UNIVERSITÀ CATTOLICA del Sacro Cuore

**DIPARTIMENTO DI POLITICA ECONOMICA**

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Working Paper n. 54 - December 2025

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**Abstract**

This paper investigates the determinants of defense burden sharing among EU member states from 1980 to 2024. Using a dataset that combines established factors with historical and institutional indicators, we analyze how structural features shape national share of total EU military expenditure. Fixed-effects panel regressions, complemented by fractional logit and probit models, reveal that economic features, colonial legacy, constitutional complexity, and technological sophistication systematically influence defense contributions among non-leader states. In addition, we show that France, Germany and the United Kingdom behave as structural leaders whose commitments remain high and largely insensitive to domestic conditions, thereby masking key relationships in full-sample estimations.

The results provide a comprehensive account of the drivers of defense effort and highlight the asymmetric foundations of collective defense in Europe.

**JEL classification:** C23, F50, H56, O52.

**Keywords:** Defense burden sharing, military spending, institutions, H2O random forest, European Union.

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## 1 Introduction

This paper investigates the determinants of defense burden sharing within the European Union from 1980 to 2024. Using a fixed-effects panel OLS model, the analysis shows that both economic size and institutional characteristics shape national contributions to the common defense effort. These relationships are less pronounced for the Union's leading contributors, whose defense commitments remain structurally high and comparatively unresponsive to domestic conditions.

The escalation of military spending since the onset of the Russian–Ukrainian conflict in 2014 (Christie et al., 2024) has renewed scholarly and policy interest in the distribution of defense responsibilities among EU member states. In economic theory, defense is typically understood as a pure public good, non-excludable and non-rival in consumption (Hartley and Sandler, 1999; George and Sandler, 2021). Because the benefits of defense extend to all members of an alliance, national contributions inevitably generate spillovers. These shared benefits mean that states jointly sustain the costs of defense while enjoying its collective returns, making the distribution of this burden a central topic in the economic literature.

Burden sharing concerns how the costs and risks associated with producing a common good are allocated among members of an alliance, with the goal of achieving a collective outcome that advantages all participants (Oma, 2012). In principle, each state should contribute equally per unit of defense provided (Sandler and Hartley, 2001). However, the theoretical benchmark rarely matches empirical reality. Alliances often display patterns of free-riding and the pursuit of private benefits (Sandler and Cauley, 1975; Sandler, 1977; Sandler and Shimizu, 2014). Because states may treat the positive spillovers generated by others as substitutes for their own effort, the resulting incentives lead to systematically uneven contributions. Some members therefore under-provide defense, relying on the spillovers created by others (Kim et al., 2024), which ultimately skews the distribution of the defense burden across the alliance.

Although a substantial body of research has analyzed defense burden sharing among NATO allies (Sandler and Forbes, 1980; Hartley and Sandler, 1999; Sandler and Shimizu, 2014; Kim and Sandler, 2020, 2024), comparatively few studies have specifically examined national contributions to collective defense within the European Union (Kollias, 2008; Haesebrouck and Thiem, 2018; Christie et al., 2024). In addition, much of the existing literature focuses on the balance between costs and benefits, aiming to identify patterns of under-contribution and free-riding among member states (Sandler and Forbes, 1980; Kollias, 2008; Sandler and Shimizu, 2014; Kim and Sandler, 2020). By contrast, relatively few studies investigate the underlying determinants that explain variation in the distribution of burden shares (Haesebrouck and Thiem, 2018; Pedersen et al., 2023), leaving a gap in our understanding of why some states contribute more or less than others. This paper addresses this gap by analyzing the factors that shape national defense burden sharing among EU member states over the period 1980–2024.

This paper is structured as follows. Section 2 reviews the literature on defense burden sharing. Section 3 presents the data and outlines the empirical strategy. Section 4 reports the main results together with robustness checks. Section 5 concludes and details limitations and further research.

## 2 Literature Review

The economic literature has examined the issue of defense burden sharing from multiple perspectives. Sandler and Forbes (1980), Hartley and Sandler (1999), Sandler and Murdoch (2000), Sandler and Hartley (2001) focus on the disproportional allocation of the defense burden among NATO allies, highlighting instances of free-riding and recurring patterns in which smaller, less affluent states benefit from the security contributions of larger and wealthier members. This line of argument draws on the *exploitation hypothesis* advanced by Olson and Zeckhauser (1966). Extending this work, Sandler and Shimizu (2014) traces the evolution of defense burden-sharing patterns across different phases of the NATO alliance.

Although evidence from the 1960s supports the exploitation hypothesis – showing that poorer member states benefited disproportionately from the contributions of wealthier allies – this pattern was not confirmed in the following decades (Khanna and Sandler, 1996; Sandler and Shimizu, 2014). A shift followed NATO's adoption of the Flexible Response doctrine in 1969. This approach introduced a nuanced form of defense publicness within the Alliance. After the dissolution of the USSR, the primary threat was increasingly associated with instability in the Balkans. Defense provision was again viewed to some extent as a more public good, thus creating conditions more conducive to free-riding (Sandler and Shimizu, 2014). In the 2010s, the exploitation hypothesis regained empirical support, following a renewed transformation of defense into a more public good (Zyla, 2016; Kim and Sandler, 2020).

Among recent contributions to the literature on burden sharing, George and Sandler (2022) document free-riding by Western NATO allies at the expense of Eastern members as Russian military spending increased. Pedersen et al. (2023) investigates potential free-riding behavior of smaller NATO allies, with particular attention to the determinants of their defense spending; Founta et al. (2025) examines the role of the US in leading NATO allies' defense expenditure.

A relatively limited body of economic literature has examined defense burden sharing within the European Union. Among these scholars, Kollias (2008) simulates the existence of a European Defense Union (EDU) to examine the balance of burdens and benefits. To this end, he identifies under- and over-contributors to the collective defense effort. Dorussen et al. (2009) explores the distribution of defense burden sharing in the EU from different perspectives of collective security – namely assurance, prevention, protection, and compellence policies. Haesebrouck and Thiem (2018) study the determinants of contribution to two military operations – EUFOR RD Congo and EUFOR Chad/CAR. Christie et al. (2024) explores the impact of increasing threats in the EU surroundings on national defense budgets.

The economic literature has measured burden sharing by means of several indicators. Hartley and Sandler (1999) emphasize that debates on burden sharing are heavily influenced by the choice of indicators employed. The earliest, most widely adopted measure is military expenditure as a percentage of GDP (Olson and Zeckhauser, 1966). Although it is still a standard indicator in numerous studies (Sandler and Forbes, 1980; Khanna and Sandler, 1996; Sandler and Murdoch, 2000; Sandler and Hartley, 2001; Sandler and Shimizu, 2014), it is not without limitations (Hartley and Sandler, 1999). Consequently, alternative measures have been used. Sandler and Hartley (2001), Kollias (2008), and Dorussen et al. (2009) favor the national share of the alliance's military expenditure, a measure suggested by Hartley and Sandler (1999). Kim and Sandler (2020) use three different measures of burden sharing: (i) military spending as a share of GDP, (ii) national share of NATO military spending, and (iii) the sum of military spending, overseas development assistance (ODA), and UN peacekeeping spending.

The empirical debate on burden sharing also concerns the choice of explanatory variables. Early studies used indicators such as the national share of the alliance's land, population, GDP, end exposed borders (Sandler and Forbes, 1980), to assess whether a country contributed its fair share. Hartley and Sandler (1999) rely on area, population, and exposed borders, a methodology further replicated in Sandler and Hartley (2001). Sandler and Murdoch (2000) introduce a measure of economic openness, defined as the national share of the alliance's total trade relative to NATO's aggregate GDP. Kollias (2008) instead uses the national shares of import and export. Dorussen et al. (2009) extends the set of benefits gained from the common defense to social protection, the number of asylum seekers, homicides and violent deaths. Following the rise of international terrorist attacks, Sandler and Shimizu (2014) introduce the threat of terrorism as an explanatory factor. Other innovative indicators include a country's peacekeeping tradition, the absence of simultaneous military engagements, and the presence of a right-leaning executive (Haesebrouck and Thiem, 2018).

Scholars have extensively contributed to the study of unequal burden sharing of collective defense within alliances, employing a variety of burden-sharing measures. However, two significant gaps remain in the literature. First, the European Union is relatively understudied, as most analyzes have focused predominantly on NATO. This is partly because the EU, unlike NATO, is not a formal defense alliance, despite its deep integration in other domains such as trade. The contribution of this paper lies also in addressing this gap by examining EU defense cooperation through the lens of burden sharing. Second, limited attention has been paid to identifying the determinants of contribution by member states within an alliance. This paper aims to address these gaps by exploring potential determinants of defense burden sharing within the European Union from 1980 to 2024. To this end, (i) we use H2O random forest regression to assess variable importance and select a sample of factors, (ii) we employ fixed-effects panel OLS models to estimate their impact, and (iii) fractional logit as robustness check.

## 3 *Data and Variable Selection*

### 3.1 Data

In order to study the determinants of defense burden sharing within the EU, our panel dataset covers the years from 1980 to 2024 and includes the 28 countries that have been EU member states, starting from the year they joined the EU. The unit of analysis is country-year. This yields 871 observations, reflecting 45 years of data and the evolving composition of the EU membership.

Variables used to perform the analyses are drawn from several data sources, namely the Central Intelligence Agency's World Factbook (CIA WF), Colonial Dates Datasets (COLDAT) (Becker, 2019), Comparative Political Data Set (CPDS)(Armingeon et al., 2024), Correlates of War (CoW)(Wingender, 2025), Eurostat, Google Maps, North Atlantic Treaty Organization (NATO), Military Balance + (MB), Nuclear Latency Dataset (NL) (Fuhrmann and Tkach, 2015), Stockholm International Peace Research Institute (SIPRI), Varieties of Democracy Dataset (V-Dem)(Coppedge et al., 2025), and the World Bank (WB).

### 3.2 Dependent variable

This study employs the logarithm of the Burden Share Index (BSI) as the key dependent variable. The BSI is a continuous measure expressed as a percentage that represents the national share of EU military expenditure. Beyond reflecting our primary subject of interest – namely, national contributions to the common defense effort within the EU – the Burden Share Index is a conventional measure of defense contribution in the economic literature (Hartley and Sandler, 1999; Sandler and Hartley, 2001; Kollias, 2008; Dorussen et al., 2009; Kim and Sandler, 2020). Its use therefore enables comparison with prior research. The BSI is computed as follows:

$$BSI_{i,t} = milex_{i,t}/milex_{EU,t} \tag{1}$$

Where:

- $milex_{i,t}$ denotes the military expenditure of country $i$ in year $t$, expressed in constant 2023 US dollars, as reported by SIPRI.
- $milex_{EU,t}$ represents the total military expenditure of the European Union in year $t$, also expressed in constant 2023 US dollars.

Specifically, $milex_{EU,t}$ is calculated as:

$$milex_{EU,t} = \sum_{i=1}^{N} milex_{i,t} \tag{2}$$

where $N$ is the number of EU member states. In other words, the EU's total military expenditure in year $t$ is obtained by summing the military expenditures of all its member states, all expressed in constant 2023 US dollars. Indeed, EU military spending is understood as the sum of national defense budgets, since coordination at the EU level remains limited (Bordignon et al., 2020; Mombelli, 2024).

Table 1 reports five-year national averages from 1980 to 2024. On average, the United Kingdom, Germany, France, and Italy have borne the largest shares of the EU defense burden, with values ranging from 11.7% to 24.3%. They are followed by Spain, the Netherlands, and Poland, whose shares range from 4.6% to 6.8%. Fig. 5 in the Appendix further illustrates country-level time series of the BSI over the same period.

