-Winston AR(1) Correction.

	Unbalanced Panels (1960-2014)					**Balanced Panels (1975-2014)**				
	1	2	3	4	5	6	7	8	9	10
GDP per capita	0.346*** (0.017)	0.376*** (0.018)	0.325*** (0.02)	0.345*** (0.017)	0.323*** (0.019)	0.327*** (0.031)	0.345*** (0.035)	0.307*** (0.034)	0.324*** (0.031)	0.312*** (0.034)
Urban Pop (% of total)	0.164*** (0.033)	0.155*** (0.034)	0.152*** (0.032)	0.172*** (0.033)	0.158*** (0.032)	0.120** (0.043)	0.141** (0.044)	0.106* (0.042)	0.142*** (0.043)	0.133** (0.041)
Pop. (% 15-64)	1.178*** (0.112)	1.058*** (0.108)	1.167*** (0.110)	1.160*** (0.107)	1.152*** (0.105)	1.655*** (0.169)	1.445*** (0.189)	1.631*** (0.164)	1.545*** (0.165)	1.536*** (0.162)
Military	0.015* (0.007)	0.011 (0.008)	-0.114* (0.045)	-0.029 (0.023)	-0.154** (0.048)	-0.021 (0.014)	-0.017 (0.014)	-0.159* (0.078)	-0.041* (0.017)	-0.123 (0.080)
Weighted Export Index	-	-0.003 (0.007)	-	-	-	-	0.002 (0.009)	-	-	-
Exports % GDP	-	-0.008 (0.007)	-	-	-	-	-0.016 (0.011)	-	-	-
Democracy	-	0.002 (0.001)	-	-	-	-	0.001 (0.001)	-	-	-
Military x GDP	-	-	0.017** (0.006)	-	0.018** (0.006)	-	-	0.017 (0.010)	-	0.010 (0.010)
Military x 1975	-	-	-	0.060* (0.026)	0.048 (0.027)	-	-	-	-	-
Military x 1985	-	-	-	0.031 (0.027)	0.020 (0.028)	-	-	-	-0.002 (0.019)	-0.003 (0.019)
Military x 1995	-	-	-	0.051 (0.027)	0.047 (0.027)	-	-	-	0.044* (0.021)	0.044* (0.021)
Military x 2005	-	-	-	0.050 (0.026)	0.043 (0.027)	-	-	-	0.045 (0.024)	0.041 (0.024)
Military x 2014	-	-	-	0.082** (0.03)	0.067* (0.03)	-	-	-	0.117*** (0.030)	0.112*** (0.030)
N	5944	5340	5944	5944	5944	2520	2160	2520	2520	2520
Countries	162	149	162	162	162	63	54	63	63	63
R-Squared	0.8843	0.9084	0.8869	0.8907	0.8932	0.903	0.9051	0.9057	0.9055	0.9075

Note: All models include unreported unit specific intercepts and period specific intercepts. Models 4, 5, 9, and 10 include unreported time interaction effects for all available years. Except Democracy, all other variables are in natural logarithm form (base *e*). *p<0.05; **p<0.01; ***p<0.001 (two-tailed)

Interactions of Military Spending and GDP

Models 3, 5, 8, and 10 in Table 4 show the interaction coefficients between military spending and economic development. The main effect of military expenditures in these models represents the percentage increase in per capita CO_2 emissions given a one percent increase in military expenditures when (the natural logarithm of) per capita GDP is zero. The interaction term indicates the second-order change in the effect of military expenditures on per capita CO2 emissions as per capita GDP increases.

Figure 5 shows the net linear effect of a 1 percent increase in military expenditures on per capita CO2 emissions conditional on per capita GDP. The conditional effect of military expenditures on per capita CO2 emissions in Figure 5 is estimated using the same covariates and cases from model 3 of Table 4, setting all other control variables to their mean values.[9]

In model 3, the interaction coefficient is positive and significant at $p < .01$, indicating that for the set of cases included in our unbalanced panels, the effect of military spending on CO2 emissions is moderated by level of economic development. Military spending in wealthier countries exerts a larger linear effect on per capita CO2 emissions than military spending in poorer countries. One plausible explanation is that wealthier countries invest in military technologies that are more carbon intensive. The interaction coefficient in model 8 for balanced panels is the same size as that reported for unbalanced panels in model 3 but fails to achieve statistical significance due to its larger standard error resulting from its comparatively smaller sample size.

