Re-examining the Resource Curse – Effects of GVC Participation on Political Violence

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1 Introduction

Our research topic is motivated by the resource curse hypothesis: the idea that when a country is overly abundant in natural resources, it may paradoxically have worse developmental outcomes including political stability. For example, if a country is very abundant in and/or reliant on oil, it can lead to an excessive appreciation of the real exchange rate and/or vulnerability to price shocks. Negative impacts from overdependence on energy resources, especially crude oil have been empirically supported in several papers such as (Chen and Hsu 2013; Korhonen and Ledyaeva 2008). Furthermore, the negative impacts can evolve into political conflicts, as argued in Cotet and Tsui 2013. Hence, we focus on the causal effects of dependence on fuel resources on political stability, measured by the share of defense spending in GDP. Further details regarding the choice of the dependent variable are provided in section 3.2.2.

To explain our choice of one of the independent variable, we need to introduce the idea of Global Value Chain (GVC). GVC is an international trade network that depicts how countries are involved in different stages of production and trade across sectors and countries, including the production of intermediate goods and services that are used in the production process of final goods and services in other sectors or countries.

In this paper, we use GVC participation rates as the measure of country-level, year-specific involvement in the fuel sector (coke, refined petroleum, and nuclear fuel)[1], which we will use as a representative sector for natural resources. We have chosen three GVC participation rates: forward, backward, and mixed. We explained how they are defined in section 3.2.3.

In addition, we analyzed the impact of a nation's natural resource endowment on political stability, utilizing oil reserves as an additional independent variable. This allows us to

[1]While crude oil, instead of fuel in general, is purportedly the more conflict-triggering resources and the subject of much relevant research, we find that it's hard to alienate crude oil trades from the GVC data. Besides, we are more interested in the empirical effects of the broadly defined resource curse that applies to most natural resources, instead of the much-studied crude oil industry.

examine the relationship between resource wealth and political dynamics, irrespective of a country's position within the global economy and its level of integration into trade networks.

The rest of the paper unfolds as follows. Section 2 reviews relevant literature, including the theoretical foundation and methodology reference of our work. Section 3 describes our data source, variable choices and transformation, as well as summary statistics. Section 4 talks three methods that we use: baseline ordinary least squares (OLS), double machine learning (DML), and clustering. The results are presented in Section 5. Different from Cappelli, Carnazza, and Vellucci 2023, we cannot find conclusive evidence for significance of the causal effects of the natural resource sector-wise on political stability. Section 6 concludes and discusses possible explanations and directions for further study.

2 Literature Review

The theoretical basis of our proposal comes from Sachs and Warner 2001 and Karl 1997. Both works found that countries that were abundant in and relied heavily on natural resources tended to be cursed with lower economic growth, due to economic dependence (vulnerability to price shocks and market volatility), worse developmental outcomes, and more political instability, due to the concentration of wealth and power in the hands of the elites. Previous studies have given a general empirical examination of the resource curse. For example, Wiens, Poast, and Clark 2014 estimated a dynamic logit model to find an increase in resource dependence decreases an autocracy's likelihood of being democratic over both the short term and long term but has no appreciable effect on democracies' likelihood of persisting. Building upon these findings, we will examine how the abundance of natural resources itself and network relations of industry sectors, specifically ones regarding natural resources such as agriculture, mining, oil, etc., which we will measure using GVC, can affect political stability of countries.

In an extension to this discourse, Cotet and Tsui 2013 re-evaluate the assumed causality between natural resource abundance and political unrest. Their rigorous application of fixed-effects models and instrumental variables sheds light on this intricate relationship, prompting a deeper examination of how natural resources correlate with political stability. Our research is inspired by their findings, aiming to further dissect the interactions between resource abundance and political dynamics. We plan to explore the varying experiences of resource-rich nations, identifying key factors that influence their political stability or instability. Moreover, it propels us to delve into the heterogeneous effects of various natural resources and the diverse contexts in which they exist, aiming to uncover the multifaceted nature of the resource curse and its implications for political stability.

Building upon these findings, our study also explores the intersection of natural resource abundance with the dynamics of global value chains (GVCs). We follow the methodology of Cappelli, Carnazza, and Vellucci 2023 that examine the role of network relations in the relationship between crude oil exports, international trade, and political stability. On the one hand, crude oil exports can provide a source of revenue for governments, leading to greater economic stability and improved social welfare. On the other hand, crude oil exports can also lead to greater political instability, as countries become more vulnerable to external shocks and suffer from the "resource curse" and "paradox of plenty" effects mentioned above. The major novelty of our paper comes from our choice of independent variable in comparison to Cappelli, Carnazza, and Vellucci 2023. While Cappelli, Carnazza, and Vellucci 2023 use network theory indicators like centrality and betweeness, we adopt GVC participation rates, a notion similar but different to network theory indicators. Network theory indicators evaluate how much the network relies on the country, while GVC participation rates reflect how reliant a country is on the global trade network. We believe that our measure is slightly more policy relevant, because a country's government has more power to vary its dependency on the global trade network via trade policies than to alter its importance in the gigantic global network due to at least two factors: constraints on its total production capacity and presence of numerous international actors. Hence, understanding how reliance on the global trade network affects political outcome can be pragmatically valuable for policymakers.

Additionally, Banerjee and Zeman 2022 explore the determinants of GVC participation, including political instability. In comparison to their work, our research contributes to the reverse causation and adds novelty to the established literature.

3 Data and Key Variables

3.1 Data Source

There are two major datasets that we use. The first one is World Integrated Trade Solution (WITS) GVC Output Tables database from Manole 2005. WITS integrates GVC Output Table from six different sources, including Asian Development Bank (ADB), Eora26, World Input-Output Database (WIOD) etc., allowing us to compute network theory characteristics and extract GVC theory indicators, and Oil reserve measures. These measures of GVC participation along with oil reserves are our independent variables.

