Pol Sci 733: MLE Paper Assignment # 2.3

National troop contributions to CSDP miltiary operations between 2003 and 2001.

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1 Introduction

This short paper analyizes national troop contributions of European Union (EU) member states to the EU's Common Security and Defense Policy (CSDP) military operations between 2003 and 2010.[1]

Troop contributions are modeled as count variable, and coefficient estimates, first differnces in exoected counts and predicted probabilities of contribution are reported for a poisson, a negative binomial and a zero-inflated negative binomial regression model. Long (1997, 217) stresses that fitting an OLS regression model on count outcomes can result in inefficient, inconsistent and biased estiamtes, and the problem of censoredness of the dependent variable cannot be solved by fitting a censored regression model, as there neither exists a latent distribution for non-participants, nor can the assumption of latent negative values be supported (Bove & Elia 2011, p. 707).

2 Data, measurement, and empirical strategy

The dependent variable National troop contributions are measured as the average annual amount of national troops deployed by a EU member state to a given CSDP miliary operation's operation-year. Troop contributions are modeled as count variable, as troop counts can only take non-negative integer values. Figures on troop contributions are obtained from the Stockholm International Peace Research Institute's (SIPRI) Multilateral Peace Operations Database (2014). Variation in troop contribu- tions is analyzed across six CSDP military operations over a time

[1] The focus on military operations is reasoned by the observation that the three types of personnel that are contributed to multilateral peacekeeping operations (PKOs)—military troops, police, and observers—are associated to different levels of risk, especially with regard to civilian and battlefield deaths (Gaibulloev et al. 2015, p. 5). Excluding the EU's policy and obeserver missions ('civilian missions' in the terminology of the European External Action Service) enables to control for unobserved operation-type specific heterogeneity in national troop deployments.

period from 2003 to 2010, and the sample includes all EU member states, except from Denmark.[2] Member state's troop deployments are considered to be a valid indicator of states' contributions to their collective security objectives (Bove & Elia 2011).

Independent variables Two key explanatory variables meausure countries' ability to contribute. Countries' ability to contribute to an international security institutions common cause is considered to be a key indicator in both the defense burden-sharing literature (cf. Olson & Zeckhauser 1966) as well as the literature on the efficacy of the EU's CSDP. Note that the overwhelming share of CSDP operational costs is financed by member states (the so-called 'costs-lie- where-they-fall principle'). This makes it generally reasonable to expect strong effects of donor-specific determinants of troop contribution. Therefore, I consider two indicators of country-specific contribution capability.

The first measures countries annual defense spending relative to gross domestic product (GDP). It is argued that member states' defense expenditure is an important determinant of their ability to contribute effectively to the CSDP (Giegerich & Wallace 2004, Grevi & Keohane 2009, de France 2013), and defense expenditure is considered to be a valid indicators of countries' abiltiy to shoulder collective defense burdens (Hartley & Sandler 1999). Figures on annual defense expenditure as share of GDP are obtained from Eurostat (2015).

The second indicator measures GDP per capita and is supposed to capture differences in national wealth. Gaibulloev et al. (2015) find that differences in national wealth directly affect countries' troop contributions to PKOs. Specifically, they argue that countries' valuation of stability and peace is positively associated to their willingness to contribute national troops to peacekeeping operations, and increases with their levels of wealth. Annual GDP per capita figures are obtained from WDI data (World Bank 2015).

In addition, I control for a list of confounding factors. A country's trade openness is included as a proxy of member states' private economic benefits from the provision of CSDP military operations, measured as the sum of in- and exports as share of GDP.[3] Proximity to the country or region of intervention is measured as a binary indicator that flags cases in which the donor and target country are located in the same region.[4] A measure of the average of total troop deployment to other peacekeeping missions in the previous three years is included to account for the troop constraint donor countries face (Bove & Elia 2011, Gaibulloev et al. 2015).[5] To account for the spillover effect that is expected to occur in national personnel contributions to mulitlateral peacekeeping operations (Gaibulloev et al. 2015), it is controlled for the average amount of troop contribution by all other CSDP members' in a given operation-year.[6] The size of the corresponding

[2] Denmark opted out of the Common European Foreign and Defense Policy, following the Danishs electorates yes vote in the on May 18, 1993.

