Determining Military Expenditures: Dynamics, Spill-Overs and Heterogeneity in Panel Data

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Abstract

This paper considers the determinants of military spending, building on an emerging literature that estimates military expenditure demand functions in cross-section and panel data, incorporating both economic and strategic effects. Increasingly pooling data is seen as a valuable way of developing the empirical and analysis and while it presents opportunities it also raises issue. Using a panel of 80 countries over the period 1988-2008 and comparing results across different panel data estimation methods it finds marked differences, particularly between the within and between estimates. The cross-section dimension suggest that per-capita income has a positive effect on the share of military spending in GDP and population a negative effect, while the time series estimates give the reverse. Most of the results for the political/strategic variables are as one might expect, but spillover effects do not seem important. Heterogeneity across countries is important, particularly in the dynamic adjustment processes, illustrating the importance of both using panel methods and recognising and modelling dynamic processes.

Keywords: Military Spending; Demand; Arms races; Spillovers; Panel data; Dynamics

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1. Introduction

There is a large literature on the demand for military expenditure, which explains it by variables such as income, population, political institutions, membership of alliances, wars and other measures of the threat, often based on the military expenditures of rivals or neighbours (Smith, 1995). Early empirical studies tended either to use time-series data for a particular country or cross-sectional data across countries. It was recognised that the cross section study conclusions might explain difference across countries, but may not assist in understanding differences within countries over time, while the individual country studies tended to be rather heterogeneous, limiting comparisons and giving limited coverage. This led to the use of pooled time series and cross section data becoming common, allowing both dimensions to be considered, Recent contributions that use the different available methods for dealing with pooled data include Collier and Hoeffler (2007), Dunne, Perlo-Freeman and Smith (2008) and Nordaus et al (2009)

There are, however, some issues in using panels that are not always recognised. One difficulty is that what is being measured in the cross-section dimension may be different from what is being measured in the time-series dimension. Indeed, the cross-section effect of a variable may be of opposite sign to the time-series effect, since each may reflect quite different theoretical processes operating over quite different time horizons. There is the further difficulty that variables that vary over country and are important in the cross-section dimension, may show little of no variation over time, so their effect cannot be estimated from time-series[1]. This problem may be reduced by using very long spans of data, but then there is the danger of structural change in the relationships. Similarly, the effect of factors that vary over time but influence all countries, such as the temperature of the Cold War, cannot be estimated from cross-section data, though they may be measured as common factors in panels, even if they are unobserved,

[1] For instance some countries may not have had wars or may have had the same political institutions over the whole sample.

Another issue that has been raised is the importance of considering the predictive performance of models rather than simply searching for statistical significance. This issue is raised by Ward et al (2010) in the context of modelling the onset of conflict, but is also relevant to the study of the determinants of military spending undertaken here.

This paper investigate these issues using a panel of 80 countries over the period 1988-2008, which is largely post Cold War. The first section briefly reviews the theoretical basis for modelling the determinants of military spending. It also considers the issues that present themselves in panel data studies, namely the treatment of heterogeneity, cross-section dependence and dynamics. Section 3 then outlines the data used and the estimated model and section 4 outlines the available pooled models and their issues. This is followed by a comparison of the results of the different pooled models in Section 5 and an evaluation of the predictive power of the models and the importance of heterogeneity in Section 6. Finally section 7 presents some conclusions.

2. Determinants of Military Spending

There are two broad groups of empirical studies in the literature on the determinants of military spending. First, there are those studies focusing on a range of economic, political and strategic determinants of military spending, with the most satisfactory empirical analyses tending to take a relatively comprehensive approach. More formal models have been developed from the neoclassical approach, which considers the country or state as maximising a social welfare function with security an integral component (Smith, 1980 and 1995). Most theoretical models lead to similar estimation equations for the empirical analysis, where the demand for military expenditure is a function of economic resources, threats to security, and political factors, such as the nature of the state.

$$M = D\,(Y, P_m, P_c, Z, T). \qquad (1)$$

where Y is income, P_m and P_c are the prices of M and C relative to an income deflator, Z demographic variables and T strategic variables. This equation can then be rewritten as shares in *Y* rather than levels to give us the demand function commonly used in empirical work (Smith, 1989, 1995). In empirical work, prices are usually dropped from the equation because either there is not a separate price deflator for military goods or because the two deflators move together. This practice has been recently criticized by Solomon (2004) who used the relative prices to estimate the demand for military expenditure in Canada.