The second dataset comes from Cotet and Tsui 2013 who provide data from multiple political instability measures, like intense war onset, coup attempts, irregular leadership transitions, etc. Specifically, after doing variance comparison, we will be using defense spending as our dependent variable. In addition, Cotet and Tsui 2013 provisions common control variables, like economic growth, inflation, democracy index, language and ethical fractionalization, for political stability, which we will also incorporate in our analysis.

3.2 Data Selection, and Variable Selection and Transformation

3.2.1 Optimizing panel size

For the GVC data, we have multiple sources from WITS, these include the previously mentioned ADB, Eora, WIOD, etc. We choose the source that has the most countries after merging with the political instability data set while maintaining an acceptable number of years of panel data. This led to us using the Eora source from WITS for our panel data. After merging and cleansing of observations whose information on key variables is missing, these datasets produce an unbalanced historical panel that comprises 142 countries from 1991 to 2005.

3.2.2 Outcome variable

In the country stability data set, we have multiple candidate variables for the outcome, including the number military coup attempts, indicator of war onset, percent leadership transitions over the following 20 years, defense burden (i.e. military spending as a fraction of GDP), etc.

We opt to use defense burden as our primary measure of political stability for several reasons. First, defense spending as a percentage of GDP captures not just the absolute amount a country invests in its military but also reflects this investment relative to the country's overall economic size. This makes it a more comprehensive indicator, encapsulating both economic and security dimensions of stability.

Moreover, defense spending can be seen as a proxy for a government's prioritization of security, potentially indicating the level of perceived threats or instability. Governments in unstable or insecure environments might allocate a higher proportion of their GDP to defense, reflecting and responding to their political and security context.

While other indicators like coup attempts or war onset provide valuable insights into specific aspects of instability, they may occur less frequently or lack the continuous and quantitative nature that defense burden offers. Similarly, leadership transitions over 20 years offer a long-term perspective but may not capture the immediate or nuanced changes in political stability that defense spending can indicate.

3.2.3 Independent Variable

In our study on the abundance of natural resources, we use oil reserves, measured in thousand million barrels, as an independent variable. By examining oil reserves, we aim to explore their potential role in influencing political stability, providing insights into the dynamics of resource wealth and governance.

Other than using oil reserves, which is pretty self-explanatory, we also use GVC pure backward, pure forward, and mixed participation measures of the Fuel sector as independent variables to assess participation in global trade networks. We run analyses for each of these measures separately.

GVC pure backward participation is the measure of only the backward participation of a country in a GVC. For example, a car manufacturer in Country A might import engines from Country B, assemble them into cars, and then export the finished cars to Country C. Here, the car manufacturer in Country A has a backward linkage to the GVC (the import of engines as inputs for manufacturing cars), and GVC backward participation for country A is a measure of exclusively this backward linkage. Backward linkage evaluates how an economy imports ("buys") intermediates to produce its exports.

GVC pure forward participation, on the other hand, is a measure of exclusively the forward linkage to the GVC, which refers to the inputs from foreign countries for further processing and further export. Forward linkage captures how an economy produces ("sells") intermediates in the GVC.

GVC mixed participation is a combination of both these measures, and we analyze each of these measures in turn to examine in more detail how and which types of different trade network participation affects countries' political stability.

According to Koopman, Wang, and Wei 2012, GVC participation rates for a country i's participation in the GVC of a certain sector s can be expressed by the upcoming equations:

$$Participation, Forward_{is} = \frac{IV_{is}}{E_{is}}; \tag{1}$$

$$Participation, Backward_{is} = \frac{FV_{is}}{E_{is}}; \tag{2}$$

$$Participation, Mix_{is} = \frac{IV_{is} + FV_{is}}{E_{is}}; \tag{3}$$

where IV_{ir} indicates the indirect value-addition export of sector s of country r, equalling the sum of domestic value-additions (DVA) created for the total export of intermediate products of sector s. This is the forward participation, or domestic value added sent to third economies. FV_{ir} represents foreign value-additions (FVA) embodied in the total exports of sector s of country i and E_{is} denotes country i's sector s's total exports. This is the backward participation, or foreign value-added content of exports.

Forward and backward participation indicators can be calculated by dividing forward participation and backward participation, respectively, by the total export, indicating how much of the exported goods are for the global value chain and how much of the exported goods are from the global value chain, respectively.

3.2.4 Using %change variables

Using the percentage change regression method can be a useful approach when dealing with panel data that includes multiple countries, particularly when their data are not necessarily on the same scale. By focusing on the percentage change or growth rates, we can eliminate the effects of scale and concentrate on the dynamics of the relationship between the variables across countries.

Some advantages of this approach include[2]:

1. Comparability: Transforming the data into percentage change allows us to compare the relationships between variables across countries, regardless of the differences in scale or the level of the variables.

2. Elasticity: The coefficients in this regression can be interpreted as elasticities, which provide meaningful and intuitive insights into the relationships between variables.

3. Stationarity: Transforming data into percentage changes can help achieve stationarity, which is an important assumption for panel data models.

However, there might be some challenges and limitations with this approach:

1. Loss of information: By transforming the data into percentage changes, we might lose some information about the level of the variables.

2. Possible distortion: Extreme values, outliers, or zero values in the data might lead to distortion in percentage changes, potentially affecting the regression results.

Thus, for control variables, we test for stationarity. For non-stationary controls, we use %change variable rather than the original variable to help eliminate the effects of different scales of different countries. For the outcome variable, defense spending, and the independent variables, which are based on GVC participation rates, since they are already percentages, we decide to conduct first differencing.

3.2.5 Other transformation

We further choose to demean the economic growth variable to account for its cyclic trend.