[3] Figures were obtained from the World Bank's (2015) World Development Indicators (WDI) data.

[4] Region identified according to World Bank (2015) region clasifications.

[5] Figures on national deployments to peacekeeping missions are obtained from the replication data of Gaibulloev et al. (2015), and is aggregated across all UN and non-UN missions by country-years.

[6] Note that the troop spillover is considered to be endogenous in the deployment decision, and omission would

ATHENA budget (if it applies), devided by the total amount of troops provided by EU members in a given operation-year. is included in order to account for the marginal renumeration resulting from that cost sharing scheme.[7] Lastely, two binary indicators flag countries' that served as framework nation in a given operation-year (as defined in SIPRI 2014), and opertion-years of operation EUFOR Althea, representing 151 out of total 250 contributions and an on average higher troop deplyoment, respecively. Table 1 reports summary statistics for all variables.

Table 1: Summary statistics.

Statistic	N	Min	Max	Median	Mean	St. Dev.
Amount of national troops deployed	306	0	1,770	7	102.40	225.07
Defense expenditure/GDP (t-1)	306	0.20	3.40	1.40	1.38	0.58
Log of p.c. GDP (avg. t-3 to t-1)	306	8.25	11.56	10.13	10.02	0.69
Trade/GDP (avg. t-3 to t-1)	306	47.32	337.93	97.16	106.81	54.69
Donor and target country in same region	306	0	1	1	0.60	0.49
Log of total PKO deployments (avg. t-3 to t-1)	306	−2.30	9.60	6.90	6.40	2.63
Avg. contribution of other members'	306	3.69	250.09	77.95	114.80	78.30
Average athena compensation	306	0.00	36.56	14.51	15.66	10.83
Framework nation	306	0	1	0	0.07	0.25
Operation EUFOR Althea	306	0	1	1	0.58	0.50

Empirical Strategy I fit a poisson, a negative binomial and a zero inflated negative binomial regression model on national troop contributions. In eac case, the mean of the distribution is modeled as a function of the independent variables, where I include all above listed explanatory and control variables. The set of country-specific control variables includes temporal lags: the one-year lag $(t-1)$ of defense expenditure/GDP, and the three-year moving averages ($t-3$ to $t-1$) of trade/GDP, per capita GDP, and the total amount of contributions to UN and non-UN PK. In addition, the moving average of per capita GDP and PKO deployments are log-transformed, to account for the right-skewedness of their distributions.

Note that Defense expenditure/GDP, trade/GDP, GDP per capita, and the sum of peacekeepers deployed to other PKOs vary across country-years; the indicator that flags whether the donor and target countries were located in the same region varies with country-operation configurations; the marginal renumeration per troop by ATHENA budget varies with operation-years; operational leadership (framework nation) and the troop-spillover indicator vary with country-operation-year configurations; and the dummy that flags operation-years of operation EUFOR Althea varies between operations only.

result in biased estimates.

[7] Figures on the amount of costs covered by the ATHENA mechanism in a given operation-year were provided on individual request by the European Concilium Public Service on June 8, 2015.

3 Results

3.1 Poisson regression model

In the PR model, the dependent variable is modeled as a random variable with a poisson distribution. The mean or rate parameter of the distribution can be modeled as a function of independent variables, so that $\mu_i = \mathrm{E}(y_i|\mathbf{X}_i) = \exp(\mathbf{X}_i\boldsymbol{\beta})$, which gives the PRM:

$$\Pr(y|\mathbf{X}_i) = \frac{\exp\big(\exp(\mathbf{X}_i\boldsymbol{\beta})\big)\exp(\mathbf{X}_i\boldsymbol{\beta})^y}{y!}$$

Given observations of the dependent variable and covariates, the maximum likelihood estimate (MLE) of $\boldsymbol{\beta}$ can be found by numerical maximation.