Table 1: Average Burden Share Index across EU member states over five-year periods.

| Country | 1980-4 | 1985-9 | 1990-4 | 1995-9 | 2000-4 | 2005-9 | 2010-4 | 2015-9 | 2020-4 | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|
| Austria | - | - | - | 1.51 | 1.40 | 1.30 | 1.29 | 1.28 | 1.45 | 1.37 |
| Belgium | 3.40 | 3.30 | 2.79 | 2.52 | 2.25 | 2.01 | 2.00 | 1.81 | 2.31 | 2.55 |
| Bulgaria | - | - | - | - | - | 0.43 | 0.32 | 0.46 | 0.56 | 0.44 |
| Croatia | - | - | - | - | - | - | 0.38 | 0.38 | 0.46 | 0.41 |
| Cyprus | - | - | - | - | 0.14 | 0.14 | 0.14 | 0.14 | 0.18 | 0.15 |
| Czechia | - | - | - | - | 1.52 | 1.42 | 1.07 | 1.17 | 1.67 | 1.34 |
| Denmark | 1.89 | 1.64 | 1.70 | 1.76 | 1.66 | 1.50 | 1.51 | 1.50 | 2.20 | 1.71 |
| Estonia | - | - | - | - | 0.13 | 0.16 | 0.19 | 0.26 | 0.35 | 0.23 |
| Finland | - | - | - | 1.10 | 1.13 | 1.29 | 1.43 | 1.39 | 1.67 | 1.33 |
| France | 21.24 | 19.94 | 20.64 | 20.00 | 18.80 | 17.69 | 18.11 | 18.38 | 19.36 | 19.35 |
| Germany | 26.23 | 23.73 | 22.35 | 19.30 | 17.41 | 14.96 | 16.22 | 17.11 | 21.40 | 19.86 |
| Greece | 3.16 | 2.38 | 2.28 | 2.83 | 2.96 | 3.04 | 2.09 | 1.96 | 2.56 | 2.57 |
| Hungary | - | - | - | - | 0.73 | 0.62 | 0.48 | 0.66 | 1.24 | 0.75 |
| Ireland | 0.40 | 0.34 | 0.39 | 0.47 | 0.50 | 0.45 | 0.43 | 0.41 | 0.42 | 0.42 |
| Italy | 10.15 | 11.05 | 11.85 | 12.73 | 13.98 | 11.92 | 10.86 | 10.02 | 12.14 | 11.63 |
| Latvia | - | - | - | - | 0.15 | 0.20 | 0.12 | 0.23 | 0.35 | 0.22 |
| Lithuania | - | - | - | - | 0.18 | 0.21 | 0.16 | 0.38 | 0.63 | 0.34 |
| Luxembourg | 0.05 | 0.05 | 0.07 | 0.08 | 0.10 | 0.09 | 0.08 | 0.12 | 0.19 | 0.09 |
| Malta | - | - | - | - | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.02 |
| Netherlands | 5.89 | 5.22 | 4.96 | 4.72 | 4.52 | 4.35 | 4.08 | 4.09 | 5.35 | 4.80 |
| Poland | - | - | - | - | 2.66 | 3.06 | 3.66 | 4.70 | 7.26 | 4.58 |
| Portugal | - | - | 0.88 | 1.08 | 1.18 | 1.23 | 1.21 | 1.14 | 1.15 | 1.31 |
| Romania | - | - | - | - | - | 0.95 | 0.92 | 1.55 | 2.05 | 1.41 |
| Slovakia | - | - | - | - | 0.51 | 0.55 | 0.43 | 0.55 | 0.81 | 0.58 |
| Slovenia | - | - | - | - | 0.23 | 0.26 | 0.22 | 0.20 | 0.27 | 0.24 |
| Spain | - | 6.62 | 6.79 | 7.13 | 7.30 | 7.00 | 6.54 | 6.25 | 7.05 | 6.84 |
| Sweden | - | - | - | 2.15 | 2.24 | 1.80 | 1.85 | 1.98 | 2.71 | 2.12 |
| UK | 27.63 | 26.35 | 25.10 | 22.52 | 23.27 | 23.95 | 24.48 | 21.85 | 20.15 | 24.30 |

As illustrated in Fig. 1, the distribution of the Burden-Sharing Index (BSI) is highly right-skewed, with a concentration of observations at relatively low levels and a long tail of countries contributing higher shares. Such skewness can bias inference and reduce the comparability of coefficients across specifications. To address

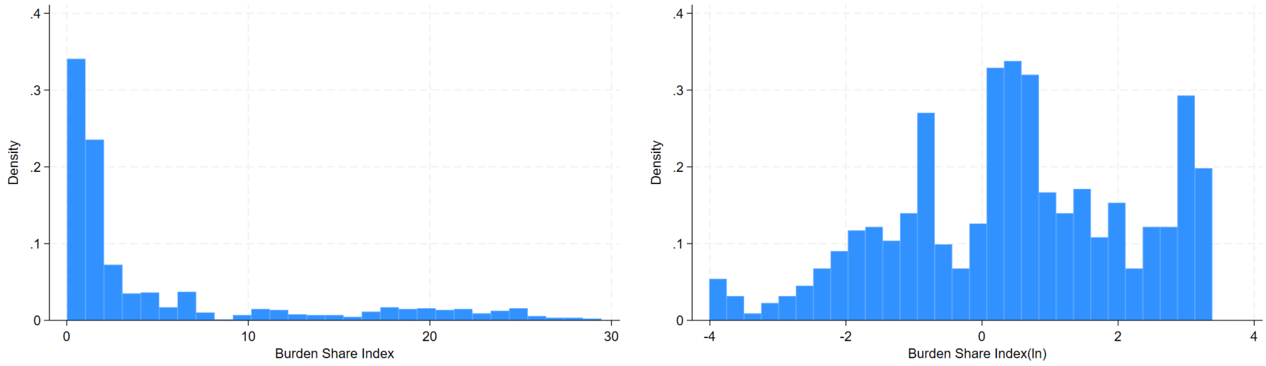



Figure 1: Distribution of the Burden Share Index (on the left) and the natural logarithm of the Burden Share Index (on the right).

this, we transform the variable using the natural logarithm. Fig. 1 also displays the distribution of the natural logarithm of the Burden Share Index.

## 3.3 Explanatory variables

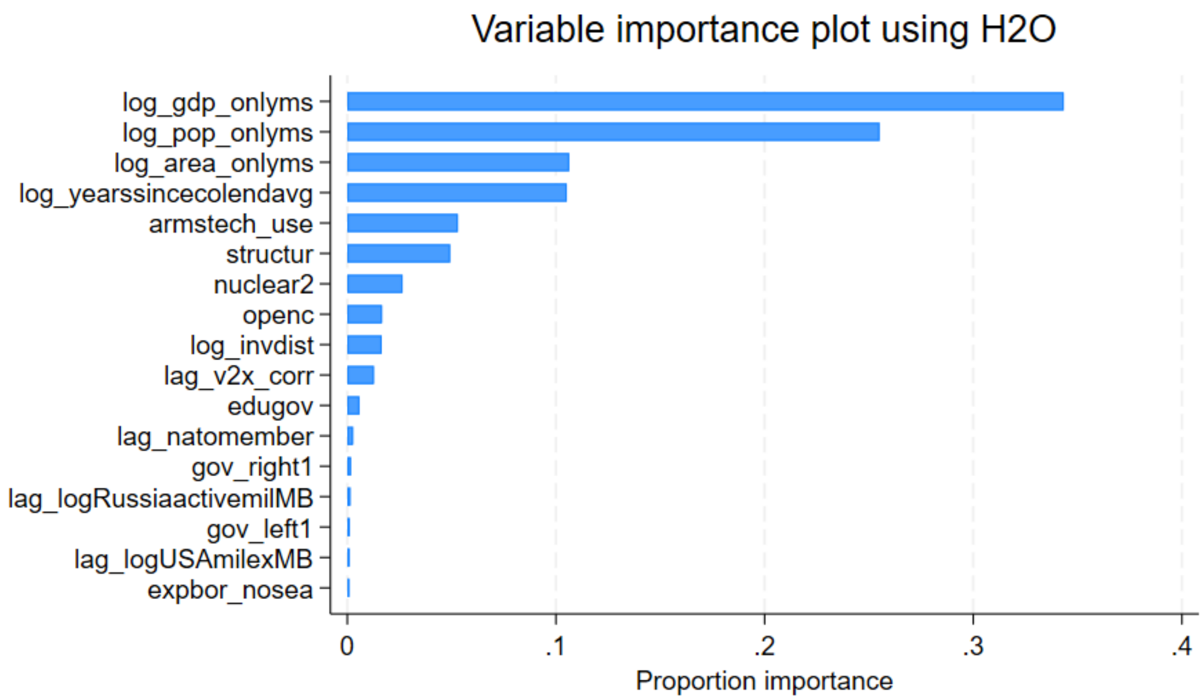
### 3.3.1 H2O Machine-Learning Random Forest variable selection

The purpose of this paper is to identify the determinants of the BSI, with particular attention to the role of institutional and economic factors. To this end, we undertake two complementary steps. First, we assemble a set of institutional variables – new to the literature – that are expected to affect the BSI. Second, we incorporate strategic (Sandler and Forbes, 1980; Hartley and Sandler, 1999; Sandler and Murdoch, 2000; Sandler and Hartley, 2001; Kollias, 2008; Dorussen et al., 2009; Sandler and Shimizu, 2014; Kim and Sandler, 2020; George and Sandler, 2022), economic (Sandler and Forbes, 1980; Hartley and Sandler, 1999; Sandler and Murdoch, 2000; Sandler and Hartley, 2001; Kollias, 2008; Dorussen et al., 2009; Sandler and Shimizu, 2014; Kim and Sandler, 2020; George and Sandler, 2022), historical (Kuokštytė et al., 2021; Kim and Sandler, 2024; Founta et al., 2025), and political determinants (Haesebrouck and Thiem, 2018; Kuokštytė et al., 2021; Balestra and Caruso, 2025) identified in prior research as relevant for explaining defense-burden allocation. Accordingly, we compile a comprehensive set of explanatory variables from multiple data sources.

To evaluate the influence of our covariates on the outcome variable, we examined the full set of potential determinants using H2O's machine-learning framework. We implemented a Random Forest regression via the H2O interface in Stata 19.5. Machine-learning–based variable importance is employed as an exploratory diagnostic tool to obtain a non-parametric ranking of potential predictors of the Burden Share Index (BSI).

A random forest is an ensemble method that constructs many regression trees, each grown on a bootstrap sample of the data and using a randomly selected subset of predictors at each split. This design reduces overfitting and allows the model to capture nonlinear relationships and interactions that may not be well represented in parametric specifications. Each tree is trained on a different subset of observations – its sampling values – ensuring diversity across trees. The forest produces variable-importance measures based on each predictor's contribution to reducing the model's loss function across all trees, providing a nonparametric assessment of the relative relevance of the covariates. The model is initialized with a fixed random seed, which controls the randomization processes involved in sampling and tree construction, ensuring that results can be replicated exactly.

In particular, the random forest procedure computes an impurity-based variable importance measure, summarizing how much each covariate reduces the loss function across all splits in the forest. This is closely related to predictive performance and provides a non-parametric ranking of variables by their contribution to the model's fit. This step does not aim at causal inference nor at providing a structural model; rather, it complements the econometric analysis by offering a data-driven indication of which covariates carry the largest predictive signal. As such, Random Forest variable importance should be interpreted as a robustness device for variable screening, not as evidence of the statistical significance of predictors in a parametric fixed-effects setting. Therefore, the aim is not prediction *per se*, rather to assess the relative importance of the variables. Figure 2 reports the results. Importance scores reflect each predictor's average contribution to reducing prediction error across all splits.



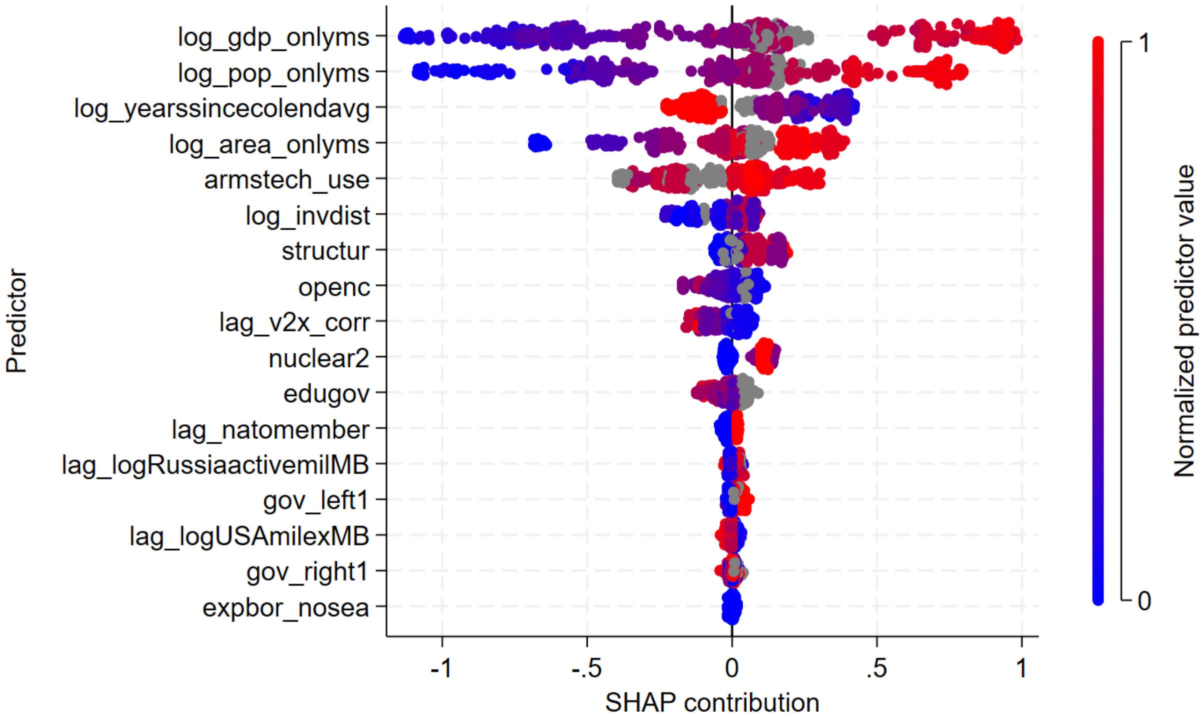

*Note: Proportional variable importance is relative to the BSI(ln) prediction.