3.3 Variable Summary and Exploratory Data Analysis

Table 1 presents the summary statistics of our key variables. Some variables in Panel D, like log population, are scaled as they are provided in our data source. Please see the data readme file under data/stability written by the data provider for complete explanation for

[2]Note that for these reasons, we use year-on-year % change of GVC measures as our independent variable

variable definition and scaling. We also plot the slightly left-skewed log distribution of participation rates, for different natural resource sectors including oil in Figure 5.

Looking at Figure 1, we see that there seems to be a positive correlation between Oil Reserves and military expenditure share. Though this relationship is not as clear in Figures 2 and 3 for the various GVC measures, this may be because of the nature of the GVC measure and the concentration of the values near 0.

Statistic	N	Mean	St. Dev.	Min	Max
Panel A. Forward GVC Participation Rates, Diff					
Agriculture, forestry, and fishing	1,958	0.001	0.009	−0.215	0.143
Mining and quary	1,958	0.0003	0.021	−0.470	0.375
Fuel	1,958	0.001	0.007	−0.098	0.104
Metals	1,958	0.001	0.009	−0.160	0.109
Panel B. Backward GVC Participation Rates, Diff					
Agriculture, forestry, and fishing	1,958	0.0003	0.002	−0.030	0.038
Mining and quary	1,958	0.0003	0.008	−0.163	0.168
Fuel	1,958	0.0002	0.002	−0.023	0.033
Metals	1,958	0.001	0.010	−0.116	0.116
Panel C. Mix GVC Participation Rates, Diff					
Agriculture, forestry, and fishing	1,958	0.003	0.027	−0.462	0.718
Mining and quary	1,958	0.001	0.046	−1.271	0.461
Fuel	1,958	0.003	0.024	−0.379	0.319
Metals	1,958	0.002	0.021	−0.238	0.316
Panel D. Selected Other Variables					
Defense Share	1471	2.535	2.426	0.000	31.800
Oil Reserves	1340	9.321	28.402	0.000	246.752
Log of share of mountainous land	1692	-0.002	0.050	-0.096	0.044
Ethnic Fractionalization Index	1,943	0.005	0.003	0.00002	0.009
Religion Fractionalization Index	1,958	0.004	0.002	0.00002	0.009
Language Fractionalization Index	1,904	0.004	0.003	0.00002	0.009
Log population (diff)	1,958	0.0002	0.0002	−0.002	0.004
legal british origin	1862	0.003	0.004	0.000	0.010
Log out of region disaster (diff)	1,958	0.001	0.007	−0.025	0.015
Economic growth (demeaned)	1,958	−0.001	0.055	−0.455	0.535
Democracy Index (diff)	1,958	0.0001	0.001	−0.007	0.007

Table 1: Summary statistics. Variables and panels labeled with “diff” are taken as percentage change by year.