Second, those based on the arms race models of Richardson (1960), which are best suited to situations in which countries are in conflict and have often have failed to perform well empirically (Dunne, 1996; Smith, 1989). The basic Richardson (1960) 'arms race' model supposes two countries whose military expenditure/level of arms/military capability, m_1 and m_2, are related at time t by the equations:

$$\frac{dm_1(t)}{dt} = a_1 + b_1 m_2(t) - c_1 m_1(t)$$

$$\frac{dm_2(t)}{dt} = a_2 + b_2 m_1(t) - c_2 m_2(t)$$

Where a_i are exogenous 'grievance' terms, b_i are 'reaction' terms, whereby each country responds to the military capability of the other, and c_i are 'fatigue' terms, usually representing some internal limitations on a country's military spending/capability. Alternatively, a discrete formulation can be made using difference equation,

$$\Delta m_{1t} = a_1 + b_1 m_{2t} + c_1 m_{1,t-1}$$

$$\Delta m_{2t} = a_2 + b_2 m_{1t} + c_2 m_{2,t-1}$$

This basic model has been developed theoretically and empirically in a variety of ways, including the explicit modelling of rational economic decision-making, different dynamic specifications, game theory approaches, and empirically with the use of approaches such as co-integration (Dunne and Smith, 2007). The search for clear empirical evidence of 'arms races' has, however, met with rather limited success, with even apparently obvious examples as the Cold War superpower arms race proving ambiguous and very much dependent on specification[2]. This has led to a

[2] India and Pakistan provides one of the few examples where researchers have been able to provide consistent evidence of a Richardsonian arms race. Even then, Oren (1994) has offered an alternative approach, based on hostility levels between the two countries, under which the apparent arms race disappears. Numerous attempts have been made to estimate arms races for Turkey and Greece, using a

these two strands of research being brought together, with arms race dynamics introduced into demand models to give a more complex structural model than the action-reaction framework and economic, political and military factors also introduced.

An early attempt to deal with strategic effects with a demand equation used the concept of a "Security Web" concept developed by Rosh (1988). This defines neighbours and other countries (such as regional powers) that can affect a nation's security as being part of a country's Security Web and averaged their military burden. Other models that include economic, political and strategic factors include Dunne & Perlo- Freeman; 2003a, 2003b and 2008; Dunne et al (2003), Gadea *et al*., 2004; Yildirim & Sezgin, 2005; Collier & Hoeffler, 2007; Nikolaidou, 2008. In addition, Murdoch and Sandler (2002, 2004) have focussed on the 'spillover effects' of military spending.

More recently, a number of authors, including Dunne and Perlo-Freeman (2003a and 2003b) and Collier and Hoeffler (2004), have sought to generalise the concept of an arms race by looking at the demand for military expenditure across a large group of countries, using either cross-section or panel data, incorporating a range of economic, political and security variables, and including variables for the aggregate military expenditure of neighbours and rivals.

To illustrate the issues involved consider a cross-section of countries $i = 1, 2, .., N$, with the average value for some military measure m_i over some time-period and other determinants x_i. If one particular country i feels threatened by an alliance of j and k; the equations for these 3 (out of N) observations take the form:

$$
\begin{aligned}
m_i &= \alpha + \beta^e (m_j + m_k) + \gamma' x_i + \varepsilon_i \\
m_j &= \alpha + \beta^e m_i + \beta^a m_k + \gamma' x_j + \varepsilon_j \\
m_k &= \alpha + \beta^e m_i + \beta^a m_j + \gamma' x_k + \varepsilon_k
\end{aligned}
$$

variety of theoretical and econometric models, without clear evidence of an arms race emerging. (E.g. Dunne, Nikolaidou and Smith (2003), and Smith, Sola and Spagnolo (2000).)

where β^e measures the arms race effect from an enemy and β^a the spillover effect from an ally. Given data on N countries and knowledge of threats and alliances, this model could be estimated by say OLS.

There are obvious practical problems; how to determine the strategic effects, the pattern of threats and alliances, how to aggregate if adding allies expenditure is not appropriate, what time period to average over, and which military measure to use. Rather than considering dyadic relations, Rosh's (1988) contribution considered the neighbours and other countries (such as regional powers) that can affect a nation's security as part of a country's Security Web and their military spending was aggregated[3]. More recently, Dunne and Perlo-Freeman (2003a) developed this approach as discussed below.