*Note: from top to bottom, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), area (*log_area_onlyms*), colonial legacy (*log_yearssincecolendavg*), arms technology (*armstech_use*), constitutional structures (*structur*), nuclear power (*nuclear*2), economic openness (*openc*), Moscow proximity (*log_invdist*), lagged political corruption (*lag_v*2*x_corr*), education expenditure as a percentage of government spending (*edugov*), lagged NATO membership (*lag_natomember*), right-wing government (*gov_right*1), lagged Russian active military (*lag_logRussiaactivemilMB*), left-wing government (*gov_left*1), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

Figure 2: Variable importance plot for 17 predictors using H2O Machine Learning Random Forest regression.

Further steps allow to check the stability of the results. First, we estimated four identical random forest regressions, gradually increasing the number of trees, starting from 100 to 2000. Increasing the number of trees enhances the stability of the estimates and reduces the variance of the model, thereby yielding more robust measures of variable importance. To ensure comparability across models, we set the random seed to 19 in all four H2O regressions. Fig. 6 in the Appendix illustrates how the relative importance of the predictors evolves as the number of trees increases. Second, fixing the number of trees, we varied the random seed to check the robustness of the results to different pseudo-random initializations (Fig. 7 in the Appendix). This ensures that variable-importance estimates do not depend on a specific random draw. Third, fixing the number of random seeds at 19 and the number of trees at 200, we varied the sampling values (Fig. 8 in the Appendix). Using different sampling values provides a means to evaluate the stability of variable importance, ensuring that the relative influence of each predictor remains consistent across specifications.

Results indicate that a subset of variables consistently contributes to explaining variation in BSI. The predictors accounting for 90% of total variable importance are (i) GDP, (ii) population, (iii) colonial legacy, (iv) area, (v) arms technology, and (vi) constitutional structures. These findings remain robust across variations in the number of trees, seeds, and different predictor sampling values.




*Note: the SHAP contribution is relative to the BSI(ln) prediction.

*Note: from top to bottom, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), colonial legacy (*log_yearssincecolendavg*), area (*log_area_onlyms*), arms technology (*armstech_use*), Moscow proximity (*log_invdist*), constitutional structures (*structur*), economic openness (*openc*), lagged political corruption (*lag_v2x_corr*), nuclear power (*nuclear2*), education expenditure as a percentage of government spending (*edugov*), lagged NATO membership (*lag_natomember*), lagged Russian active military (*lag_logRussiaactivemilMB*), left-wing government (*gov_left1*), lagged US military expenditure (*lag_logUSAmilexMB*), right-wing government (*gov_right1*), territorial exposed borders (*expbor_nosea*).

Figure 3: Shapely Additive explanations using H2O Machine Learning Random Forest regression.

Figure 3 provides a more granular assessment of the marginal contributions of the seven most important predictors. The figure presents shapely additive explanations (SHAP) feature importance using a bee swarm plot that ranks predictors according to their contribution to the Burden Share Index. The SHAP approach offers a comprehensive understanding of both global and local contributions of individual variables. The horizontal axis indicates the SHAP contribution of each predictor, with positive or negative values showing the direction and magnitude of their impact on the prediction. The color gradient represents the normalized value of the predictors, ranging from blue (low values) to red (high values).

A brief methodological clarification is warranted. Random Forest variable-importance measures – such as the mean reduction in squared error – capture how much each predictor contributes to lowering the model's loss function (typically the mean squared error) across all splits and trees in the forest. These metrics therefore summarize the overall contribution of each variable to improving the fit of the model within the ensemble. In contrast, SHAP values decompose individual predictions into additive contributions of each predictor, identifying how each variable increases or decreases the predicted outcome for every observation. SHAP values are thus local contributions to the prediction; aggregating them across observations (for example, by taking the mean absolute SHAP value) yields a global measure of variable importance. As a result, SHAP-based importance rankings may differ from classical Random Forest importance metrics, especially in the presence of non-linearities or correlated predictors.

The SHAP analysis broadly confirms the findings obtained from the classical Random Forest variable-importance measures. Overall, the ranking of predictors is largely consistent, although some differences emerge due to the distinct nature of SHAP-based importance. The proximity to Moscow increases in relevance, displaying a relatively clear distinction between low and high normalized values of the predictor. Preliminary interpretations suggest that higher levels of GDP, population, and area exert a positive marginal contribution to the predicted value of BSI(ln). Conversely, greater temporal distance from a country's colonial past tends to exert a negative contribution to the prediction. The contribution of arms-technology levels is more difficult to interpret, likely reflecting interactions with other institutional or economic variables. Institutional complexity appears to exhibit a nonlinear pattern: low normalized values contribute negatively to the prediction, middle values positively, whereas high values remain positive but closer to zero, indicating diminishing marginal effects. Proximity to Moscow also emerges as a relatively important contributor, although its directional effect is less clearly delineated in the SHAP distribution. Taken together, the SHAP results reinforce the central role of economic and institutional factors in shaping the burden-sharing pattern, while also highlighting the contribution of strategic-threat variables.

### 3.3.2 Institutional and economic factors

Random Forest tools allow the selection of a parsimonious set of explanatory variables that account for the variation in the Burden Share Index. These variables can be grouped into three categories: (i) institutional variables, (ii) economic variables, and (iii) control variables well-established in the literature.

The institutional dimension includes two variables: (i) distance to the colonial past and (ii) institutional complexity. The colonial-distance variable is constructed in four steps using COLDAT. First, for each country $i$, we collect the end year of each colonial possession. Second, we compute the country-level average end year of colonial rule. Third, we calculate the number of years elapsed between this average end year and time $t$. Countries without a colonial past are assigned the value 999. Finally, the measure is expressed in logarithmic form. This variable thus captures the temporal distance from a country's colonial legacy.

The second institutional variable is an index of institutional complexity derived from the Comparative Political Data Set (CPDS), built according to Huber et al. (1993). This variable aggregates five components: (i) federalism (absent, weak, strong), (ii) type of government (parliamentary, presidential, or other), (iii) proportionality of representation (proportional, modified proportional, majoritarian), (iv) strength of bicameralism (absent, weak, strong), and (v) the presence of frequent referenda. Higher values denote more complex institutional arrangements and tighter constraints on central-government decision-making. Figure 9 in the Appendix illustrates the distribution of institutional complexity across EU member states.

The analysis incorporates one economic variable that is novel relative to the existing burden-sharing literature: the national level of arms technology. Derived from the Correlates of War dataset, this variable records the highest arms-technology category employed by country $i$ at time $t$. This ordinal indicator ranges from 0 to 29, while within the EU values range from 14 to 29. Figure 10 in the Appendix presents the distribution of arms-technology levels.

### 3.3.3 Control variables

The analysis includes a set of economic and geographic control variables that are standard in the burden-sharing and defense-as-a-public-good literature. First, the logarithm of Gross Domestic Product (GDP) is incorporated to account for differences in economic capacity, which are theorized to influence the proportion of the defense burden borne by each country (Sandler and Forbes, 1980; Hartley and Sandler, 1999; Sandler and Murdoch, 2000; Sandler and Hartley, 2001; Kollias, 2008; Dorussen et al., 2009; Sandler and Shimizu, 2014; Kim and Sandler, 2020; George and Sandler, 2022). Second, the logarithm of population (World Bank; Eurostat) and the logarithm of national area (Eurostat; World Bank) are included to reflect how demographic and territorial scale shape security requirements and, in turn, defense-spending behavior (Sandler and Forbes, 1980; Hartley and Sandler, 1999; Sandler and Murdoch, 2000; Sandler and Hartley, 2001; Kollias, 2008; Dorussen et al., 2009; Sandler and Shimizu, 2014; Kim and Sandler, 2020; George and Sandler, 2022).

Table 2: Descriptive Statistics

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Burden Share Index | 871 | 5.17 | 7.36 | 0.02 | 29.45 |
| Burden Share Index(ln) | 871 | 0.47 | 1.74 | -4.01 | 3.38 |
| GDP(ln) | 871 | 26.26 | 1.51 | 22.69 | 28.94 |
| Population(ln) | 871 | 16.05 | 1.44 | 12.80 | 18.24 |
| Area(ln) | 871 | 11.28 | 1.57 | 5.77 | 13.21 |
| Colonial legacy(ln) | 871 | 5.91 | 1.28 | 2.93 | 6.91 |
| Arms technology | 794 | 23.48 | 3.59 | 14 | 29 |
| Constitutional structures | 817 | 1 | 1.24 | 0 | 4 |
| Observations | 871 | | | | |

Table 2 summarizes the descriptive statistics for variables used to perform the estimates. Table 6 in the Appendix provides a comprehensive overview of the variables, detailing their metadata and sources.

## 4 *Methodology and Results*

The empirical strategy relies on a fixed-effects panel ordinary least squares (OLS) model with standard errors clustered at country-level. The full specification of the model is presented below.

$$BSI(ln)_{i,t} = \beta_1 colonial_{i,t} + \beta_2 structures_{i,t} + \beta_3 armstech_{i,t} + \beta_4 X_{i,t} + \alpha_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

Where the subscript $i$ = Austria, ..., United Kingdom indicates the country, and $t$ = 1980, ..., 2024 indicates the year. Our dependent variable is $BSI_{i,t}$, the share of European defense spending borne by country $i$ at time $t$. The explanatory variables issued by the Random Forest variable importance regression include (i) the logarithm of the distance to the colonial past in country $i$ at time $t$, (ii) the level of constitutional structures in country $i$ at time $t$, (iii) the level of the most advanced arms technology employed in country $i$ at time $t$, and (iv) a vector of control variables identified in prior literature on military expenditure and defense as a public good, namely, the logarithm of area, population, and GDP of country $i$ at time $t$. In addition, $\alpha_i$ and $\gamma_t$ capture country- and time-specific fixed effects, respectively. $\varepsilon_{it}$ is the idiosyncratic error term. All specifications includes clustering of standard errors at country level.

Table 3: Fixed-Effects panel OLS model, 1980-2024

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| BSI(ln) | | | | |
| Colonial legacy(ln) | -0.725** | -0.674** | -0.375* | -0.402** |
| | (0.282) | (0.254) | (0.202) | (0.189) |
| Constitutional structures | -0.018 | -0.042 | -0.048 | -0.056 |
| | (0.049) | (0.049) | (0.040) | (0.038) |
| Arms technology=22 | | 0.207 | 0.048 | 0.052 |
| | | (0.174) | (0.137) | (0.149) |
| Arms technology=23 | | 0.010 | -0.150 | -0.153 |
| | | (0.196) | (0.158) | (0.165) |
| Arms technology=24 | | 0.009 | -0.089 | -0.088 |
| | | (0.161) | (0.130) | (0.137) |
| Arms technology=25 | | -0.007 | -0.020 | -0.036 |
| | | (0.119) | (0.110) | (0.118) |
| Arms technology=26 | | 0.041 | 0.058 | 0.039 |
| | | (0.094) | (0.090) | (0.095) |
| Arms technology=27 | | -0.087 | -0.015 | -0.033 |
| | | (0.071) | (0.077) | (0.0765) |
| Arms technology=28 | | -0.137** | -0.064 | -0.070 |
| | | (0.057) | (0.052) | (0.045) |
| GDP(ln) | | | 0.553 | 0.682* |
| | | | (0.336) | (0.353) |
| Population(ln) | | | | -0.697 |
| | | | | (0.799) |
| Area(ln) | | | | -0.013 |
| | | | | (0.843) |
| Country FE | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes |
| $R^2$ | 0.395 | 0.410 | 0.480 | 0.497 |
| Log-Lik | 346.4 | 336.5 | 385.0 | 398.3 |
| BIC | -511.7 | -506.8 | -603.8 | -623.8 |
| AIC | -638.8 | -622.9 | -719.9 | -744.6 |
| VIF | 3.05 | 3.10 | 3.34 | 4.43 |
| N | 817 | 769 | 769 | 769 |

Standard errors clustered at country level in parentheses.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 4.1 Baseline estimates

Table 3 reports the estimates from the fixed-effects panel OLS model for all EU member states over the period 1980–2024, using the set of explanatory variables selected through the Random Forest selection.