Interactions of Military Spending and Time

Models 4, 5, 9, and 10 report interactions between military spending and time, allowing us to assess the extent to which the magnitude of the net effect of militarism on per capita carbon emissions has increased or decreased over time. For models which include the interaction between military spending and time, the main coefficient for military spending represents the unit change in per capita carbon emissions in 1960 (models 4 and 5) or 1975 (models 9 and 10) for each additional one percent of GDP allocated to military spending for the same year. The total effect of military spending on carbon emissions for other years is the sum of the coefficient for military spending and its interaction term.

The main effects of military expenditures for unbalanced panels in model 4 and 5 are both negative. The coefficient in model 5 is statistically significant at $p < .01$. In 1960, an additional 1 percent of GDP allocated to military spending coincided with an average *decline* in per capita carbon emissions of .029 percent for the unbalanced sample in model 4. The interaction of military spending and the year 2014 is positive and statistically significant both in model 4 and in model 9, indicating that the effect of militarism on carbon emissions has increased in magnitude for both unbalanced (since 1960) and balanced (since 1975) panels, respectively.

[9] One difference between model 3 of Table 4 and the regression represented in Figure 6 is that the latter uses a lagged dependent variable as an independent regressor to correct for AR1 residual correlation rather than the PW method.

To save space, Table 4 includes only the military-time interaction coefficients for 1975, 1985, 1995, 2005, and 2014. We depict the full set of military-time interaction coefficients from models 4 and 9 in Figure 6. Importantly, beginning in 1988, all mean estimates for the interaction coefficients are above zero. In addition, all but three interactions during this period have 95 percent confidence intervals that exclude zero.[10] Collectively, these results suggest that although the *independent* effect of the military on carbon (net of other covariates) is relatively small on average, it is nevertheless becoming increasingly important as a contributor to anthropogenic carbon emissions.

Time Sensitivity Analyses

To determine the extent to which the relationship between military spending and CO2 emissions changes across time as well as to assess the sensitivity of the results in Table 4, we re-estimate the military spending coefficient from model 1, systematically varying both which years are included and how many. We perform 45 regressions each on both unbalanced and balanced panel data for a total of 180 separate panel regressions. We report the coefficients and p-values of military spending for all 180 replications in Figure 7.

Figure 7 consists of four series consisting of 45 regressions each. The x-axis represents the total number of years included in a regression, ranging from 10 to 54 years of data. Reading from left to right, an additional year is incrementally added to each series. The two series in the left column are 'forward' series, the first regression of which includes 10 years of data from 1960-1970, with each subsequent regression extending the last year by one. The two series in the right column are 'backward' series, the first regression of which includes 10 years of data from 2004-2014, with each subsequent regression reducing the starting year by one.

It is important to note that for the unbalanced panel series, the sample size always increases as additional years are included. In contrast, the sample size of the forward and backward balanced panel series of regressions is limited to the number of countries for which data are available in 1960 or 2014, respectively. In the forward panel series (top-left), for example, the number of sampled countries never exceeds 45. Because data are more available in 2014, however, the maximum sample size for the backward panel series (top-right) is 132.

[10] The only exceptions are military-time interactions for balanced panels in years 2003, 2004, and 2007.

Table 5. Comparison of Different Model Specifications (Unbalanced Panels – 1960-2014)