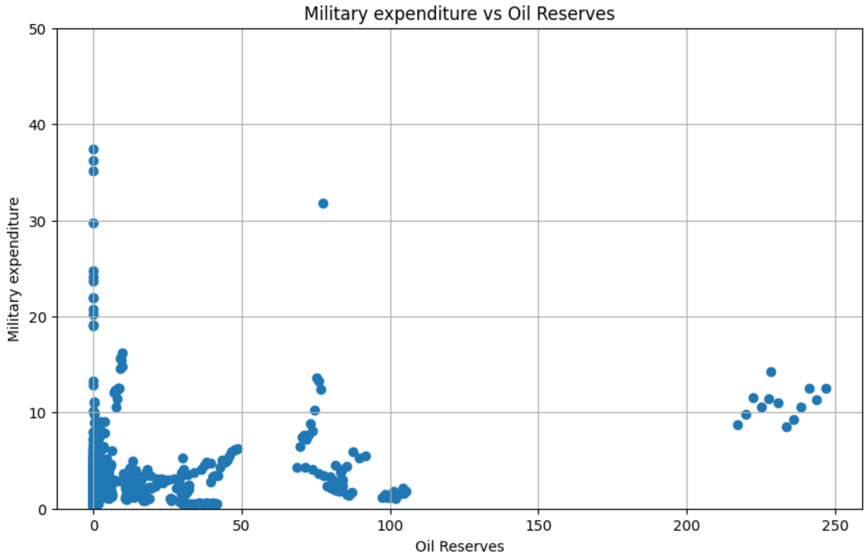

Figure 1: Military expenditure on Oil Reserves

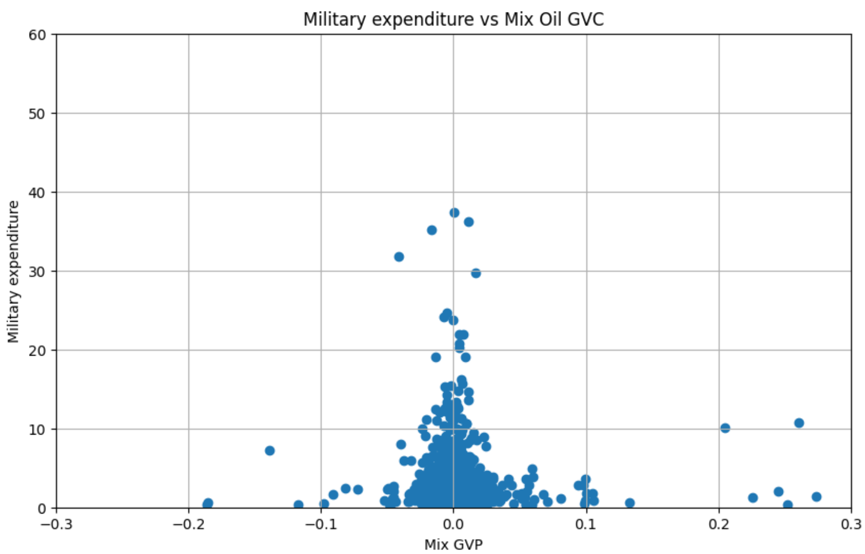

Figure 2: Military expenditure by Mixed oil GVC rates

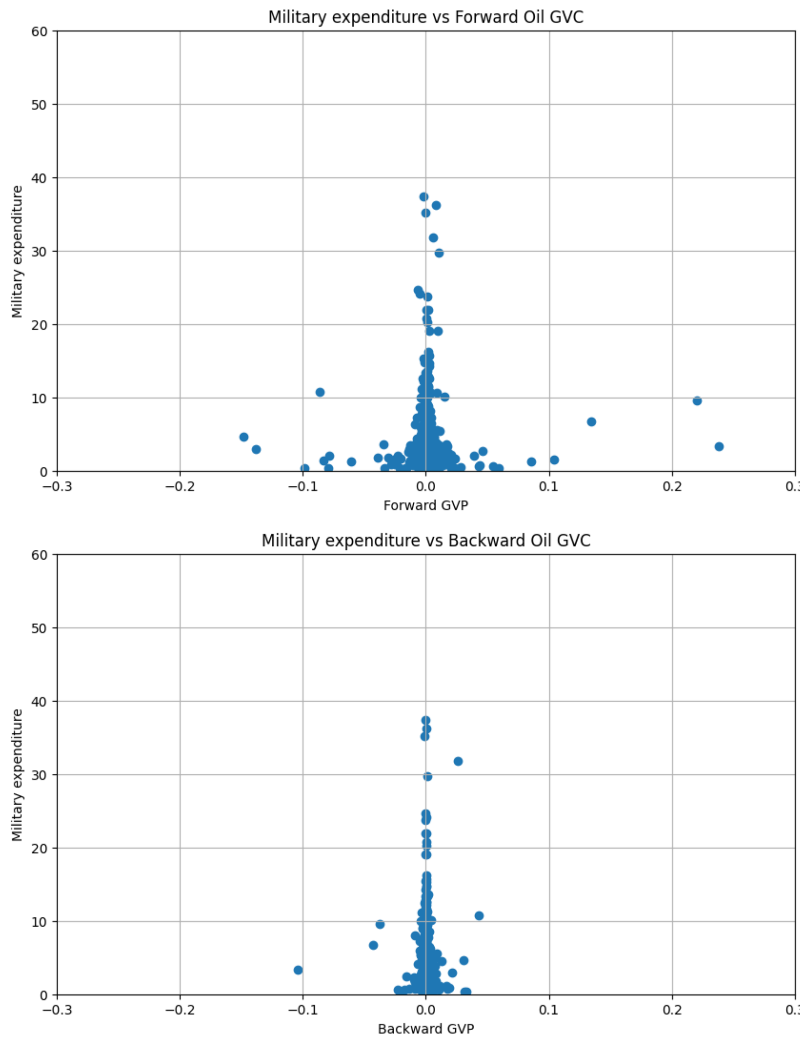

Figure 3: Military expenditure by Forward and Backward Oil GVC rates

4 Methodology

4.1 Baseline OLS

To investigate the relationship between Fuel Sector GVC participation and countries' political stability, as well as the relationship between the size of a country's oil reserve and its political stability, we initially utilize an OLS model as our baseline model for the analysis.

4.1.1 Model

Our baseline OLS regression model equation is:

$$y_{it} = \alpha + \beta A_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it} \tag{4}$$

$Y_{i,t}$ is the defense burden (as a percentage of GDP) of country i in year t, a comprehensive indicator of countries' political stability. $A_{i,t}$ could be: (1) the GVC participation (more specifically, the year-on-year percentage change of GVC, reasons for which previously discussed) in the fuel sector of country i in year t, which for our analysis, will be either GVC pure backward, pure forward, or mixed participation; (2) the size of country i's oil reserves in year t. $X_{i,t}$ are the controls for country i in year t, these control variables are either non-stationary controls, which include population, population density, country output, economic growth, and democracy, or stationary controls, which include mountain-index, ethnic, religion, and language fractionalization, as well as British colonial legacy and OPEC membership. These control variables are included to account for potential confounding factors, and the choice of these controls are based in Cotet and Tsui 2013. μ_i and λ_t represent country fixed effects and time fixed effects respectively, and $\epsilon_{i,t}$ is the error term.

4.1.2 Assumptions

Our model follows standard OLS assumptions: (1) we assume that the relationship between the size of oil reserves and political stability, as well as the relationship between Fuel Sector GVC participation and political stability, are both linear given the nature of the data; (2) regarding the independence assumption, we assume that accounting for within-country and year fixed effects controls for unobserved heterogeneity; (3) regarding the exogeneity assumption, we assume that the size of oil reserves and Fuel Sector GVC participation rates are predetermined factors and not influenced by within-country year-to-year political changes. Through positing that the historical size of oil reserves and established patterns of Fuel Sector GVC participation are exogenous to the annual measures of political stability, given that these factors are rooted in longer-term economic structures and policies rather than immediate political fluctuations, our assumptions allow the model to mitigate potential reverse causality concerns of which a country's political stability could ostensibly affect GVC participation and the decision-making process of the size of oil reserves.

Admittedly, the degree of validity for some of these assumptions' is debatable. For this reason, we also utilized further analysis methods to corroborate our baseline OLS model analysis results.

4.2 Double Machine Learning

While OLS regression is widely used in estimating linear relationships between variables, it has limitations, particularly in handling confounding factors that may bias estimates. Hence, we incorporate double machine learning (DML) techniques into our analyses. DML allows for flexible modeling of non-linear relationships, enabling us to capture more complex interactions within our data. Furthermore, since we include fixed effects for individual countries, DML manages the high dimensionality in our data analysis.