There are also econometric issues, such as the problem of simultaneity, but it is not the standard one, where the right hand side variable may be determined by another equation. All N military expenditures are determined by the same equation. It is more like a lagged dependent variable issue and the conditions for consistent estimation by OLS are the same as that case: m_i can be treated as predetermined in the equation for m_j if $E(\varepsilon_i \varepsilon_j) = 0$. If there are correlated shocks to different countries or spatial serial correlation, this assumption will not hold (Dunne and Smith, 2007).

Collier and Hoeffler (2004) estimate arms race multipliers by considering the two country case:

$$m_i = a_i + bm_j$$

An exogenous unit increase in a_i would cause an increase in the other countries military expenditure by bm_j feeding back on m_i and giving a total effect of $1/(1-b)$ on spending by country i. They distinguish own expenditure and neighbour expenditure arms race multipliers.

[3] Rosh calculates the degree of militarisation of a nation's Security Web by averaging the military burdens of those countries in the web, finding it to have a significant positive effect on a country's military burden.

Using cross-section data, rather than time-series for individual countries increases the sample size considerably and allows one to measure the effect of variables which tend not to vary very much within countries. The cost of this benefit is the assumption that the arms race and alliance parameters are the same across all countries. This assumption can be weakened and allowing the coefficients to differ across countries and collect the independent variables in a vector z_i gives the model

$$m_i = \alpha_i + \beta_i' z_i + \varepsilon_i$$

with $\alpha_i = \alpha + \nu_i$, $\beta_i = \beta + \eta_i$. When $\alpha = E(\alpha_i)$, $\beta = E(\beta_i)$ and η_i and ν_i are random, independent of the regressors, OLS will provide consistent estimates of β. These assumptions are, however, quite strong and with the availability of panel data models of the form

$$m_{it} = \alpha_i + \beta_i' z_{it} + \varepsilon_{it}$$

can be estimated and the homogeneity or independence assumptions tested (Dunne and Smith, 2007). With panel data one can employ a larger sample and allow for heterogeneity in the responses of different countries. One standard way of allowing for heterogeneity is to estimate a separate time-series model for each country, but this is not possible in this study as some of the independent variables show no time-series variation[4]. The available models are discussed in the next section.

It should also be noted that the maintained assumptions of linearity, exogeneity and the choice and measurement of the set of independent variables might all be questioned. The identification issue is important, we look at the effect of GDP on military expenditure while there is a large literature that looks at the effect of military expenditure on GDP growth and other economic variables (Agostino et al, 2011). For instance in a recent paper, Acemoglu and Yared (2010) give evidence that suggests that higher military expenditure is associated with lower growth in trade. Dunne and

[4] A central issue in the choice of estimator is the relative size of N and T. The traditional panel literature deals with cases where N is large and T small, maybe only two or three time periods. Asymptotic analysis is done letting $N \to \infty$. The time-series literature deals with the case where T is large and N small and asymptotics let $T \to \infty$. Recently there has been interest in panel time-series where N and T are of the same orders of magnitude and asymptotics let both $N \to \infty$ and $T \to \infty$ in some way. What estimators are appropriate in the three cases differs.

Perlo-Freeman(2003a) suggest that a major problem is in the identification of threat and the arms race specifications are not adequate. Nordhaus, Oneal and Russet (2009) find a novel way of introducing a measure of threat by constructing a direct measure based on the predicted probability of war, but this variable shows little time-series variation for a country and, as we shall see, the simple pooling methods they use can be inadequate in dealing with heterogeneity.

3. Pooled Estimators

Denoting the vector of independent variables by x_{it}, the dependent variable, the log share by s_{it}, and the country means by $\overline{s}_i$. The available pooled estimators assume homogeneity of the slope coefficients of the covariates, x_{it}, $x_{i,t-1}$ and $s_{i,t-1}$, but differ in their treatment of intercept heterogeneity and dynamics. It is useful to decompose the total variation into the within country component and the between country component, so for the dependent variable

$$\sum_i \sum_t (s_{it} - \overline{s}) = \sum_i \sum_t (s_{it} - \overline{s}_i) + T\sum_i (\overline{s}_i - \overline{s}),$$

and similarly for the other variables. We consider a range of models and estimators. The cross-section (CS) uses only the between country variation:

CS: $\overline{s}_i = \alpha + \beta' \overline{x}_i + \overline{\varepsilon}_i.$

The pooled OLS (POLS), used above, gives equal weight to within country and between country variation:

POLS: $s_{it} = \alpha + \beta' x_{it} + \varepsilon_{it}.$

The one way fixed effect (FE1) used above, uses only the within country variation:

FE1:
$$s_{it} = \alpha_i + \beta' x_{it} + \varepsilon_{it},$$
$$(s_{it} - \overline{s}_i) = \beta'(x_{it} - \overline{x}_i) + \varepsilon_{it}.$$

Strictly speaking, we should distinguish the parameters: the β in the within equation is a different parameter from the β in the between equation. In static models, if the coefficients, α_i and β_i are randomly distributed, independently of the x_{it}, all these estimators will produce unbiased estimators of the expected values of the coefficients $E(\alpha_i)$ and $E(\beta_i)$. However, this independence assumption may not hold and the cross-section (between country) effects can be very different from the time-series (within country) effects and the two estimates may even be of opposite sign

The two way fixed effect (FE2) also allows for a completely flexible common factor that influences each country equally:

FE2: $s_{it} = \alpha_i + \alpha_t + \beta' x_{it} + \varepsilon_{it}$.

The common factor α_t may reflect changes in the global strategic environment:

These four models are static, we also estimate two dynamic versions of the two way fixed effect model. The partial adjustment model (PAM), with two way fixed effects (FE2PAM) allows for a lagged dependent variable:

FE2PAM: $\Delta s_{it} = \alpha_i + \alpha_t + \lambda(\theta' x_{it} - s_{i,t-1}) + \varepsilon_{it}$.

The coefficient vector θ measures long run effects, λ is an adjustment coefficient which measures the proportion of the deviation from the long-run target removed in any period. The error correction model (ECM) with two way fixed effects (FE2ECM) allows for lags of the dependent and independent variables:

FE2ECM: $\Delta s_{it} = \alpha_i + \alpha_t + \lambda(\theta' x_{it} - s_{i,t-1}) + \delta' \Delta x_{it} + \varepsilon_{it}$

This parameterisation of the ECM is more convenient than the usual one, which would include $x_{i,t-1}$, rather than x_{it} because it nests the partial adjustment model.

Note that the following three, reparameterised models are statistically identical

$$s_{it} = \alpha_0 + \beta_0 x_{it} + \beta_1 x_{i,t-1} + \alpha_1 s_{i,t-1} + u_{it}$$
$$\Delta s_{it} = \alpha_0 + \beta_0 \Delta x_{it} + (\beta_0 + \beta_1) x_{i,t-1} + (\alpha_1 - 1) s_{i,t-1} + u_{it}$$
$$\Delta s_{it} = \alpha_0 - \beta_1 \Delta x_{it} + (\beta_0 + \beta_1) x_{it} + (\alpha_1 - 1) s_{i,t-1} + u_{it}$$

Even though they appear to have different dependent and independent variables. In contrast to reparameterisations, which are not testable, restrictions are testable. In this case the restrictions $\beta_1 = \alpha_1 = 0$ gives the static levels model and the restrictions $\beta_0 + \beta_1 = \alpha_1 - 1 = 0$ give the first difference model. The final pooled model we consider is pooled OLS on first differences (POLSFD), which removes the level terms from the ECM:

POLSFD: $\Delta s_{it} = \alpha + \beta' \Delta x_{it} + \varepsilon_{it}$.

In this study we have 80 countries and 20 time series observations, which puts us on the margin of small T, with relatively large N for this type of study. Dealing with small T creates a number of issues that have led to the development of different methods of analysis than those considered so far. For small T, the fixed effect estimator of the coefficient of the lagged dependent variable is biased downwards, suggesting faster adjustment. In addition, time invariant country characteristics may be correlated with explanatory variables.

4. Data and Estimation Model

Specifying the demand model as model in the usual manner implies making military burden a function of economic, demographic and political/strategic variables. This is operationalised by taking the dependent variable is the logarithm of the share of military expenditure, LSM, (the logarithmic model fits better), denoted in the equations by $s_{it} = m_{it} - y_{it}$. The economic independent variables are LY the logarithm of GDP in constant US dollars, from SIPRI, y_{it}, and LPOP the logarithm of population, pop_{it}. Notice that the following reparameterised models are statistically identical

$$m_{it} = \alpha + \beta y_{it} + \gamma pop_{it} + u_{it}$$
$$m_{it} - y_{it} = \alpha + (\beta - 1)(y_{it} - pop_{it}) + (\gamma + \beta - 1) pop_{it} + u_{it}$$

Whether we regress log military expenditure on log GDP and population or the log share on log per-capita income and log population, they give an identical fit. The fact that one explains the share and the other the level is irrelevant.