	Prais-Winsten (Common AR1)			Prais-Winsten (Panel-Specific AR1)			OLS with lagged DV (pop. weighted)			OLS with lagged DV			First Differences		
	1*	2	3	4	5	6	7	8	9	10	11	12	13	14	15
GDP p.c.	.345***	.343***	.453***	.351***	.354***	.480***	.051***	.034***	.006**	.046***	.034***	.017***	.413***	.425***	.425***
	(.017)	(.019)	(.016)	(.019)	(.017)	(.015)	(.006)	(.006)	(.002)	(.006)	(.006)	(.002)	(.014)	(.013)	(.013)
Urban Pop.	.157***	.116***	.002	.169***	.163***	-.066	.050***	.017*	-.005	.024**	-.005	-.008**	.073	.232***	.232***
(% of total)	(.033)	(.025)	(.033)	(.044)	(.025)	(.037)	(.009)	(.007)	(.003)	(.008)	(.006)	(.003)	(.062)	(.059)	(.059)
Pop.	1.168***	.638***	1.322***	1.030***	.466***	1.404***	.154***	.092***	.126***	.230***	.153***	.034*	.764***	.655***	.655***
(% 15-64)	(.112)	(.108)	(.141)	(.128)	(.111)	(.152)	(.027)	(.027)	(.024)	(.027)	(.025)	(.015)	(.163)	(.151)	(.151)
Military	.015	.019*	.035***	.009	.012	.056***	.009	.017***	.006**	.001	.004	.012***	.028***	.024***	.024***
	(.007)	(.007)	(.008)	(.007)	(.007)	(.010)	(.005)	(.005)	(.002)	(.004)	(.004)	(.003)	(.006)	(.006)	(.006)
Country Dummies	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year Dummies	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
AR(1)	0.843	0.854	0.947	0.79	0.814	0.937	0.895	0.907	0.98	0.861	0.868	0.969	--	--	--
R-Squared	0.883	0.866	0.561	0.968	0.954	0.825	0.998	0.998	0.997	0.995	0.995	0.994	0.193	0.164	0.164
Total Obs.	5926	5926	5926	5926	5926	5926	5878	5878	5878	5878	5878	5878	5926	5926	5926

Model 1 is also included in Table 4. For panel-specific PW correction, AR1 is the mean across panels. For OLS, AR1 refers to the coefficient for the lagged DV.

Table 6. Comparison of Different Model Specifications (Balanced Panels – 1975-2014)

	Prais-Winsten				OLS with lagged DV (pop. weighted)			OLS with lagged DV			First Differences		
	1*	2	3	4PS	5	6	7	8	9	10	11	12	13
GDP p.c.	.327***	.251***	.472***	.542***	.060***	.031***	-.001	.054***	.019	.004	.327***	.346***	.346***
	(.031)	(.032)	(.023)	(.020)	(.011)	(.008)	(.003)	(.013)	(.010)	(.004)	(.029)	(.028)	(.028)
Urban Pop. (% of total)	.120**	-.038	.004	-.190***	.017	-.002	.005	.019*	-.010	.003	.069	.102	.102
	(.043)	(.037)	(.042)	(.038)	(.015)	(.015)	(.004)	(.009)	(.009)	(.004)	(.098)	(.098)	(.098)
Pop. (% 15-64)	1.655***	1.248***	.886***	1.176***	.184***	.107**	.086***	.286***	.190***	.055*	1.041***	1.096***	1.096***
	(.169)	(.149)	(.180)	(.189)	(.040)	(.037)	(.024)	(.044)	(.041)	(.024)	(.236)	(.232)	(.232)
Military	-.021	-.010	.036*	.037**	-.007	.001	.006	-.014*	-.004	.012**	-.002	-.011	-.011
	(.014)	(.013)	(.015)	(.013)	(.008)	(.007)	(.003)	(.007)	(.005)	(.004)	(.013)	(.013)	(.013)
Country Dummies	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year Dummies	Yes	No	No	No	Yes	No	No	Yes	No	No	Yes	No	No
AR(1)	0.847	0.863	0.949	0.949	0.888	0.91	0.986	0.86	0.879	0.98	--	--	--
R-Squared	0.903	0.883	0.626	0.766	0.998	0.998	0.998	0.996	0.996	0.995	0.095	0.07	0.07
Total Obs.	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520

Model 1 is identical to Model 6 in Table 4. Model 4 uses panel-specific AR1 estimation. For OLS models, AR1 refers to the coefficient for the lagged DV

In contrast to the two backward-series in the right column, the two forward-series in the left column have approximately the same shape, with upward and downward trends occurring across roughly the same periods. The balanced forward-series (top-right), moreover, exhibits the most volatility and sampling variability of all four series.