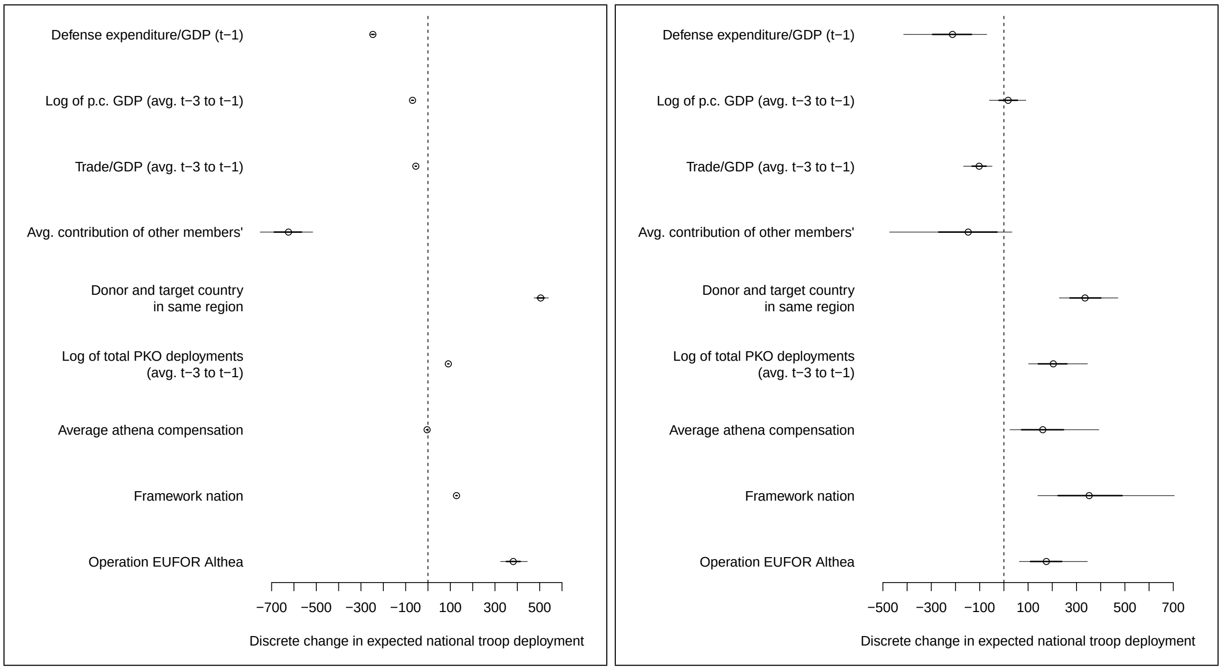
A one-percentage point increase in defense expenditure/GDP in the previous year is found to decrease the expected count of national troop contributions by 60 percents. Given that the empirical range is bound by .2 and 3.4 percent defense expenditure, this is a substantial effect. Moving fro the 25 to the 75 percentile values (from 1 to 1.6 percents), for instance, is predicted to decrease troop deployment by 36 percent. A one-unit increase in the log of GDP per capita (averaged over the previous three years), an increase that approximates the intervall between the 25 and the 75 percentile, decreases the expected count of national troop deployment by 25 percent. Again, this effect is substantial, though smaller in magnitude compared to that of increases in defense expenditure. In summary, the coefficient estimates of the PRM suggest that independent from which indicator is concerned, more capable countries contribute less troops to CSDP military operations.

It is, however, worth stressing that the estimates of PRM are often overconfident due to overdispersion. In case of overdispersion, the standard errors are likely to small and the significance levels of the coefficient estimates are overly optimistic. This overconfidence is illustrated in Figure 1a, which plots the average changes in expected troop contributions for discrete changes in the independent variables. When averaging over the data and 1,000 sets of coefficients drawn from a multivariate distribution defined by the point estimates and the variance-covariance matrix of the PRM, the 95% confidence bounds are extremly small. I therefore turn to the results of a negative binomial model, which allows to account for overdispersion in the distribution of the expected count of the dependent variable.