4.2.1 PLR Model

We use the fraction of military spending in GDP, a continuous variable, as a measure of political stability. We apply DML techniques to a partial linear regression (PLR) model to assess the causal influence of fuel sector GVC participation rates on military spending. The PLR model is particularly suited to our analysis as it allows for potential non-linear relationships between the covariates and the outcome while still focusing on the linear effect of the treatment. The PLR can be defined as

$$Y = \alpha + \beta D + f(X) + \epsilon,$$

where Y represents the outcome, D represents treatment variable in question, and $X = (X_1, ..., X_p)$ is a high-dimensional vector of covariates. ϵ denotes the error term. α is a constant, β represents the linear effect of GVC participation on military spending, and $f(X)$ captures the non-linear effects of the covariates.

We begin by introducing the nuisance functions to aid this process:

$$\begin{aligned} \mu(x) &= \mathbb{E}[Y \mid x] \\ m(x) &= \mathrm{P}(D = 1 \mid x) \end{aligned}$$

To control for the confounding effect of X and obtain a more accurate estimate of the treatment effect, we employ DML techniques. This involves partitioning the data into k folds and, for each fold, fitting nuisance models to predict the outcome Y and the treatment D from X on the other folds. These predicted values are then used to adjust the original Y and D values, isolating the purified effect of GVC participation on military spending. The PLR with DML takes the form:

$$\begin{aligned} Y = \alpha + \beta D + f(X) + \epsilon \\ D = g(X) + \eta \end{aligned}$$

Incorporating predictions from the nuisance functions,

$$\begin{aligned} Y^* &= Y - \hat{\mu}(X) \\ D^* &= D - \hat{m}(X) \end{aligned}$$

where Y^* and $D*$ represent the residuals of Y and D after adjusting for the estimated effects of X. These residuals are then utilized to stimate the causal effect β of D on Y through:

$$Y^* = \beta D^* + \epsilon.$$

4.3 LASSO

Prior to further heterogeneous analyses, we employ Lasso regression to select features and enhance Interpretability for our clustering model.

Tables 2 and 3 showcase the feature importance derived from the Lasso regression for Defense Share and Oil Reserves, respectively. For Defense Share, the negative coefficients of 'Decade' and 'Religion Fractionalization' suggest a reduction in defense spending over time and with increased religious fragmentation. Conversely, the 'Legacy British' feature's positive influence intimates that historical connections to Britain may correlate with heightened defense expenditures.

In analyzing Oil Reserves, the notably positive coefficient of 'Log Population Density (diff)' indicates a robust correlation with oil reserves, while 'Religion Fractionalization' and 'Economic Growth Demeaned' display negative relationships, signifying that increased religious diversity and adjusted economic growth are related to lower oil reserves. Moreover, the positive associations of 'Democracy (diff)' and 'Legacy British' reflect the intricate interplay of political and historical dimensions in economic resource outcomes.

Table 2: Feature Importance for Outcome Variable Defense Share

Feature	Importance
Decade	-0.437
Religion Fractionalization	-0.817
Log Outreg (diff)	0.045
Economic Growth Demeaned	-1.291
Democracy (diff)	-0.075
Log Mountain	0.049
Ethnic Fractionalization	-0.270
Legacy British	0.838
Log Population Density (diff)	0.754

Table 3: Feature Importance for Outcome Variable Oil Reserves

Feature	Importance
Decade	-0.576
Religion Fractionalization	-16.243
Log Outreg (diff)	-0.484
Economic Growth Demeaned	-17.129
Democracy (diff)	3.820
Log Mountain	4.629
Ethnic Fractionalization	-7.067
Legacy British	7.179
Log Population Density (diff)	15.237

4.4 Clustering

It is likely that countries' political stability outcomes develop in groups. However, we do not directly observe these groups. To get at this possible unobserved group heterogeneity, we use the ML Clustering approach.

4.4.1 Clustering Model

Given a dataset $\{X_i\}_{i=1}^n$, where each X_i represents a data point with features related to oil reserves/oil GVC (Global Value Chain), and military expenditure, along with various control variables chosen using LASSO, we want to group these points into clusters that minimize within-cluster variance. We use the K-means clustering algorithm for this purpose.

The K-means algorithm seeks to partition the n observations into k $(\leq n)$ sets $S = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS). Mathematically, this is represented as finding:

$$(\hat{h}, \hat{k}_1, \hat{k}_2, \ldots, \hat{k}_n) = \arg \min_{h,k_1,\ldots,k_n} \sum_{i=1}^{n} \|X_i - h(k_i)\|_2^2$$

where X_i is the i-th data point, $h(k_i)$ is the centroid of the cluster to which X_i is assigned, and $\|\cdot\|_2$ denotes the Euclidean distance. The goal is to find cluster centroids h and an assignment of each data point to a cluster k_i, such that the sum of squared distances from each point to its assigned centroid is minimized.

The initial assignment of k_i and h can be random or based on a heuristic, and the algorithm iteratively updates these assignments to reduce the WCSS. The process is repeated until the assignments no longer change significantly, indicating convergence to a solution.

This clustering approach enables the grouping of countries or regions based on their military expenditure in relation to their oil reserves/participation in oil GVC(along with important controls), to get at the unobserved group heterogeneity.

Specifically, we use the Elbow method to choose K for the Kmean algorithm. For each independent, we get elbows as follows in Figure 5. We choose K at the "elbow", where WCSS stops decreasing as fast, we choose K = 18, 21, 20, 21 for the independent variables of Oil reserve, GVC mixed, forward, and backward respectively.

5 Results

We present our regression results with one specific political outcome, military expenditure, and four different independent variables: Oil reserves and GVC forward, backward, and mixed participation rates.