Among the covariates, the colonial legacy variable exhibits a consistently negative and statistically significant effect across all specifications. This pattern points to a structural legacy effect. The robustness of sign and significance across specifications suggests that the decline in burden sharing is not merely mechanical: states without a colonial legacy, or whose imperial era ended much earlier, appear structurally less engaged in the EU collective defense effort. Across all specifications, constitutional structures exhibit consistently small and negative effects, with no statistically significant association with defense-burden participation. This indicates that once time-invariant political characteristics are absorbed by fixed effects, cross-country variation in institutional complexity does not meaningfully affect participation. Similarly, military technological sophistication generally shows no significant association with the BSI, except for a negative effect of technology 28 with respect to the baseline (14), which loses significance when the model is further enriched. Categories below level 22 were omitted, as they are fully absorbed by the fixed-effects specification. In particular, the effect of GDP appears to capture some of the significance of arms technology. GDP itself displays a positive – though only marginally significant – association with defense-burden participation in the richest specification, highlighting the link between economic size and defense contributions. Population size and area, by contrast, do not exhibit any significant effect in any specification, suggesting that demographic scale does not drive defense participation once institutional and economic characteristics are controlled for.

Taken together, these results indicate that relatively few variables shape national contributions to defense. In particular, having an increasingly distant colonial past – or the lack thereof – appears to decrease participation, while larger economic size is associated with higher BSI. Constitutional structures, the level of military technology, and demographic variables such as population and area exhibit no significant impact.

The discrepancy between Random Forest variable importance and the fixed-effects regression coefficients is expected and economically interpretable. Several of the variables that emerge as highly important in the non-parametric model – such as population, institutional complexity, and arms technology – exhibit very limited within-country temporal variation in the European Union. In addition, GDP, population, and area are strongly collinear, which inflates standard errors when included jointly in a linear FE specification. Consequently, variables that play a substantial role in predicting BSI in the Random Forest may fail to achieve statistical significance in the FE regressions, not because they lack substantive relevance, but because the econometric estimator relies on a different source of identification.

## 4.2 Baseline estimates without leaders

Following the baseline interpretation and the variable selection derived from the random-forest procedure, we suspect that an underlying structural mechanism – linked to the informal leadership role of a subset of member states – may be influencing both significance patterns and coefficient magnitudes in the full-sample estimates. The United Kingdom, France, and Germany act *de facto* as the principal security providers within the European defense architecture. Their contributions are expected to remain consistently high irrespective of domestic institutional configurations or short-run political dynamics, as their leadership role entails a structural commitment to maintaining a stable defense posture. As a result, these countries do not necessarily adjust their burden-sharing behavior in response to the institutional or economic drivers that shape the behavior of the median member state. Given their disproportionate weight in the sample and their potentially limited responsiveness to underlying covariates, they may introduce high leverage that attenuate or obscure relationships for the rest of the Union.

To address this issue, we apply a threshold that identifies observations above 15% of the burden-sharing index as outliers and excludes them from the sample. This cutoff is intended to separate structural leaders from regular contributors. In the period 2015–2019 – when all three were still EU members – France, Germany and the United Kingdom together accounted for over half of total defense spending, with shares of 18.38%, 17.11% and 21.85% respectively (Table 1). We therefore re-estimate the model on a restricted sample excluding these leaders, under the expectation that, once these structurally unresponsive states are removed, the estimated relationships linking institutional and economic characteristics to the burden-sharing index may become clearer and statistically stronger. This approach allows us to assess whether the baseline findings were dampened by the presence of dominant actors whose contributions are driven by strategic obligations rather than by the institutional or structural mechanisms under investigation.

Table 4 shows notable differences in the estimation compared with the full-sample results reported in Table 3, confirming that the exclusion of the three leader states uncovers dynamics that were previously overshadowed.

The negative effect of colonial legacy persists across most specifications, consistent with the baseline model, although its statistical significance is somewhat reduced when controlling for economic size. Constitutional structures, which showed no statistical relevance in the full sample, now become significant in the richest specification. This suggests that institutional constraints meaningfully shape defense-burden adjustments among non-leader countries, whereas the presence of structurally committed leaders had previously dampened this relationship. For the arms-technology categories, the reduced sample exhibits a significant and more internally coherent pattern. While the full-sample results mostly showed negative and non-significant effects, the reduced sample produces more consistent positive effects for categories 25 to 28, with stronger statistical precision. The effect is partially absorbed when controlling for economic features (GDP, area, and population), yet it still persists. This indicates that technological sophistication plays a more detectable role once the behavior of leader states – whose defense burdens are comparatively insensitive to production capabilities – is excluded.

Economic covariates show some shifts in their patterns, although the overall direction remains consistent with the full-sample model. GDP loses statistical significance across specifications, yet the associated p-values remain close to the 0.10 threshold (0.139 in the fully saturated model). The diminished relevance of economic size suggests that budgetary capacity or larger economic size is not a key determinant of defense participation among small- and medium-sized EU member states. Spatial controls also display notable changes. Area becomes positive and significant after excluding leaders, indicating that territorial size is more salient for states not structurally required to sustain high defense contributions. Population, in contrast, remains non-significant. Overall, economic variables continue to play a role – particularly area in the richest specification – though evidence for GDP is weaker.

Overall, the improved significance pattern and higher explanatory power (as seen in the rise of $R^2$ values across comparable specifications) suggest that excluding the dominant security providers reduces noise arising from observations that do not respond to institutional or economic variation. In other words, by removing countries whose contributions are shaped primarily by strategic obligations rather than by the explanatory mechanisms of interest, the model recovers relationships that were previously attenuated in the full sample.

To further validate the stability of these findings, we also re-estimate variable importance through an H2O Machine Learning Random Forest regression on the reduced sample (reported in Fig. 11 in the Appendix). The

Table 4: Fixed-Effects panel OLS model, 1980-2024 - leader countries excluded

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| BSI(ln) | | | | |
| Colonial legacy(ln) | -0.788** | -0.688** | -0.385 | -0.417* |
| | (0.291) | (0.263) | (0.259) | (0.232) |
| Constitutional structures | -0.0272 | -0.0835 | -0.0896 | -0.113*** |
| | (0.0514) | (0.0559) | (0.0532) | (0.0315) |
| Arms technology=22 | | 0.685*** | 0.398** | 0.376* |
| | | (0.220) | (0.180) | (0.192) |
| Arms technology=23 | | 0.444* | 0.180 | 0.162 |
| | | (0.232) | (0.188) | (0.197) |
| Arms technology=24 | | 0.496** | 0.253 | 0.231 |
| | | (0.207) | (0.169) | (0.175) |
| Arms technology=25 | | 0.443*** | 0.305** | 0.263* |
| | | (0.143) | (0.122) | (0.140) |
| Arms technology=26 | | 0.423*** | 0.331*** | 0.268** |
| | | (0.119) | (0.100) | (0.117) |
| Arms technology=27 | | 0.251*** | 0.236*** | 0.177* |
| | | (0.0732) | (0.0726) | (0.0873) |
| Arms technology=28 | | 0.109** | 0.106** | 0.0889* |
| | | (0.0440) | (0.0404) | (0.0471) |
| GDP(ln) | | | 0.480 | 0.594 |
| | | | (0.359) | (0.386) |
| Population(ln) | | | | -0.604 |
| | | | | (0.827) |
| Area(ln) | | | | 10.60** |
| | | | | (4.647) |
| Country FE | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes |
| $R^2$ | 0.422 | 0.456 | 0.502 | 0.527 |
| Log-Lik | 270.6 | 269.7 | 298.5 | 315.2 |
| BIC | -384.4 | -396.9 | -454.5 | -481.4 |
| AIC | -493.3 | -495.4 | -553.0 | -584.5 |
| VIF | 3.57 | 3.21 | 3.39 | 4.25 |
| N | 690 | 652 | 652 | 652 |

Standard errors clustered at country level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ranking of predictors remains highly stable relative to the full-sample exercise. We also use alternative numbers of trees and multiple random seeds confirm that the reduced-sample importance measures are not sensitive to algorithmic variation (Fig. 12 and 13 in the Appendix) . Taken together, the fixed-effects estimates and the machine-learning diagnostics provide evidence that the removal of leader countries yields a cleaner empirical environment in which the institutional and structural determinants of EU burden-sharing can be more accurately identified.

## 4.3 Robustness checks

To assess the stability of our baseline findings, we estimate an alternative specification of the model using a nonlinear fractional-response framework. Since the Burden Share Index is bounded between 0 and 1 when expressed in fractional form, we re-estimate the model by applying a pooled fractional logit estimator. This approach is particularly well suited for proportional dependent variables and does not impose the restrictive linearity assumptions of the fixed-effects OLS specification. The model includes a full set of year dummies to capture common shocks and temporal heterogeneity, and standard errors are clustered at the country level to account for within-country serial correlation. As in the baseline no-leaders specification, these robustness checks are estimated on the sample excluding France, Germany, and the United Kingdom.

Table 5 reports the results. Because fractional models are nonlinear, coefficients cannot be directly interpreted in terms of marginal effects. Only the direction and statistical significance of the associations are meaningful without further post-estimation analysis. Despite these differences in interpretation, the overall pattern of findings is highly consistent with the no-leaders OLS specification. Colonial legacy retains a negative sign when included, aligning with the baseline model, although significance weakens once additional controls are introduced. Constitutional complexity exhibits a negative and statistically significant association with the BSI in the fully specified model – mirroring the direction and significance obtained in the OLS estimation, even though the magnitude is not directly comparable. The arms-technology covariates display strong and positive associations in most categories, consistent with the pattern observed in the fixed-effects results, where higher technological capability correlates with greater defense-spending contributions. The sign for GDP remains fully consistent with the no-leaders specification, confirming that structural country characteristics operate in the same direction across estimation strategies. Different patterns emerge with respect to area and population. While in the panel OLS model area was positive and significant and population was not significant, in the full fractional logit model the effect of area loses significance, whereas population becomes positive and significant. This difference likely reflects both model choice and specification. The fractional logit accounts for the bounded nature of BSI, while country fixed effects and the nonlinear transformation can shift the significance of variables with limited within-country variation. This may suggest that population plays a more direct role in burden-sharing under the fractional specification, whereas the effect of geographic area is less robust once the functional form and country heterogeneity are considered. Overall, economic variables continue to play a role across all models.