In the backward series for unbalanced panels (bottom-right), all military coefficients are positive across all regressions. The coefficient is largest for the 2004-2014 period, then declines as earlier data are added, and remains relatively stable once approximately 20 years of data have been included. In the forward series of regressions for unbalanced panels (bottom-left), the military coefficients are initially close to zero and even become negative for periods covering 1960 to 1971-1974 and again for periods covering 1960 to 1982-1987. The coefficients rise in periods covering 1960 to 1985-1995 and remain above zero after 1987. The two unbalanced panel series appear to converge for all regressions covering over 35 years of data.

The high coefficients in the balanced forward-series (top-left) for years 1960 to 1974-1979 are somewhat puzzling. Two of these regressions (1960-1976 and 1960-1977) reach statistical significance with p-values below .05 despite having much smaller sample sizes (N=44) compared their unbalanced counterparts (N>85) covering the same period and which do not achieve statistical significance. These results collectively suggest that the largest net linear effect of military spending on per capita CO2 emissions occur after 1990, but also that these estimates are highly sensitive to the set of countries included in the analysis.

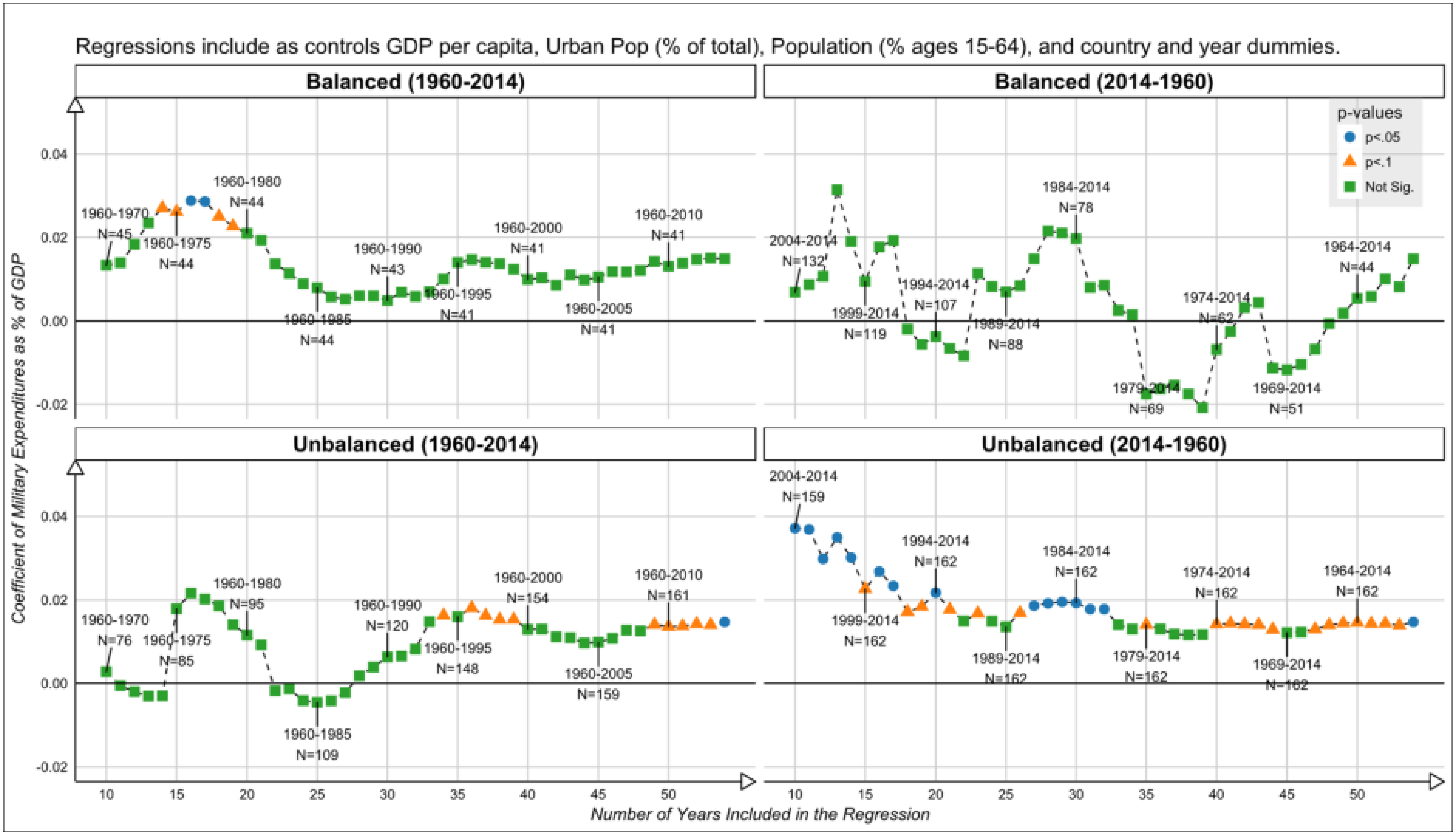
Comparison of Different Estimation Methods