The political independent variables are: POL the difference between the democracy score and the autocracy score in the Polity 4 data base, ranging from -10 (autocracy) to +10 (democracy); WAR a combined variable for civil or external war ranging from 0-3 depending on the intensity of the conflict; NATO =1 if member of NATO; WP=1 if member of the Warsaw Pact, which ended in 1990.

We also consider two measures to capture weak dependence among military expenditures of countries. LWEB is the logarithm of the sum of real military expenditures in US constant prices in the security web of the country. A country's Security Web is the set of counties that are considered to affect a given country's security (Rosh, 1988; Dunne and Perlo-Freeman, 2003a). These are mostly neighbours, but may also include regional powers and sometimes more distant rivals (e.g. Cuba-South Africa during the Angola war). The military spending of superpowers is usually excluded from a country's Security Web, where it is considered that it would be impossible to defend against the superpower with conventional military expenditure. LRIV is the log of the sum of rivals real military expenditure, a subset of the Security Web consisting of those powers considered hostile to the country in question. The classification of countries as mutually hostile is based on an analysis of a number of datasets, including the HIIK Database of Violent and Non-violent Conflicts, and the UCDP Dyadic dataset of armed conflict events. The previous study also used a further subset, Enemies, but this latter variable was insignificant, suggesting that the effect of those classified as ‘Enemies’ and those merely considered ‘Potential Enemies’ was not significantly different. Thus only the broader class of Potential Enemies (or Rivals) is used here.

For comparability across countries, GDP and military expenditure are expressed in constant US dollars. The share of military expenditure is based on the ratio of current price military expenditure to GDP, so does not equal the ratio of real military expenditure to real GDP, because of relative price effects. Some of these variables, e.g. GDP, are almost certainly I(1), however the panel levels regressions can estimate average long-run effects, even where the variables are I(1) and do not cointegrate, Phillips and Moon (1999).

5. Comparing Pooled Estimates

The models presented in section 3 were estimated for countries $i = 1, 2, ..., 80$ and for years $t = 1989, ..., 2008$ (1988 is used for lags), with x_{it} the vector of independent variables containing LY, LPOP, POL, WAR, LRIV, LWEB, NATO and WP. Table 2 gives estimates of the β_h or θ_h (long-run effects) of each of the independent variables for the various estimators. It also gives the maximised log likelihood, MLL, the number of coefficients estimated, k, the Schwarz Bayesian information criterion: $BIC = MLL - 0.5k\ln(NT)$; the Akaike Information Criterion: $AIC = MLL - k$;[5] the number of observations NOBS; and the adjustment coefficient λ, which is unity in

[5] The BIC penalises extra parameters more heavily than standard likelihood ratio, LR, tests, which penalise extra parameters more heavily than the AIC. Consider two models that differ by one parameter, the unrestricted has maximised log likelihood MLLU, the restricted MLLR, with LR=2(MLLU_MLLR). Then the AIC will choose the unrestricted model if LR>2, the likelihood ratio test if LR>3.84, at the 5% level, and for our sample of 1600, the BIC if LR>7.37. If the true model is within the set considered the BIC is consistent in that it will choose the true model as the sample size goes to infinity, but if the true model is not in the set considered the AIC may choose a model that approximates it better. The experience in forecasting is that more parsimonious models predict better, suggesting, like the BIC, an implied significance level smaller than the usual 5%.

the case of static levels models (instantaneous adjustment is assumed) and zero in the case of first difference models, there is no long-run equilibrium to adjust to. Standard errors are not reported, since the focus here is on the size of the effect[6].

Table 2 indicates that in terms of fit, country effects (different intercepts for each country) are very important (first differencing removes country intercepts), time effects less so and the BIC would suggest that they are not needed. Adding a lagged dependent variable is very important; adding lags of the independent variable less so, though the BIC suggests that they are needed. The AIC would choose the model with the most parameters, the FE2ECM, the BIC one of the simplest, pooled OLS on first differences. Intercepts are not significantly different in the first difference models (these would correspond to differential trends) and while a random effect, RE, model would be more efficient than pooled OLS, the RE and OLS coefficients are not very different. The first difference model does well because it removes both country effects and serial correlation.