Figure 4 presents the average marginal effects of all covariates from the full fractional logit model on the (BSI) in fractional form (from 0 to 1) for EU member states. Each point represents the estimated effect of a one-unit increase in the variable, holding all other factors at their observed values, and the whiskers indicate 95% confidence intervals. The plot shows that higher levels of constitutional complexity are associated with slightly lower BSI values, holding all other factors constant, although the magnitude of this effect is relatively small compared with the other variables. Arms-technology levels exert a meaningful positive effect on BSI that varies across categories, with the largest marginal impact observed across the model. Similarly, increases

Table 5: Robustness Check: Fractional Logit (1980-2024, leaders excluded)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| BSI | | | | |
| Colonial legacy(ln) | -0.491$^{*}$ | -0.457$^{***}$ | -0.037 | 0.006 |
| | (0.252) | (0.168) | (0.042) | (0.051) |
| Constitutional structures | 0.173 | 0.114 | -0.036 | -0.063$^{**}$ |
| | (0.218) | (0.090) | (0.026) | (0.028) |
| Arms technology=17 | | 1.060$^{***}$ | 1.547$^{***}$ | 1.058$^{***}$ |
| | | (0.119) | (0.030) | (0.163) |
| Arms technology=18 | | 1.618$^{***}$ | 0.309$^{***}$ | 0.003 |
| | | (0.000) | (0.114) | (0.083) |
| Arms technology=19 | | 1.080$^{***}$ | 1.241$^{***}$ | 0.822$^{***}$ |
| | | (0.109) | (0.050) | (0.083) |
| Arms technology=20 | | 1.063$^{***}$ | 1.571$^{***}$ | 1.158$^{***}$ |
| | | (0.195) | (0.070) | (0.139) |
| Arms technology=22 | | 2.749$^{***}$ | 1.086$^{***}$ | 0.639$^{***}$ |
| | | (0.110) | (0.153) | (0.120) |
| Arms technology=23 | | 3.262$^{***}$ | 1.153$^{***}$ | 0.595$^{***}$ |
| | | (0.165) | (0.291) | (0.221) |
| Arms technology=24 | | 2.108$^{***}$ | 1.312$^{***}$ | 0.854$^{***}$ |
| | | (0.305) | (0.164) | (0.142) |
| Arms technology=25 | | 3.034$^{***}$ | 1.477$^{***}$ | 0.996$^{***}$ |
| | | (0.143) | (0.164) | (0.139) |
| Arms technology=26 | | 3.631$^{***}$ | 1.823$^{***}$ | 1.163$^{***}$ |
| | | (0.211) | (0.268) | (0.194) |
| Arms technology=27 | | 3.455$^{***}$ | 1.722$^{***}$ | 1.160$^{***}$ |
| | | (0.298) | (0.304) | (0.237) |
| Arms technology=28 | | 3.202$^{***}$ | 1.528$^{***}$ | 1.034$^{***}$ |
| | | (0.376) | (0.256) | (0.193) |
| Arms technology=29 | | 3.060$^{***}$ | 1.406$^{***}$ | 0.945$^{***}$ |
| | | (0.443) | (0.244) | (0.194) |
| GDP(ln) | | | 0.904$^{***}$ | 0.669$^{***}$ |
| | | | (0.072) | (0.095) |
| Area(ln) | | | | -0.0703 |
| | | | | (0.046) |
| Population(ln) | | | | 0.406$^{***}$ |
| | | | | (0.080) |
| Constant | -1.076 | -3.655$^{***}$ | -28.19$^{***}$ | -27.54$^{***}$ |
| | (1.348) | (0.726) | (1.854) | (2.120) |
| Pseudo $R^2$ | 0.068 | 0.111 | 0.130 | 0.131 |
| Log-Lik | -71.65 | -66.74 | -65.33 | -65.24 |
| BIC | 300.2 | 282.5 | 273.2 | 273.0 |
| AIC | 191.3 | 179.5 | 174.7 | 174.5 |
| N | 690 | 652 | 652 | 652 |

Standard errors clustered at country-level in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

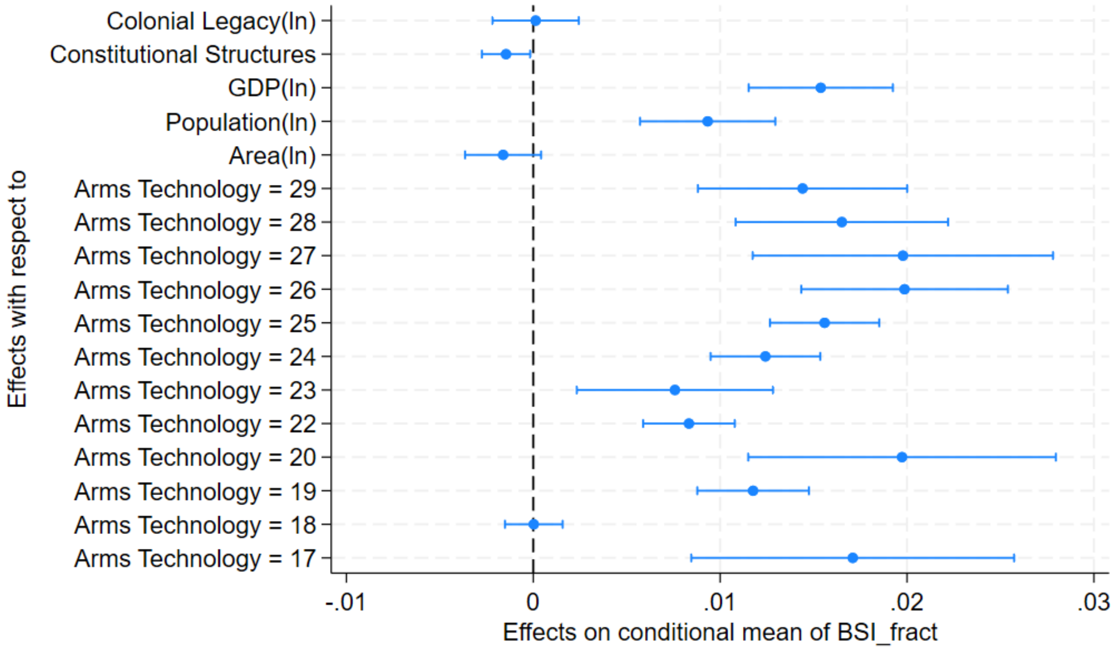



Figure 4: Fractional logit regression - average marginal effects (95% confidence intervals)

in GDP and population raise expected BSI, indicating that wealthier and more populous countries contribute proportionally more to EU defense efforts. By contrast, colonial legacy and geographic area do not display statistically significant effects. Overall, the marginal effect plot generally supports the findings from the fixed-effects panel OLS model. Economic and structural characteristics consistently shape defense participation, and the results are robust to accounting for the fractional nature of BSI.

As an additional check, we also estimate a fractional probit model and its average marginal effects, reported in Table 7 and Fig. 15 in the Appendix. The probit specification delivers qualitatively similar results in terms of sign and significance patterns, further corroborating the robustness of our conclusions.

Taken together, these results reinforce the substantive conclusions of the baseline model: (i) institutional and economic factors shape EU countries' participation in defense, and (ii) excluding the military leaders clarifies the fundamental relationships between institutional features, structural characteristics, and member states' fiscal contributions. The alternative estimation strategy further confirms that our findings are robust and do not depend on the assumptions of the linear fixed-effects framework.

## 5 *Conclusion*

This paper has examined the determinants of defense burden sharing among EU member states over 1980–2024. The dependent variable, the logarithm of the Burden Share Index, captures each country's share of total EU military expenditure. The explanatory framework combines well-established predictors from the burden-sharing literature with additional historical and institutional indicators. As an exploratory step, H2O random forests were used to gauge variable relevance, and the stability of importance rankings across alternative tuning choices ensured that only the most robust predictors were retained for the econometric analysis.

The core empirical strategy relies on fixed-effects panel regressions estimated both on the full sample and on a reduced sample that excludes countries contributing more than 15% of total EU defense spending – namely France, Germany and the United Kingdom. These states account for a structurally dominant share of the common defense effort and effectively play the role of system leaders. Their contributions remain persistently high and are comparatively unresponsive to domestic institutional or economic variation. The comparison across samples confirms this logic. Once the leaders are removed, the effects of historical and institutional covariates become clearer and more stable, technological capacity shows a more consistent association with burden share, and the behavior of economic controls aligns more closely with theoretical expectations. The increase in explanatory power and the more orderly significance patterns indicate that excluding the dominant providers reveals the mechanisms shaping the decisions of medium and smaller states that were previously overshadowed.

Robustness checks using fractional logit and fractional probit estimators, which accommodate the bounded nature of the dependent variable, corroborate these conclusions. The direction and significance of the key covariates remain consistent with the linear estimates, indicating that the results are not driven by functional-form considerations.

Overall, the study offers three main contributions. First, it provides an integrated empirical account of how historical, institutional, economic and strategic factors jointly shape defense effort within the EU. Second, it shows that institutional and economic variables meaningfully structure the distribution of the defense burden among member states. Third, it demonstrates that the behavior of the leading contributors masks underlying relationships in the full sample, as their roles oblige them to maintain high commitments irrespective of domestic conditions. These findings deepen our understanding of the foundations of collective defense in Europe and clarify the structural asymmetries shaping burden-sharing behavior across member states.

## 5.1 Limitations

Further research will refine and extend the empirical analysis in several directions. First, additional robustness checks will consider the national share of equipment expenditure in total EU spending as an alternative measure of burden sharing. Second, the analysis is constrained by the limited within-country variation of certain institutional variables, which restricts the precise identification of their individual effects. Future work could explore alternative model specifications, employ more flexible estimators, or adapt the operationalization of these variables to better capture their influence.