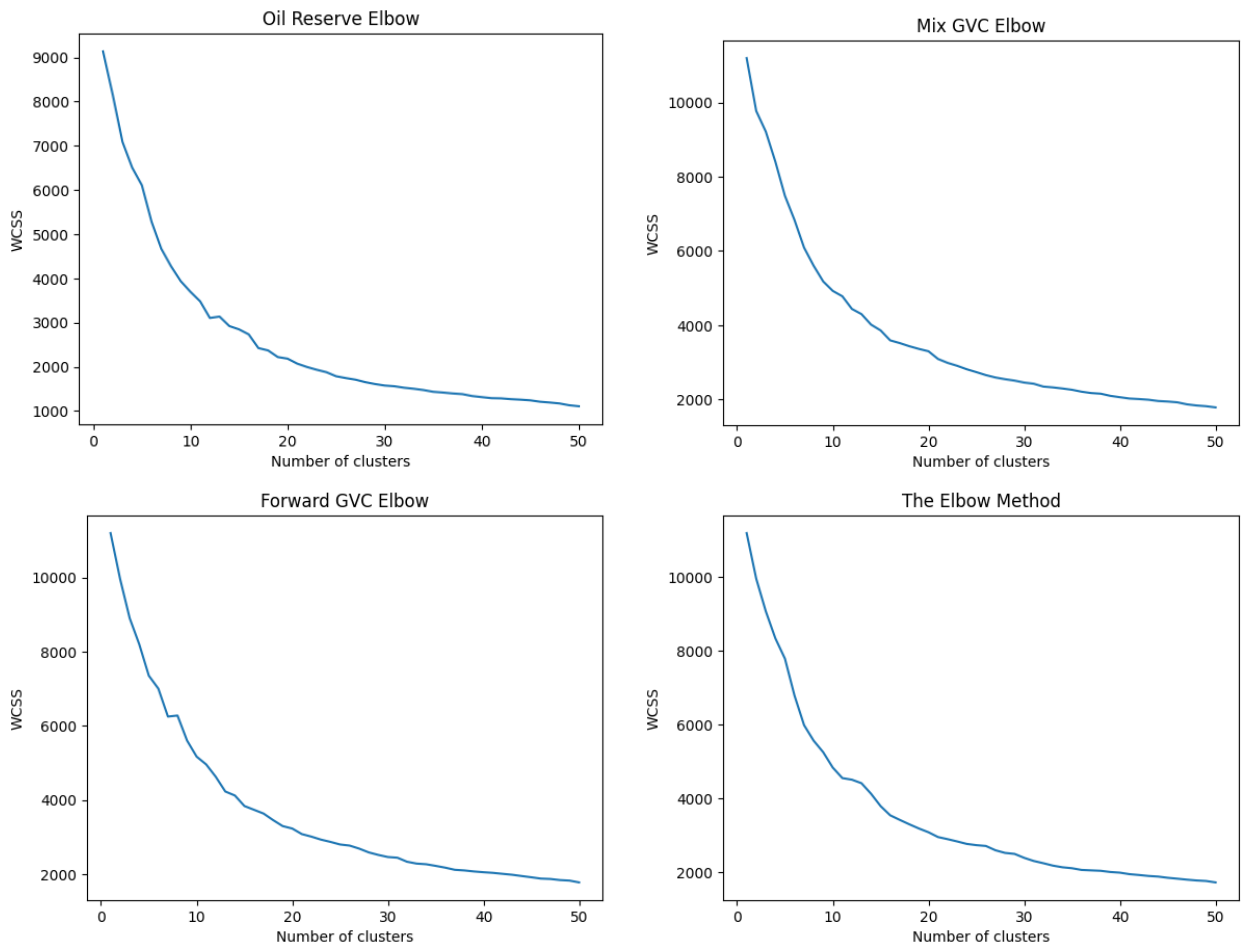

Figure 4: Elbow Method for selecting K

In summary, our analysis plan is that for each set of independent and dependent variables, we have three model designs:

1. without stationary controls;
2. with stationary controls;
3. with FE and without stationary controls.

Note that we don't run models with both (country)fixed effects and stationary controls at the same time, as that would likely cause multicollinearity issues.

5.1 Baseline OLS results

Table 4 shows the Baseline OLS regression results for each of the 4 independent variables and 3 specifications. We see that Oil reserve estimate is consistently positive and significant across all three specifications, while GVC forward is consistently insignificant across specifications. GVC mix and backward are significant when including fixed effects, and have opposite sign.

Independent var	Fixed Effect	Stationary Controls	$\hat{\beta}$	$\hat{\sigma}$	P-value
Oil rsv	True	False	0.0583	0.020	0.004
Oil rsv	False	True	0.0318	0.003	0.000
Oil rsv	False	False	0.0292	0.002	0.000
GVC Mix	True	False	-3.2328	1.452	0.026
GVC Mix	False	True	-4.2341	3.138	0.177
GVC Mix	False	False	-4.8739	3.248	0.134
GVC Forward	True	False	-1.2960	5.017	0.796
GVC Forward	False	True	7.8722	10.577	0.457
GVC Forward	False	False	8.3239	10.897	0.445
GVC Backward	True	False	29.2065	12.026	0.015
GVC Backward	False	True	11.6867	25.977	0.653
GVC Backward	False	False	32.9853	26.690	0.217

Table 4: Baseline OLS results

5.2 Double ML Results

Table 5 shows the estimated PLR results from the double ML model using fuel sector GVC participation rates as the treatment. Table 6 shows the estimated PLR results with oil reserves as the treatment variable. The results are all insignificant. Even the smallest p-value that we found surpasses 0.3.