3.2 Zero-inflated negative binomial model

The negative binomial regresion model (NBRM) accounts for unobserved heterogeneity, which causes the problem of overdispersion, by modelling the conditional mean as a random variable, such that the expected value of the random error ($\exp(\epsilon)$) is defined to equal δ_i. (In the PRM, it is assumed that $\mathrm{E}(\delta_i) = 1$.) Assuming that $g(\delta)$, the probability density function (pdf) of δ, follows

Figure 1: Average change in expected national troop contribution for discrete change in predictors.



(a) PRM (b) NBRM

Discrete changes computed for difference between expected count at 5 and 95 percentile in case of continous variables, and for change from zero to one in case of binary indicator. Thin line represent 95%, thick lines 68% confidence intervalls. Thin lines represent 95%, thick lines 68% confidence intervalls. Predictions averaged over individuals' actual values on other covariates and over 1,000 sets of simulated coefficient estimates (drawn from multivariate normal of ordered regression model).

a gamma distribution, the negative binomial regression model is defined as

$$\Pr(y|\mathbf{X}_i) = \frac{\Gamma(y_i + v_i)}{y_i!\Gamma(v_i)} \Big(\frac{v_i}{v_i + \tilde{\mu_i}}\Big)^{v_i} \Big(\frac{\tilde{\mu_i}}{v_i + \tilde{\mu_i}}\Big)^{y_i} \text{ with } \tilde{\mu_i} = \exp(\mathbf{X}_i\boldsymbol{\beta} + \epsilon),$$

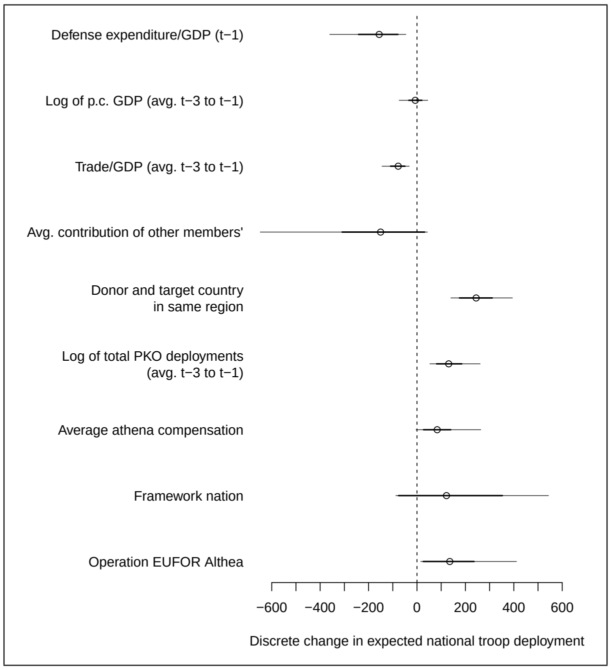
where the identifying assumption is that v is the same for all individuals (i.e., the variance of δ is constant).[8] Modelling the mean as a function of explanatory variables, and given this identifying assumption, the NBRM can be estimated by maximum likelihood.

Before turning the the coefficient estiamtes and average changes in expected troop contributions, note that fitting the NBRM on the same set of variables as in the case of the PRM above provides substantial evidence for overdispersion: The test for overdispersion (according to Cameron & Trivedi 1990) gives reasons to rejecet the null-hypothesis of equidispersion ($p < 0.004$)

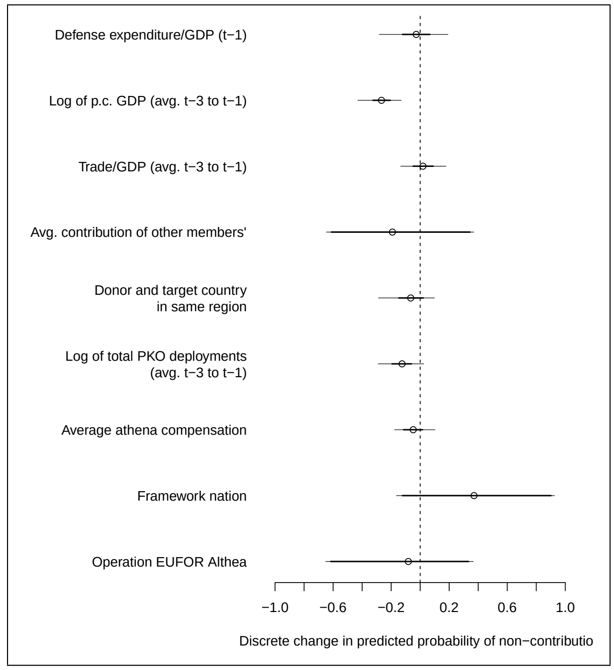
Generally, the coefficients of the NBRM are smaller in terms of magnitude, and the standard errors are larger, due to the non-zero dispersion parameter. Figure 1b depicts the lower confidence