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# 7 Appendix

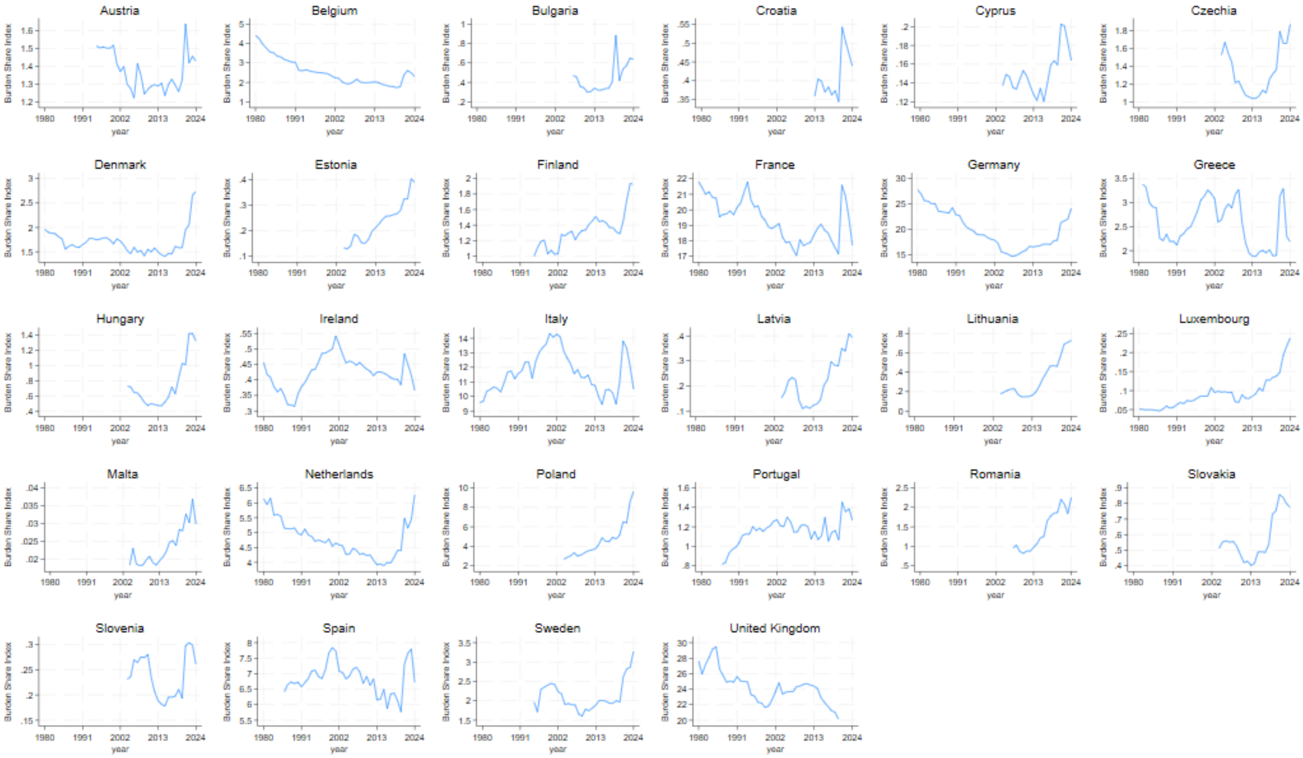


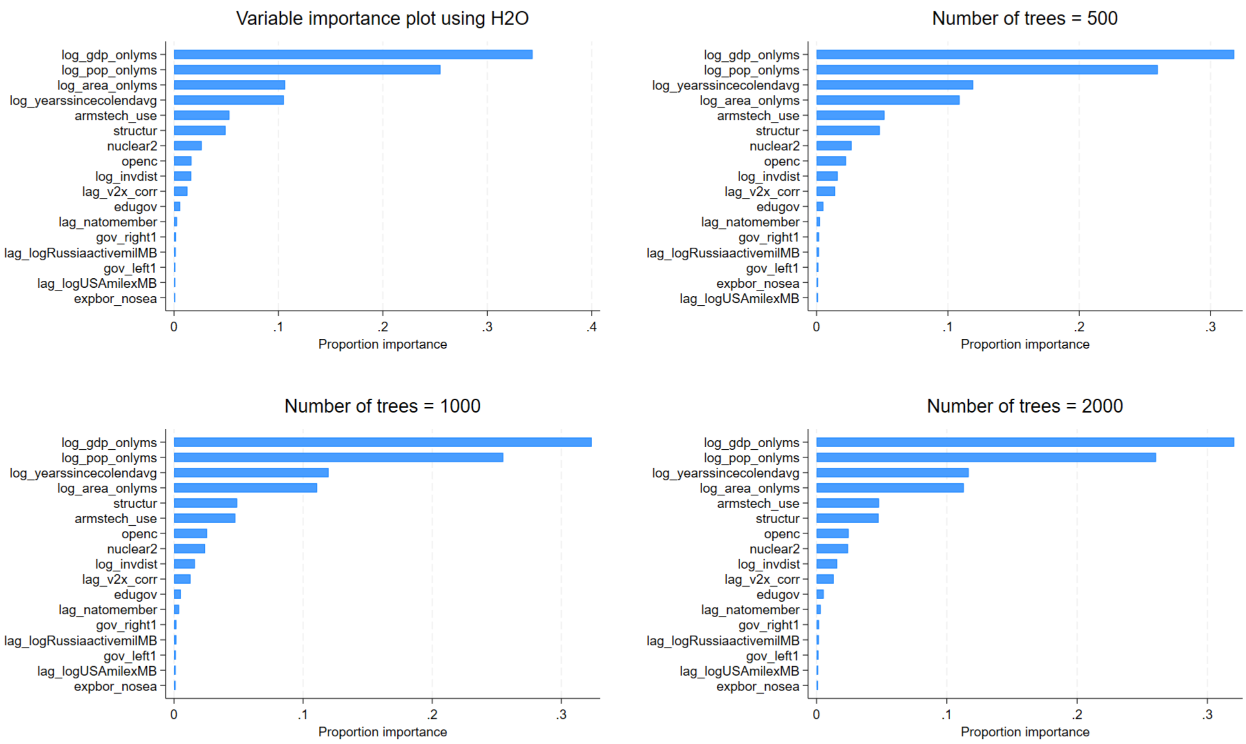

Figure 5: Country-level time series of Burden Share Index.

Table 6: Variables Metadata

| Variable | Unit | Description | Source |
|---|---|---|---|
| Area | log of sq. km | Natural logarithm of the national territory expressed in square kilometres. | WB |
| Arms technology | categories | Indicator of arms technological sophistication, ranging from 0 to 29. In the EU, it ranges from 14 to 29. | CoW |
| Burden Share Index | log and 0-1 | National share of EU defense spending, expressed both as a fraction from 0 to 1 and in natural logarithm. | SIPRI |
| Colonial legacy | log of years | Natural logarithm of the number of years since the average end of the country's colonial possessions. A value of 999 indicates that the country never held colonial territories. | COLDAT |

*Continued on next page*

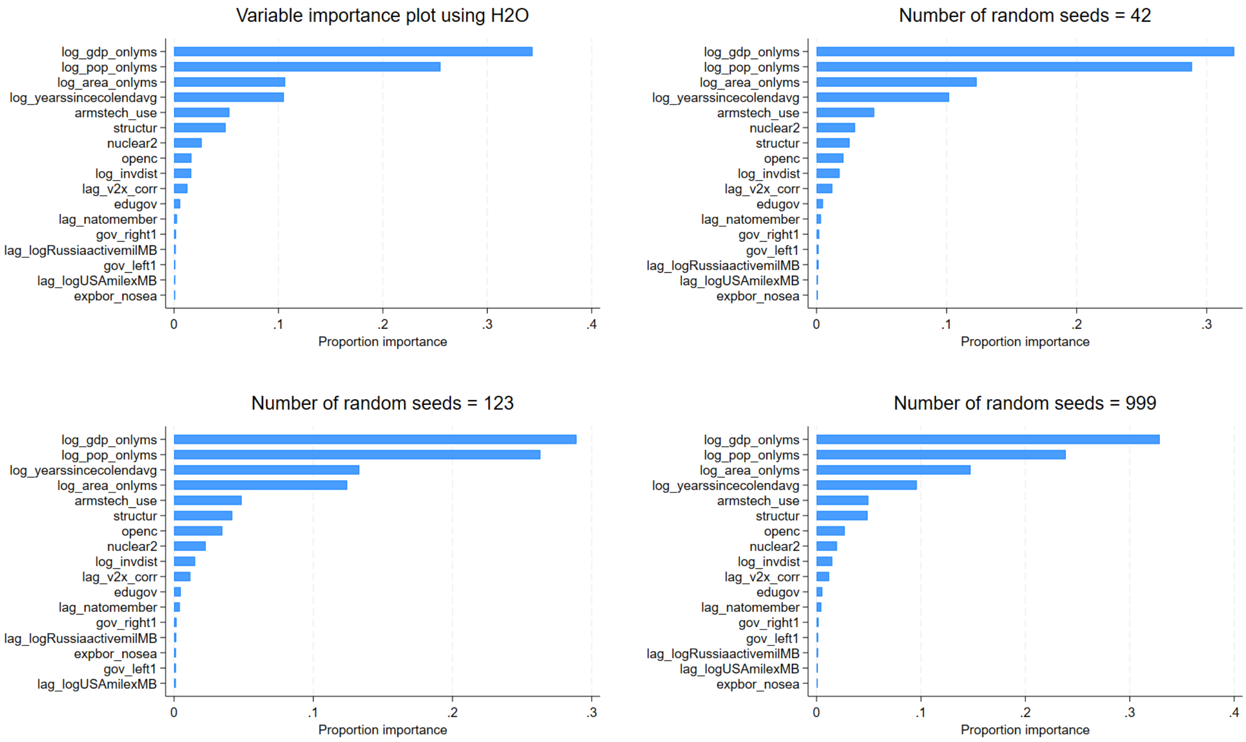
| Variable | Unit | Description | Source |
|---|---|---|---|
| Constitutional structures | index | Index capturing constitutional arrangements, including federalism, type of government, proportional representation, bicameralism, and frequency of referenda. | CPDS |
| Corruption | 0–1 | Public sector corruption index, lagged by one year. | V-Dem |
| Economic openness | % | Openness of the economy, measured as total trade (sum of import and export) as a percentage of GDP. | CPDS |
| Education expenditure | % | Expenditure on education as a percentage of government expenditure. | WB |
| Exposed borders | km | Total length of a country's territorial borders with non-EU states, measured in kilometers. | CIA |
| GDP | log of US$ | Natural logarithm of Gross Domestic Product expressed in constant 2023 US dollars. | WB |
| Left-wing government | % | Government composition: cabinet posts held by left-wing parties as a percentage of total cabinet posts, weighted by days in office. | CPDS |
| NATO membership | dummy | Binary indicator equal to 1 if the country is a NATO member in a given year (lagged), and 0 otherwise. | NATO |
| Nuclear status | categorical | Categorical indicator of a country's nuclear position: 0 = no capability, 1 = civilian nuclear energy, 2 = nuclear latency, 3 = military nuclear capability. | NL |
| Population | log of persons | Natural logarithm of the total population. | WB |
| Proximity to Moscow | log of km | Natural logarithm of the inverse distance between the country's capital city and Moscow. Higher values indicate closer proximity. | Google Maps |
| Right-wing government | % | Government composition: cabinet posts held by right-wing parties as a percentage of total cabinet posts, weighted by days in office. | CPDS |
| Russian active military | log of thousands of persons | Natural logarithm of the size of Russia's active-duty military personnel (in thousands), lagged by one year. | MB |
| USA military spending | mln of USD (2023 constant) | Military expenditure of the United States, measured in millions of constant 2023 USD and lagged by one year. | SIPRI |




*Note: Proportional variable importance is relative to the BSI(ln) prediction. The first figure is the baseline regression with 200 trees.

*Note: from top to bottom of the first figure, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), area (*log_area_onlyms*), colonial legacy (*log_yearssincecolendavg*), arms technology (*armstech_use*), constitutional structures (*structur*), nuclear power (*nuclear*2), economic openness (*openc*), Moscow proximity (*log_invdist*), lagged political corruption (*lag_v*2*x_corr*), education expenditure as a percentage of government spending (*edugov*), lagged NATO membership (*lag_natomember*), right-wing government (*gov_right*1), lagged Russian active military (*lag_logRussiaactivemilMB*), left-wing government (*gov_left*1), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

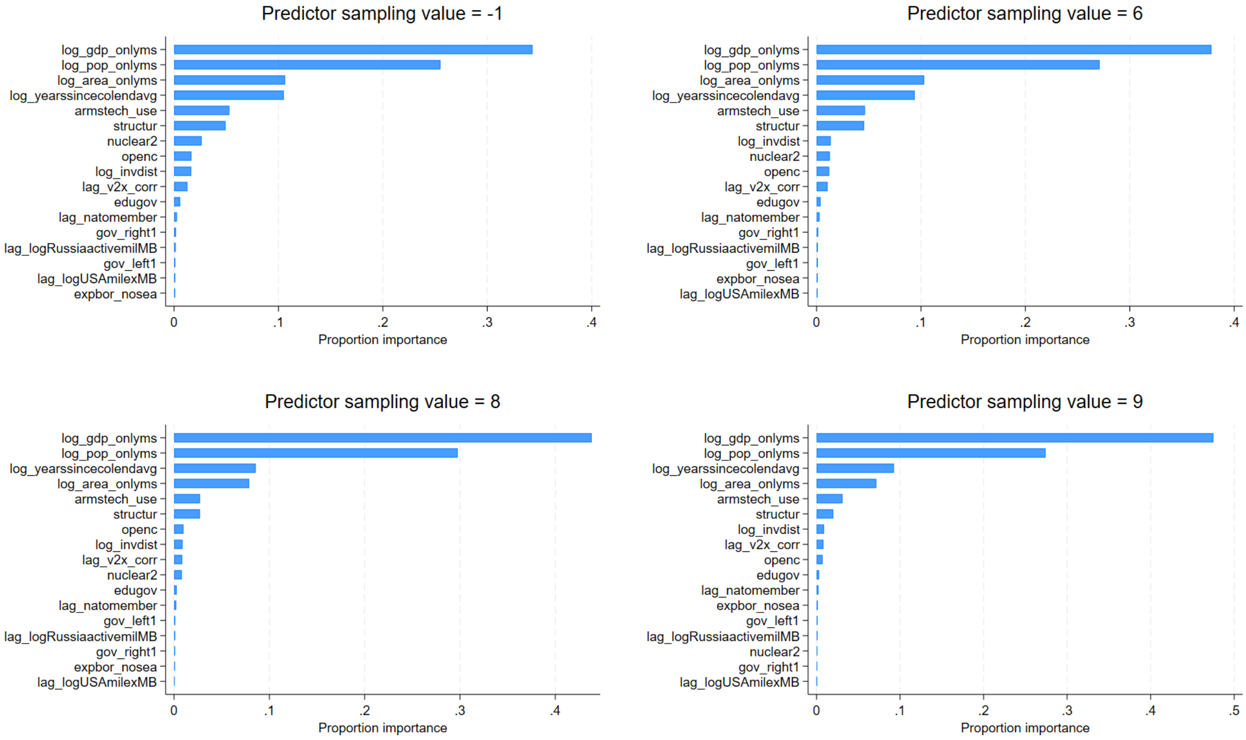
Figure 6: H2O Random Forest variable importance plot for 17 predictors using different numbers of trees.




*Note: Proportional variable importance is relative to the BSI(ln) prediction. The first figure is the baseline regression with 19 seeds trees.

*Note: from top to bottom of the first figure, variables represent GDP ($log\_gdp\_onlyms$) population ($log\_pop\_onlyms$), area ($log\_area\_onlyms$), colonial legacy ($log\_yearssincecolendavg$), arms technology ($armstech\_use$), constitutional structures ($structur$), nuclear power ($nuclear2$), economic openness ($openc$), Moscow proximity ($log\_invdist$), lagged political corruption ($lag\_v2x\_corr$), education expenditure as a percentage of government spending ($edugov$), lagged NATO membership ($lag\_natomember$), right-wing government ($gov\_right1$), lagged Russian active military ($lag\_logRussiaactivemilMB$), left-wing government ($gov\_left1$), lagged US military expenditure ($lag\_logUSAmilexMB$), territorial exposed borders ($expbor\_nosea$).