GVC Type	Time Fixed Effects	Stationary Controls	$\hat{\beta}$	$\hat{\sigma}$	P-value
Forward	True	True	-6.0028	10.6271	0.5722
Forward	True	False	-4.5679	8.3487	0.5843
Forward	False	True	2.9257	5.2573	0.5779
Forward	False	False	0.0561	5.7985	0.9923
Backward	True	True	-376.2269	424.9421	0.376
Backward	True	False	-394.2124	433.5249	0.3632
Backward	False	True	-215.1774	296.9244	0.4686
Backward	False	False	-242.9255	321.8868	0.4504
Mix	True	True	30.3654	30.828	0.3246
Mix	True	False	27.9613	29.8732	0.3493
Mix	False	True	8.7627	14.192	0.5369
Mix	False	False	6.2062	10.5182	0.5552

Table 5: PLR Identification DML Results - GVC Participation

Treatment	**Time Fixed Effects**	**Stationary Controls**	$\hat{\boldsymbol{\beta}}$	$\hat{\boldsymbol{\sigma}}$	**P-value**
Oil Reserve	True	True	23.9816	27.1266	0.3767
Oil Reserve	True	False	31.7023	34.166	0.3535
Oil Reserve	False	True	12.6405	14.5728	0.3857
Oil Reserve	False	False	8.9729	11.6547	0.4414

Table 6: PLR Identification DML Results - Oil Reserve

5.3 Clustering Results

Table 5 shows the ML Clustering Results for Oil reserves and each of the three measures of GVC.

	Oil Reserves	GVC		
		Mixed	Forward	Backward
$\hat{\beta}$	0.0141***	-2.7034	18.9720*	-55.9923*
$\hat{\sigma}$	0.004	2.919	9.617	25.044

Table 7: Clustering Results

We see that using Clustering, the oil reserves estimate is positive and significant, the forward GVC estimate is positive and significant, and the backward GVC estimate is negative and significant. The mixed GVC estimate is insignificant, which makes sense since it is a combination of forward and backward GVC measures, which have effects in opposite signs.

6 Conclusion & Discussion

Regarding our results of the baseline model, one main observation for the OLS regression exploring the relationship between the size of a country's oil reserve and its political stability is that the coefficient for oil reserves is positive and statistically significant across all specifications. This suggests that large sizes of oil reserves are associated with higher defense burden and this effect is robust whether fixed effects and stationary controls are included or not. Intuitively speaking, this consistent positive association could imply that countries with substantial oil reserves have greater financial resources at their disposal, which may lead to increased defense spending as a stabilizing force of within the country.

For the OLS model investigating the relationship between Fuel Sector GVC participation and countries' political stability, the results varied. For GVC mixed participation, the coefficient is negative and statistically significant when fixed effects are included, suggesting that countries with a mix of forward and backward GVC participation might be associated with lower political stability. However, such negative correlation is no longer statistically significant when fixed effects are moved or when stationary controls are added. For GVC forward participation, there is no indication of a clear association between the forward participation and a country's political stability in any specification given the high p-values in each case. For GVC backward participation, the coefficient is positive and statistically significant when fixed effects are included, suggesting that countries with a backward GVC participation might be associated with greater political stability. Similar to the case of mixed GVC participation, nonetheless, such significance disappears when stationary controls are included and fixed effects are removed. Hence, an identifiable trend from the results is that the relationships between various forms of GVC participation and political stability are more sensitive to the inclusion, or exclusion, of fixed effects and stationary controls than that of size of oil reserves and political stability.

The insignificance of the results regressing GVC participation as the independent variable could be explained by the nature of the Fuel sector of GVC. In particular, given that the Fuel sector of GVC is an aggregate measure that also includes coke, refined petroleum, and nuclear fuel, there is a lack of direct measure of oil abundance. This might unable the variable to capture the isolated effect of oil abundance alone on political stability, contributing to the insignificance of the GVC measures. Another noteworthy observation is that we only see significant results for GVC participation (mixed and backward) when the fixed effects are included and stationary controls are excluded. A possible explanation could be that the effect of GVC participation on political stability is conditional upon intrinsic, country-specific characteristics. In other words, the relationship between GVC participation and political stability could hinge on specific attributes unique to each country, such that GVC engagement might have either a positive or negative influence on the stability of different nations depending on their individual circumstances.

Although our OLS regression yields some statistically significant results, none of our DML results exhibit statistical significance. While this transition may seem counterintuitive, it is not problematic because DML improves overall model performance. OLS regression assumes a linear relationship between the independent and dependent variables, whereas our PLR identification with DML techniques accounts for nonlinearities, controls for confounding factors more effectively, and minimizes biases by design. Consequently, variables that initially appeared significant in the OLS framework may lose significance when analyzed within the DML context.

It is intuitive that political stability outcomes for countries might group by geographical factors such as because of mountain ranges, seas, etc., geopolitical factors such as alliances and trade blocks etc, and historical factors, but we do not directly observe these groups. This is why we use the ML clustering approach to get at these unobserved groups and any heterogeneity in effects for our independent variable(s). Running our clustering analysis, we see that there is positive significant results for both Oil reserves and forward oil GVC participation, i.e. that more oil reserves/oil forward GVC associated with more military expenditure share. There is negative significant results for backward oil GVC participation, i.e. that more backward GVC associated with less military expenditure share, and insignificant results for mixed GVC. Since forward GVC measures more of a seller-side/exporter trade activity, it makes sense that it agrees in direction to the effect of oil reserves, as higher oil reserves usually linked with more oil exports(in some sense this alignment in results can support robustness).

However, our analysis is not without its limitations. First, the use of defense share as a proxy measuring political stability may not capture the full complexity of the political landscape. Defense share could be influenced by a multitude of factors beyond just stability, such as geopolitical strategies or economic constraints, which may not necessarily reflect the internal political conditions.

In addition, there is the potential issue of reverse causality between defense share and our independent variables of GVC measures. If defense share is indeed a representation of political stability, then increased stability might lead to higher GVC participation due to improved investment climates and international trust. These considerations are important to keep in mind when interpreting our analysis.