To achieve a more comprehensive understanding of the relationship between military expenditures and carbon emissions, we report in Table 5 and Table 6 different estimations of the same set of variables using unbalanced and balanced panels, respectively. The models in Table 5 and Table 6 replicate models 1 and 6 from Table 4, varying both the AR1 correction and the use of fixed effects. Specifically, we compare four different corrections for first-order autoregressive correlation (AR1) in the residuals: (1) the Prais-Winsten (PW) correction assuming a common AR1 process across all panels (the method used for all models in Table 4); (2) the PW correction assuming panel-specific AR1 processes; (3) models incorporating as a regressor a one-year, panel-specific lagged dependent variable (DV)[1]; and (4) models that transform all variables into their first-difference

For each AR1 correction procedure, we compare the estimated coefficients and robust standard errors across three different models: two-way fixed effects models (including both country and year dummies), one-way fixed effects models (including only country dummies), and

[1] In other words, for each CO2 estimate for country *i* in year *t*, it's lagged value is $CO2_{i,t-1}$.

Figure 7. Coefficients of Military Expenditures from Regressions Including Different Years (Two-Way Fixed Effects with AR1 Correction)



models incorporating no fixed effects. Finally, for the lagged dependent variable approach, we also report estimates from three population-weighted regressions, yielding in total 36 unique panel regression models.[1] For the PW unbalanced panel regressions, removing country and time dummies increases the size of the military coefficient and decreases its p-value. The military coefficients in models 3 and 6, for example, have p-values smaller than .001 and are more than twice as large as their two-way fixed effects counterparts. Interestingly, among the OLS population-weighted models 7-9, the one-way fixed effects model 8 has the largest military coefficient size and smallest p-value. Among the FD models 13-15, the two-way fixed effects model has the largest military coefficient size.

The sign of the military coefficient across all models in Table 5 are positive. In contrast, the sign of the military coefficient is negative in 8 out of 13 regressions using balanced panels as reported in Table 6. The most striking change in the military coefficient occurs between OLS models 8 and 10. Specifically, the removal of both (time and unit) fixed effects changes the military coefficient from -.014 ($p<.05$) in model 8 to .012 ($p<.01$) in model 10.

Conclusion and Discussion

An important finding of this study is that the relationship between *changes* in military spending and *changes* in per capita carbon emissions within countries is less robust than the association between *levels* of military spending and per capita carbon emissions at any given time. The results of 54 separate robust MM regressions on cross-sectional data from 1960 to 2014 presented in Figure 4 unequivocally show an enduring relationship between militarism and carbon emissions: countries that allocate relatively higher percentages of their total GDP to the military have higher average per capita CO_2 emissions, even after controlling for the size of the economy, urbanization, and adult population. The mutually reinforcing nature of military, political, and economic dominance could explain the cross-sectional associations between *levels* of military spending and carbon emissions. Providing a satisfactory answer to why countries with higher levels of military spending yield higher average carbon emissions levels *compared to countries with similar per capita GDPs*, however, requires further research and a more detailed examination of the data than we can provide here.