Figure 7: H2O Random Forest variable importance plot for 17 predictors using different numbers of random seeds.




*Note: Proportional variable importance is relative to the BSI(ln) prediction.

*Note: from top to bottom of the first figure, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), area (*log_area_onlyms*), colonial legacy (*log_yearssincecolendavg*), arms technology (*armstech_use*), constitutional structures (*structur*), nuclear power (*nuclear*2), economic openness (*openc*), Moscow proximity (*log_invdist*), lagged political corruption (*lag_v*2*x_corr*), education expenditure as a percentage of government spending (*edugov*), lagged NATO membership (*lag_natomember*), right-wing government (*gov_right*1), lagged Russian active military (*lag_logRussiaactivemilMB*), left-wing government (*gov_left*1), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

Figure 8: H2O Random Forest variable importance plot for 17 predictors using different sampling values.

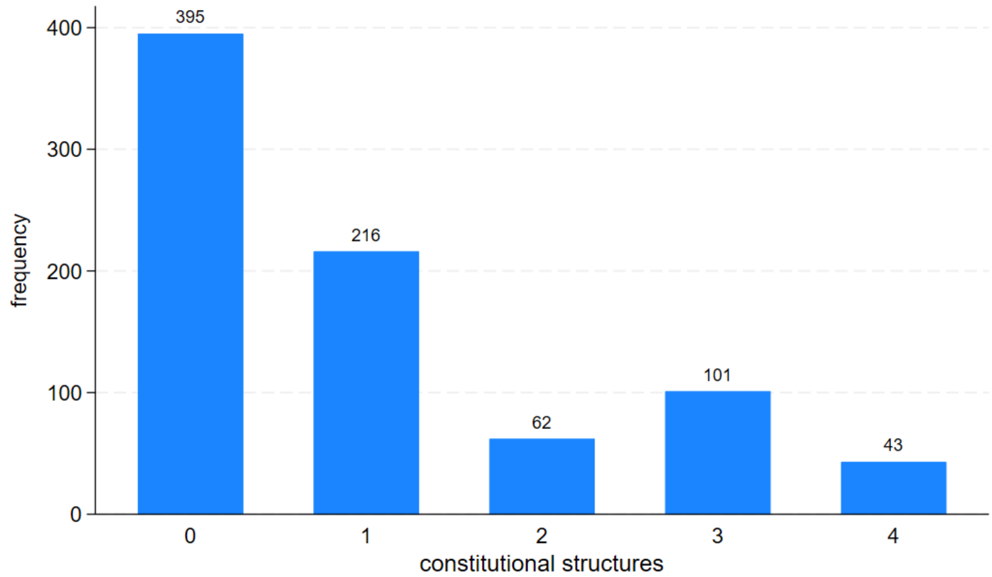



Figure 9: Distribution of constitutional structures levels.

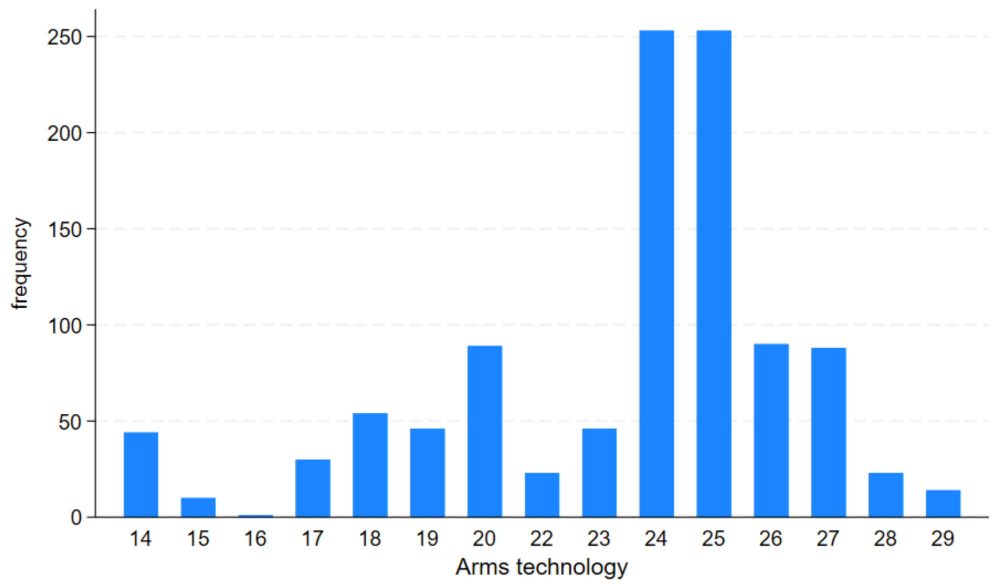
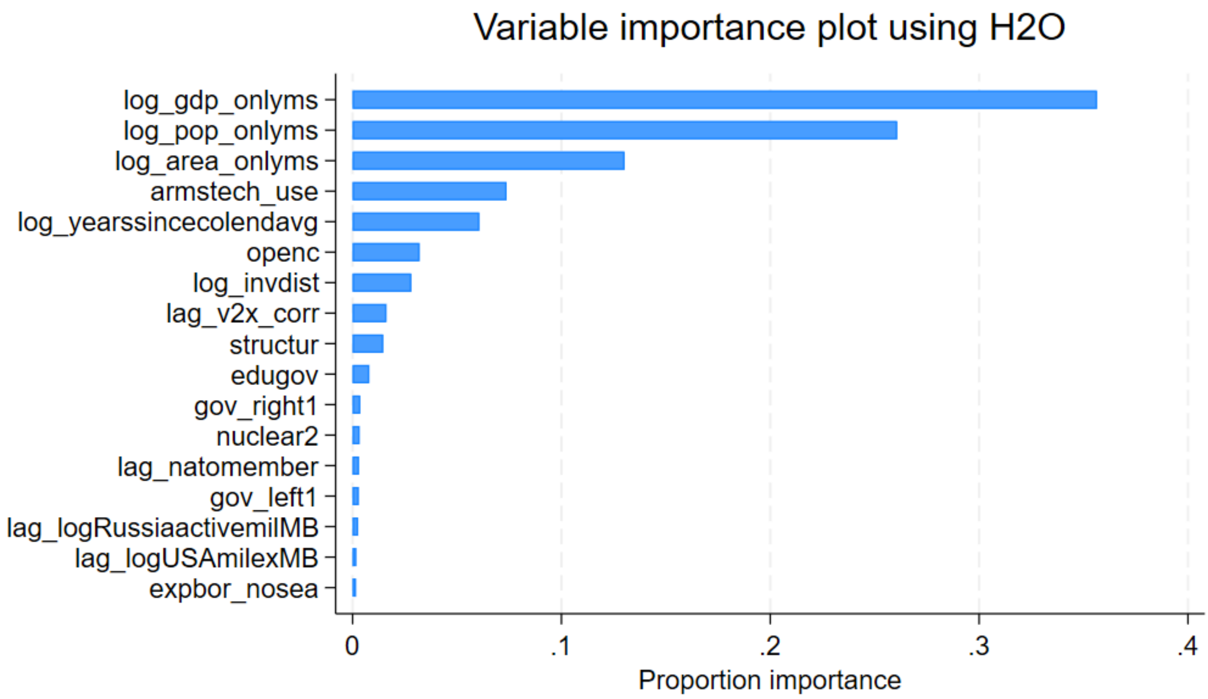


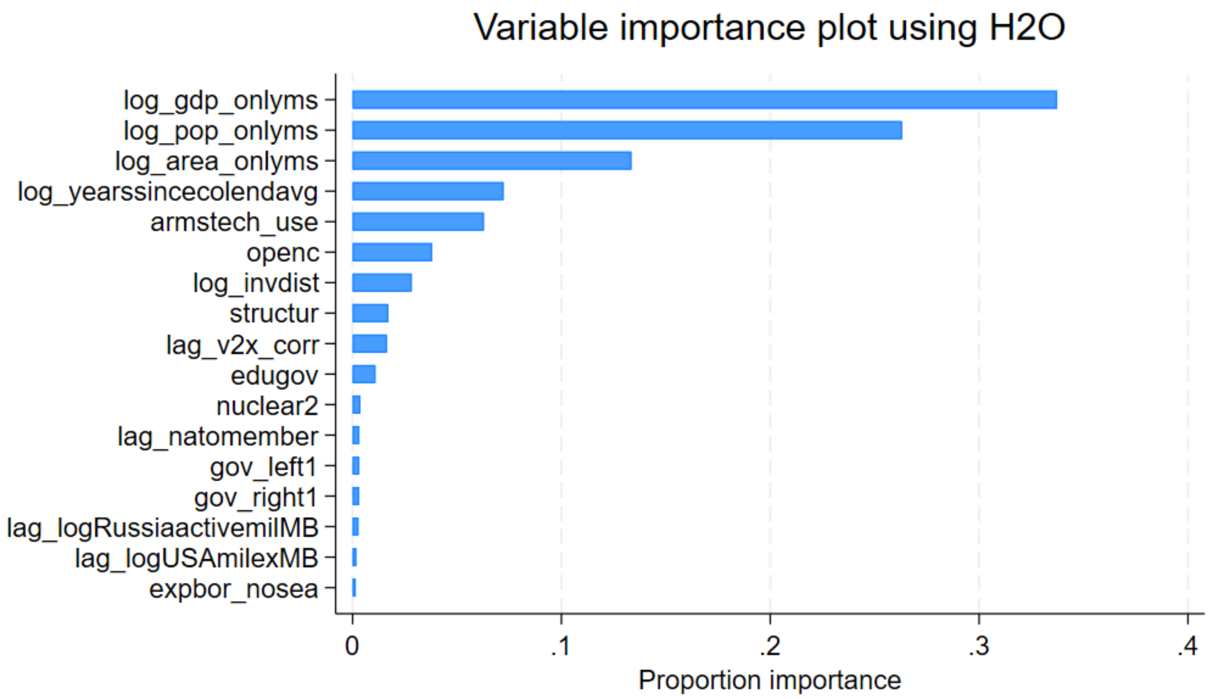

Figure 10: Distribution of arms technology levels.




*Note: Proportional variable importance is relative to the BSI(ln) prediction.

*Note: from top to bottom, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), area (*log_area_onlyms*), arms technology (*armstech_use*), colonial legacy (*log_yearssincecolendavg*), economic openness (*openc*), Moscow proximity (*log_invdist*), lagged political corruption (*lag_v2x_corr*), constitutional structures (*structur*), education expenditure as a percentage of government spending (*edugov*), right-wing government (*gov_right1*), nuclear power (*nuclear2*), lagged NATO membership (*lag_natomember*), left-wing government (*gov_left1*), lagged Russian active military (*lag_logRussiaactivemilMB*), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

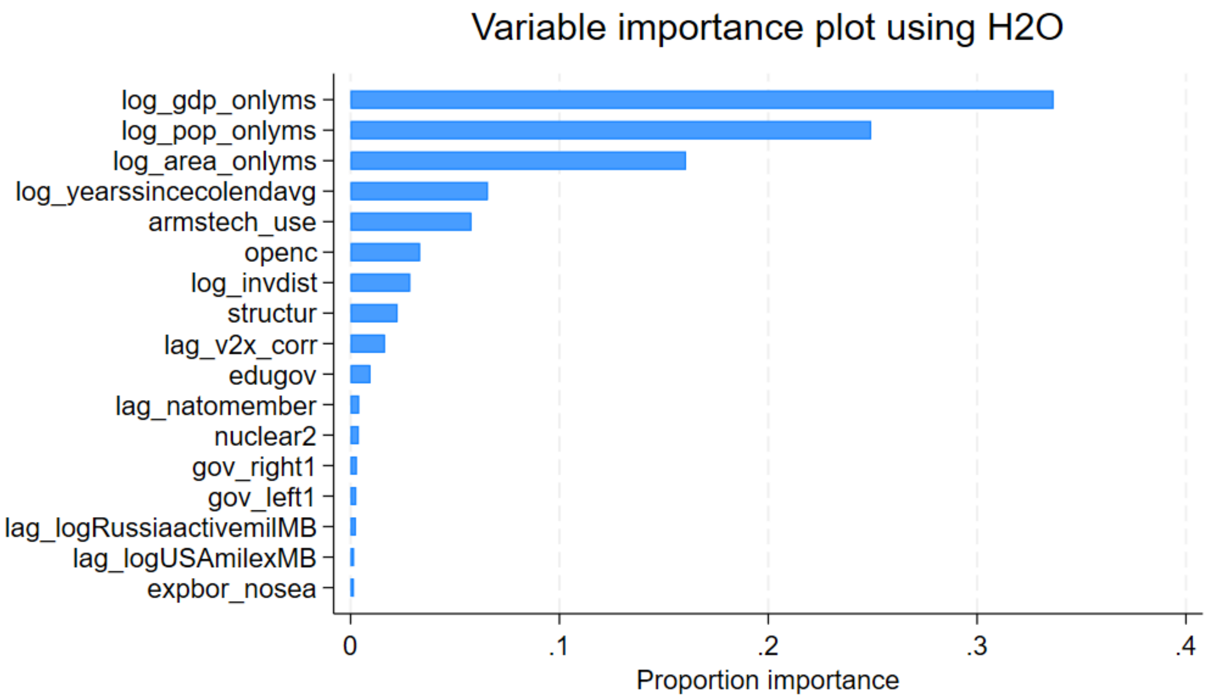
Figure 11: Variable importance plot for 17 predictors using H2O Machine Learning Random Forest regression – leaders of the alliance excluded.