[8] That is, $v_i = \alpha^1$ for $\alpha > 0$, where α is the dispersion parameter of the NBRM.

Figure 2: Average change in (A) expected national troop contribution and (B) predicted probability of non-contribution for discrete change in predictors.



(A) Count model, ZINBRM



(B) Zero model, ZINBRM

Discrete changes computed for difference between expected count at 5 and 95 percentile in case of continous variables, and for change from zero to one in case of binary indicator. Thin line represent 95%, thick lines 68% confidence intervalls. Thin lines represent 95%, thick lines 68% confidence intervalls. Predictions averaged over individuals' actual values on other covariates and over 1,000 sets of simulated coefficient estimates (drawn from multivariate normal of ordered regression model).

in the estimates of the NBRM. The 95% confidence intervalls are very much larger as in the case PRM, resulting in the conclusion that the effects of a majority of predictors, including GDP per capita, are statistically indistinguishable from zero. While a one-percent increase in defense expenditure/GDP is associated to an average 45 percent decrease in troop deplyoment, the sign on the coefficient on GDP per capita is turned compared to the PRM and is found to be statistically indistinguishable from zero. In sum, the results of the NBRM lead us to question the estimates of the PRM. Specifically, though the substantial negative effect of increases in defense expenditure/GDP on troop contributions is re-affirmed, we can no longer conclude that the same applies to the effect of GDP per capita.

A further remark of both the results of the NBRM and the PRM need to be made. Note that it is reasonable to consider non-contributions (i.e., zero counts) to arise from a decision-making process that is qualitatively different from that of deciding on deployment of a positive-valued amount of troops. On could conceptualize this as a selection into contribution, where the decision of how much troops to contribute is preceeded by the question whether to participate at all.

3.3 Zero-inflation

A class of zero-modified count models reflects this consideration. Particularly, zero-inflated count models (ZICM) allow to model a different data generating process for zero counts than for positive-valued counts. Generally, ZICM distinguish between two processes from which zero counts arise. The first is the process producing any non-negative count, the second process is specific to a group of always-zeros, that is, a process that determines zero-counts only.

The results from fitting a zero-inflated negative binomial regression model (ZINBRM) are shown in Figure 2. Panel A reports average changes in the expected count of national troop deployment for discrete changes in the independent variables. The corresponding estimates reflects the count-producing process of the ZICM. A one-percentage point increase in defense expenditure/GDP in the previous year is again found to reduce the expected number of national troops deployed to a operation-year by a substantial 50 percent, and the difference in the expected troop contribution predicted at the 5 and the 95 percentile value of defense expenditure— admittedly a large change— amounts to an average 156 troops when averaging over the data. Figure 3a plots the average expected troop contribution at different levels of defense expenditure, while averaging over the data. The effect of GDP per capita on the count of troops is, however, statistically indistinguishable from zero. This corobarates the finding of the NBRM.

Panel B of Figure 2 reports the average change in the predicted probability of non-contribution for discrete changes in the predictors. This corresponds to the process that exclusively determines zero counts. Note that the dependent variable in the zero model is being member of the group of non-contributors. Negative effects thus make contribution more likely.