Given more time, future research steps could include changing or including more outcome variables to ones that may be a better or more comprehensive measure of political stability and employing instrumental variables that can provide a more definitive analysis of causality when needed. In addition, to further extend upon the interpretability and robustness of our clustering analysis, we can incorporate methodology from papers like Bonhomme and Manresa, 2015.

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Appendix

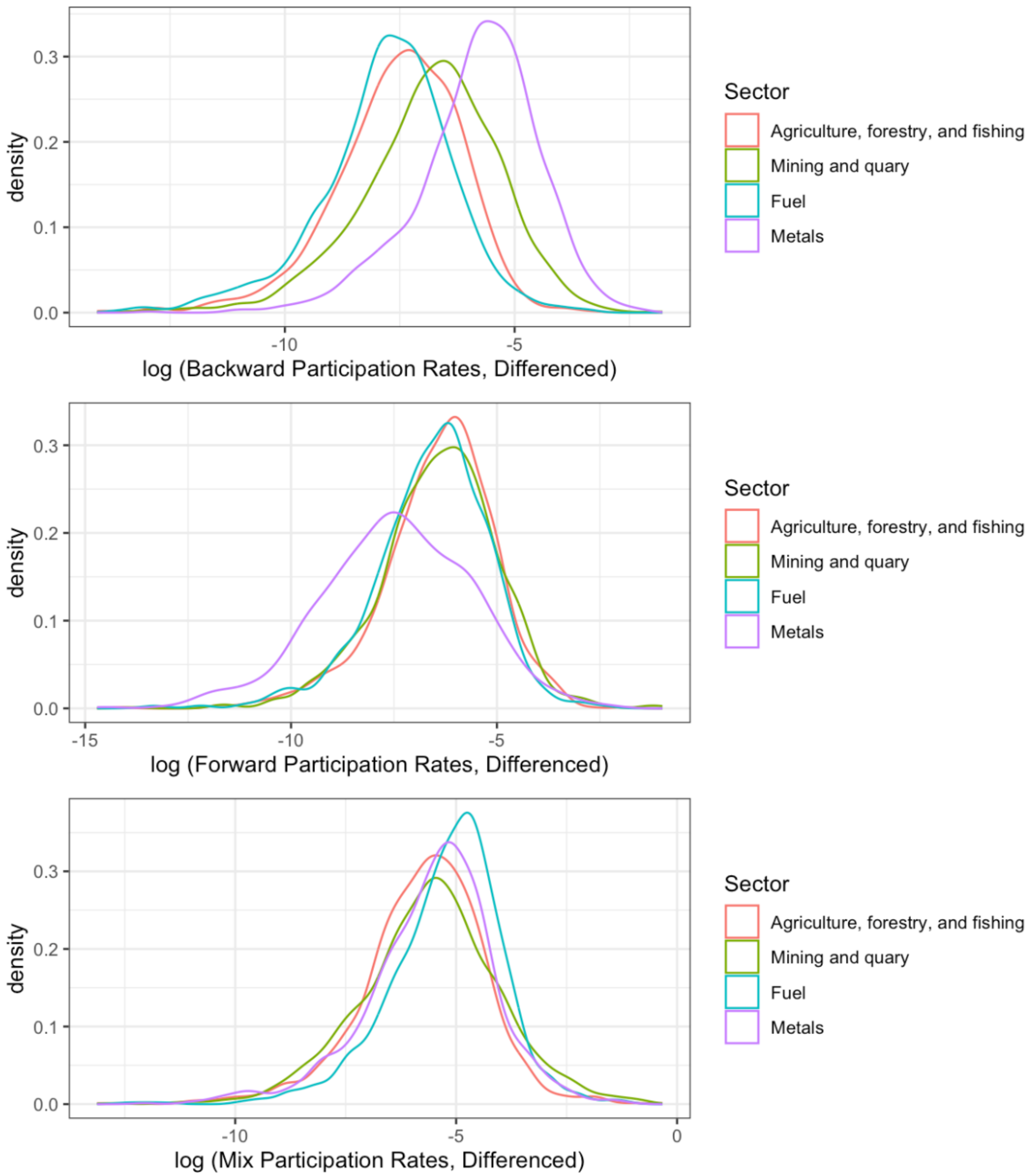

Figure 5: Log distribution of GVC participation rate across 4 natural resource sectors

The following are few of the most significant clusters that overlap between Oil reserve and GVC Forward(export direction trade) independent variables:

- Clusters 3 and 2 with countries: Angola (AGO), Bolivia (BOL), Brazil (BRA), Central African Republic (CAF), Canada (CAN), Cameroon (CMR), Colombia (COL), Ecuador (ECU), Guinea (GIN), Indonesia (IDN), Kenya (KEN), Madagascar (MDG), Mexico (MEX), Mali (MLI), Mozambique (MOZ), Malawi (MWI), Malaysia (MYS), Namibia (NAM), Niger (NER), Nigeria (NGA), Nicaragua (NIC), Nepal (NPL), Panama (PAN), Peru (PER), Sierra Leone (SLE), Chad (TCD), Thailand (THA), Tanzania (TZA), Uganda (UGA).
- Cluster 1 and Cluster 2 with overlapping countries: Angola (AGO), Brazil (BRA), Central African Republic (CAF), Canada (CAN), Cameroon (CMR), Colombia (COL), Ecuador (ECU), Guinea (GIN), Kenya (KEN), Madagascar (MDG), Mexico (MEX), Mali (MLI), Mozambique (MOZ), Malawi (MWI), Malaysia (MYS), Namibia (NAM), Nigeria (NGA), Nicaragua (NIC), Peru (PER), Sierra Leone (SLE), Chad (TCD), Thailand (THA), Tanzania (TZA), Uganda (UGA), Zambia (ZMB).
- Cluster 1 and Cluster 0 with overlapping countries: Burundi (BDI), Egypt (EGY).