*Note: Proportional variable importance is relative to the BSI(ln) prediction.

*Note: from top to bottom, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), area (*log_area_onlyms*), colonial legacy (*log_yearssincecolendavg*), arms technology (*armstech_use*), economic openness (*openc*), Moscow proximity (*log_invdist*), constitutional structures (*structur*), lagged political corruption (*lag_v2x_corr*), education expenditure as a percentage of government spending (*edugov*), nuclear power (*nuclear2*), lagged NATO membership (*lag_natomember*), left-wing government (*gov_left1*), right-wing government (*gov_right1*), lagged Russian active military (*lag_logRussiaactivemilMB*), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

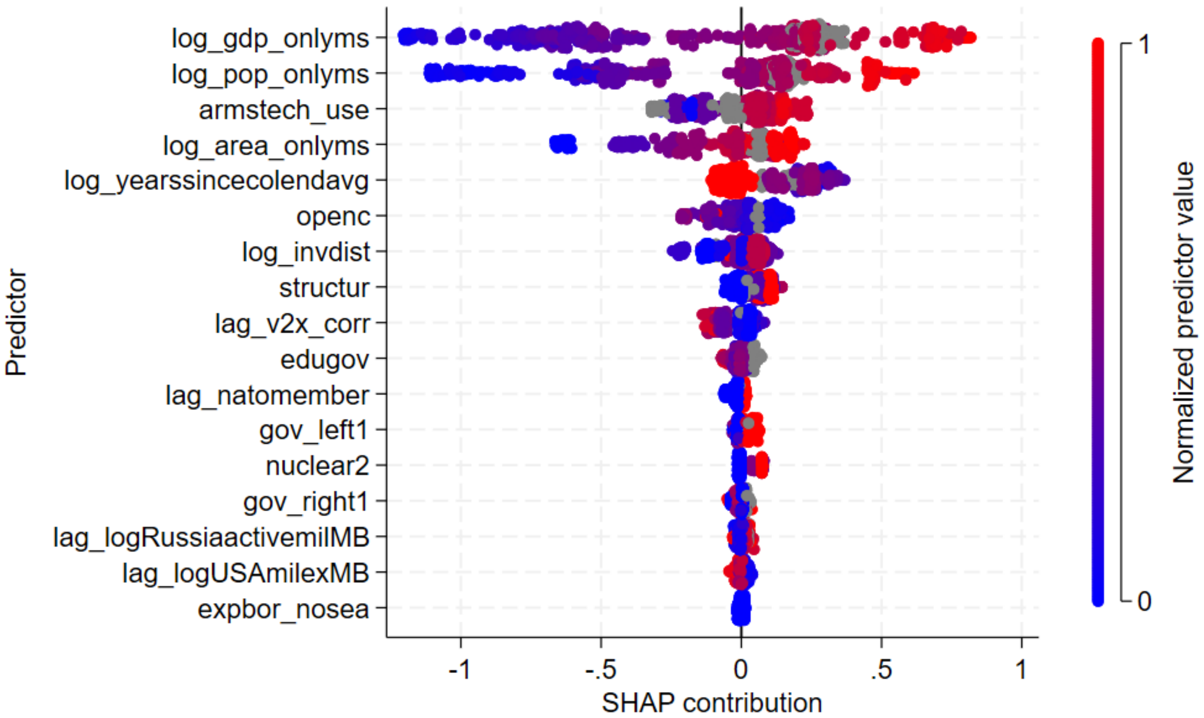
Figure 12: Variable importance plot for 17 predictors using H2O Machine Learning Random Forest regression using 1000 trees – leaders of the alliance excluded.




*Note: Proportional variable importance is relative to the BSI(ln) prediction.

*Note: from top to bottom, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), area (*log_area_onlyms*), colonial legacy (*log_yearssincecolendavg*), arms technology (*armstech_use*), economic openness (*openc*), Moscow proximity (*log_invdist*), constitutional structures (*structur*), lagged political corruption (*lag_v2x_corr*), education expenditure as a percentage of government spending (*edugov*), lagged NATO membership (*lag_natomember*), nuclear power (*nuclear*2), right-wing government (*gov_right*1), left-wing government (*gov_left*1), lagged Russian active military (*lag_logRussiaactivemilMB*), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

Figure 13: Variable importance plot for 17 predictors using H2O Machine Learning Random Forest regression using 999 random seeds – leaders of the alliance excluded.




*Note: the SHAP contribution is relative to the BSI(ln) prediction.

*Note: from top to bottom, variables represent GDP (*log_gdp_onlyms*) population (*log_pop_onlyms*), arms technology (*armstech_use*), area (*log_area_onlyms*), colonial legacy (*log_yearssincecolendavg*), economic openness (*openc*), Moscow proximity (*log_invdist*), constitutional structures (*structur*), lagged political corruption (*lag_v2x_corr*), education expenditure as a percentage of government spending (*edugov*), lagged NATO membership (*lag_natomember*), left-wing government (*gov_left1*), nuclear power (*nuclear2*), right-wing government (*gov_right1*), lagged Russian active military (*lag_logRussiaactivemilMB*), lagged US military expenditure (*lag_logUSAmilexMB*), territorial exposed borders (*expbor_nosea*).

Figure 14: Shapely Additive explanations using H2O Machine Learning Random Forest regression – leaders of the alliance excluded.

Table 7: Robustness Check: Fractional Probit (1980-2024, leaders excluded)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| BSI | | | | |
| Colonial legacy(ln) | -0.211** | -0.187** | -0.023 | -0.006 |
| | (0.106) | (0.076) | (0.019) | (0.022) |
| Constitutional structures | 0.082 | 0.054 | -0.018 | -0.035** |
| | (0.089) | (0.043) | (0.014) | (0.014) |
| Arms technology=17 | | 0.357*** | 0.549*** | 0.295*** |
| | | (0.050) | (0.019) | (0.071) |
| Arms technology=18 | | 0.510*** | -0.052 | -0.227*** |
| | | (0.001) | (0.061) | (0.046) |
| Arms technology=19 | | 0.346*** | 0.407*** | 0.198*** |
| | | (0.050) | (0.023) | (0.038) |
| Arms technology=20 | | 0.346*** | 0.550*** | 0.338*** |
| | | (0.070) | (0.035) | (0.070) |
| Arms technology=22 | | 0.898*** | 0.198** | -0.043 |
| | | (0.046) | (0.084) | (0.064) |
| Arms technology=23 | | 1.154*** | 0.260* | -0.048 |
| | | (0.070) | (0.143) | (0.123) |
| Arms technology=24 | | 0.664*** | 0.289*** | 0.040 |
| | | (0.127) | (0.077) | (0.069) |
| Arms technology=25 | | 1.037*** | 0.360*** | 0.100 |
| | | (0.060) | (0.075) | (0.069) |
| Arms technology=26 | | 1.307*** | 0.521*** | 0.162 |
| | | (0.081) | (0.123) | (0.101) |
| Arms technology=27 | | 1.238*** | 0.470*** | 0.167 |
| | | (0.122) | (0.144) | (0.121) |
| Arms technology=28 | | 1.122*** | 0.363*** | 0.099 |
| | | (0.165) | (0.126) | (0.099) |
| Arms technology=29 | | 1.071*** | 0.311** | 0.064 |
| | | (0.197) | (0.127) | (0.104) |
| GDP(ln) | | | 0.389*** | 0.282*** |
| | | | (0.040) | (0.039) |
| Area(ln) | | | | -0.023 |
| | | | | (0.023) |
| Population(ln) | | | | 0.188*** |
| | | | | (0.041) |
| Constant | -0.831 | -1.703*** | -12.20*** | -11.97*** |
| | (0.588) | (0.353) | (1.039) | (0.934) |
| Pseudo $R^2$ | 0.070 | 0.110 | 0.130 | 0.131 |
| Log-Lik | -71.50 | -66.81 | -65.38 | -65.26 |
| BIC | 299.9 | 282.7 | 273.3 | 273.1 |
| AIC | 191.0 | 179.6 | 174.8 | 174.5 |
| N | 690 | 652 | 652 | 652 |

Standard errors clustered at country level in parentheses in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

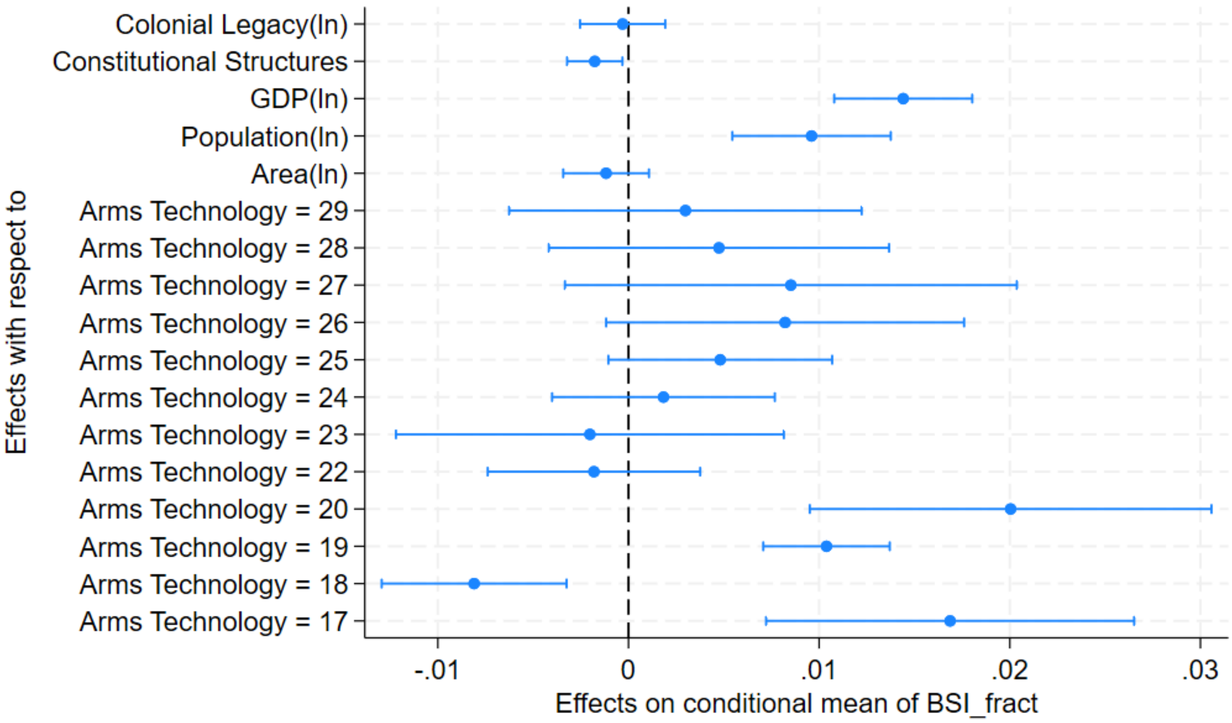



Figure 15: Fractional probit regression - average marginal effects (95% confidence intervals)

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