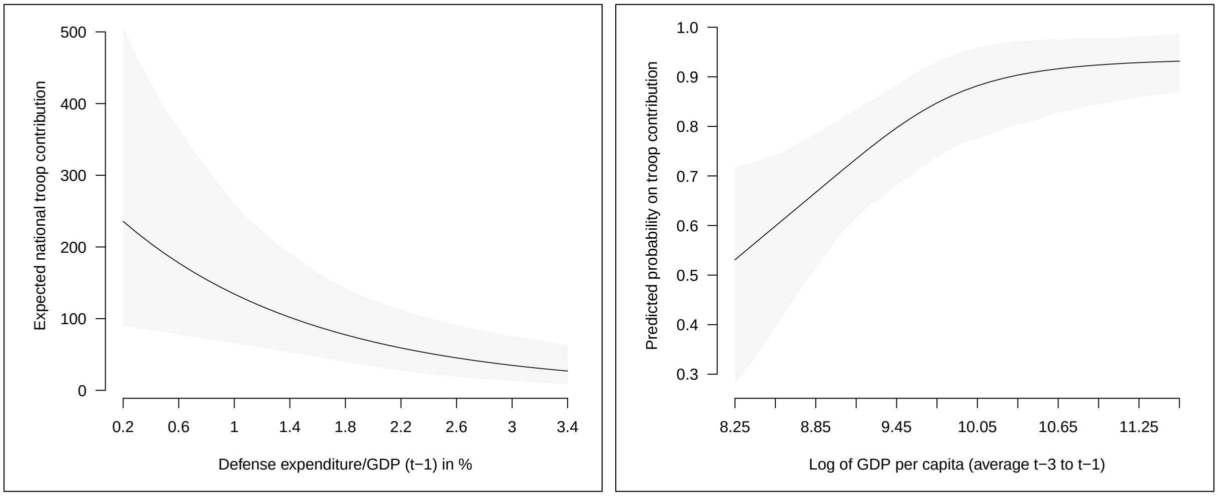
This, for instance, applies to the effect of GDP per capita. The a one-unit increase in the average logged GDP per capita over the previous three years makes contribution 1.89 times more likely, and, when averaging over the data, countries with an average logged GDP per capita in the previous three years of 10.9 (95 percentile value) have a 26 percent higher probability of contributing national troops to an operation-year than countries with an of 8.8 an average logged GDP per capita in the previous three years of (5 percentile value).[9] Figure 3b plots this relationship. The higher the (log of) GDP per capita has been in the preceeding three years (on average), the higher probability of contributing national troops to an operation year.

Acounting for the differences in the processes that determine troop contribution (or not) and the amount of troop contribution suggests an interesting insight: While states with higher levels of defense spending contribute less than one would expect if troop contribution were proportional to defense expenditure, wealthy states are in generally more likley to participate, i.e., contribute at least one troop to CSDP military operations.

A final remark with regard to this finding is, however, indispensible. Eye-balling the data, it

[9] Note that fitting a hurdle model, that distinguishes between a binary process for generating zeros and non-zeros and a truncated count model (there thus exists no overlapp in DGPs of zero-counts), gives similar results with regard to the effect of GDP per capita in the zero model.

FIGURE 3: Change in (A) expected national troop contribution as a function of defense expenditure/GDP and (B) predicted probability of troop contribution as a function of log of GDP per capita.



(A) Predictions from count model of ZINBRM (B) Pred. from inverse of zero model of ZINBRM

Shaded areas indicate 95% confidence intervalls. Predictions averaged over individuals' actual values on other covariates and over 1,000 sets of simulated coefficient estimates (drawn from multivariate normal of ordered regression model).

becomes clear that many smaller EU countries with high GDP per capita, such as Luxembourg, have frequently contributed only very few national troops to CSDP military operations. It is not unlikely that the results of the zero model are at least partially driven by this few, very small contributions. A sensitivity analysis, thus, would be in order.

4 Conclusion

EU member states' national troop contributions to CSDP military operations are affected by states' ability to contribute. Fitting a zero-inflated negative binomial model on the count of national troops contributed has revealed that richer countries are more likely to contribute a positive number of troops. The expected amount of troops contributed, however, is lower for states with higher defense expenditure – another indicator of the ability to contribute.

5 References

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