We remind the reader that standard errors are estimates of sampling variability based on the assumption that cases are selected at random, and a p-value value tells us the probability under the

[1] The number 36 is the sum of models in Table 4, 5, and 6 minus the first models in Table 5 and Table 6 that are identical to models 1 and 4 in Table 4, respectively. In unreported analyses, we also estimated a measure of per capita GDP adjusted by removing the military spending component of total GDP and then dividing by that adjusted GDP by population. The results were substantively identical.

null hypothesis that a sample statistic could be obtained due to sampling variability, that is, by chance. Our cases, however, are not selected randomly. Moreover, generalizing our empirical estimates to unobserved cases becomes less theoretically and substantively important as the proportion of cases that remain unobserved diminishes. By 2014, there are only 11 countries to which our results *could* be generalized.[2] Consequently, we are less concerned with reporting p-values than we are with explaining and interpreting our reported coefficients, whatever values they may be.[3] Moreover, to the extent that generalizing across *observed* countries is our goal, we give more weight to the unbalanced panel than to the balanced panel estimates.

In contrast to those reported in the cross-sectional regressions, the military coefficients for most of our fixed effects, panel regressions are much smaller. One reason for the smaller panel regression coefficients relative to their cross-sectional counterparts is that the former includes additional unit and period dummies (i.e. indicator variables). Even if military spending alone constituted the bulk of carbon emissions and varied *across* countries independently of economic growth and population, so long as the proportion of GDP allocated to the military did not vary *within* countries, its estimated coefficient in our fixed effects models would be zero. Most importantly, we regard the small size of the military coefficients and their variance across model specifications as evidence against the critical assumption underlying our regression models, namely that *the relationship between military spending and carbon emissions is characterized by a single equation for all countries across all time periods*. The differences between the coefficients from balanced and unbalanced panels and between regressions performed across different time periods both suggest heterogeneity in the extent to which military expenditures exert independent effects on carbon emissions.

We emphasize that militarism causes many forms of human and environmental harm. In this study, we attempt to assess the general importance of militaries across countries as independent contributors to just one type of harm, namely, carbon emissions. One important limitation inherent to our model design is that we are unable to assess the indirect effects that militarism, mediated through population and economic growth, have on carbon emissions. Moreover, contemporaneous covariance is not the only possible form that the relationship between militarism and environmental degradation can take. For instance, military strength has historically served as a precondition for economic power and vice-versa. It is significant to note that the so-called "golden

[2] This list consists of 11 countries: Andorra, Bhutan, North Korea, Kosovo, Liechtenstein, Myanmar, Somalia, Suriname, Syria, Tonga, and Vanuatu. It is not our intention to establish that our reported coefficients extend to this finite set of excluded cases.

[3] We remind the reader also that, according to classical null hypothesis testing, large p-values neither confirm nor confer a higher posterior probability upon the null hypothesis. On the contrary, even when statistically insignificant, the most likely coefficients given the available data are the small, but non-zero values we report.

age" of state-centric capitalism (1950-1973)— associated with unprecedented productivity growth in core countries and its impact on Earth system processes following WWII— was a continuation of the economic boom generated by the war effort (Hobsbawm 1994). During this period, economic growth was highest in the former white settler colonies (e.g. Australia, Canada, and the United States) and lowest in the Tropics where colonizers "established a narrow extractive exploitation that persisted after independence" (Mann 2013:22).

The crisis of state-centric capitalism (measured by a general decline in the rate of profit) during the mid-1970s incited a sweeping restructuring of capital that continues to this day. Changes associated with this restructuring include trends commonly associated with "neoliberal" capitalism: financialization, the shift toward monetary, supply side economics bolstered by the nation state, the transformation of business and labor, and the creation of an infrastructure conducive to the formation of a global economy. In recent decades, as multinational corporations have shifted most industrial production to export zones in the Global South, labor and raw materials appropriated from the periphery tend to realize their value in the consumption-based centers of wealthier nations which, in turn, export polluting technologies and hazardous waste back to the Global South (Frey 2015). Hence, the recent explosion of "green" technologies, including the "greening" of many cities in the Global North, is in part made possible by outsourcing dirty industry elsewhere (Parr 2013). Furthermore, as Bond (2016) has recently demonstrated regarding the convergence of the U.S. defense and military communities in the Arctic, the underlying logics of the Treadmill of Production and the Treadmill of Destruction interpenetrate and may, at times, reinforce one another.

Areas for future research include utilizing alternative model designs such as path analysis and instrumental variable regression to better capture both the direct and indirect effects of militarism on carbon emissions; and specifying the points of contact and divergence between state, society and the economic imperative of capital to better understand the environmental impact of particular manifestations of social power.

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