The measures of fit indicate the importance of country heterogeneity and dynamics and the estimates are quite sensitive to the estimation method used. The coefficients of POL, WAR, LRIV, LWEB and WP keep the same sign across all specifications, NATO is positive in all but one specification. These signs are what one might expect: more democratic governments spend less on the military; countries at war spend more, higher military expenditure by rivals and countries within the countries security web increase military expenditure as does membership of NATO or the Warsaw Pact. Even where the sign does not change, the size of the effect can differ substantially between specifications, the cross-section estimates of the effects of WAR, NATO and WP are much larger than the time-series estimates. The effects of military expenditures by rivals or by the security web are fairly small in all specifications.

The sensitivity to specification is most marked in the coefficients of the two economic variables, the logarithms of per-capita GDP and population. These are both trended variables with a large cross-section variation. In cross-section income has a positive effect and population a negative effect, in time series the reverse. There is a clear

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[6] In addition, calculation of robust standard errors for some of these models is non-standard, since the errors may be I(1).

difference between what is being measured in cross-section from what is being measured in time-series. The difference between POLS and FE suggests that the intercepts, α_i are positively correlated with income, since the pooled estimates are larger than the ones that allow for country effects, but the position is less clear with population. Whereas the FE1 estimates and POLSFD coefficients of income are similar, they are very different for population.

Table 2. Alternative Pooled estimates

Dependent variable LSM

	CS	POLS	FE1	FE2	FE2PAM	FE2ECM	POLSFD
LYPC	0.142	0.098	-0.574	-0.366	-0.537	-0.449	-0.421
LPOP	-0.114	-0.107	-0.416	0.157	0.395	0.448	0.122
POLITY	-0.071	-0.056	-0.002	-0.001	-0.009	-0.003	-0.007
WAR	0.319	0.209	0.119	0.135	0.194	0.204	0.035
LRIV	0.034	0.040	0.019	0.018	0.022	0.020	0.012
LWEB	0.059	0.054	0.037	0.037	0.033	0.011	0.047
NATO	0.626	0.578	-0.070	0.015	0.157	0.187	0.047
WP	6.361	0.998	0.383	0.263	0.248	0.266	0.104
MLL		-1371	196	234	938	980	811
K	9	9	88	107	108	116	9
BIC		-1404	-128	-161	539	552	777
AIC		-1380	108	127	830	864	802
NOBS	80	1600	1600	1600	1600	1600	1600
lambda	1	1	1	1	0.267	0.262	0

The time and country intercepts have means of zero. The time intercepts in the FE2ECM model show a downward trend with year to year fluctuations, from about 0.05 to -0.05. The lowest country intercept was -0.81 for India, with Nigeria, Bangladesh, Indonesia, Philippines, Ethiopia and Ghana all below -0.5. The highest country intercept was +0.85 for Kuwait, with Oman, Bahrain, Singapore, Cyprus, Israel and Saudi Arabia all above 0.5.

Overall, most of the results for the political variables were as one might expect with more democratic governments spending less on the military, countries at war spending more, higher military expenditure by rivals and countries within the countries security web increase military expenditure as does membership of NATO or the Warsaw Pact. The effect of the economic variables was less clear, with cross-section estimates giving income per capita a positive coefficient and population a negative one and the time series estimates giving the reverse. Heterogeneity across countries seems to be important is important, particularly in the dynamics, but spillover effects do not seem that important, with the coefficients on Rivals and Web quite small.

6. Prediction and heterogeneous estimators

The importance of evaluating models by their predictive power has been recently emphasised by Ward et al. (2010), who argue that in the studies of conflict too much time has been spent on finding statistically significant relationships and too little on finding variables that improve the ability to predict civil wars. They suggest that failure to use predictive failure tests in the literature has limited research and led to misleading conclusions. This is something the demand for military spending has also failed to consider and in the context of this analysis it seems sensible to ask how much of the time-series variation in s_{it} can be explained by the predicted values from the pooled model (POLS) above: $\hat{s}_{it} = \hat{\alpha} + \hat{\beta}' x_{it}$, when more parameter heterogeneity in the dynamics is allowed for.

This is done by first estimating a heterogeneous partial adjustment model:

$$\Delta s_{it} = \alpha_i + \lambda_i (\hat{s}_{it} - s_{it-1}) + \varepsilon_{it}.$$

Now if the predictions from the pooled model help explain the change in the shares in a particular country, the adjustment parameter λ_i will be significantly positive. If $\lambda_i = 0$ then the log share of military expenditure is just a random walk with drift[7].

Summing over the 80 country regressions, the heterogeneous partial adjustment model has a total MLL of 1545 and a BIC of 921, where the number of parameters estimated is $169 = 2 \times 80 + 9$. This is a much higher value of the BIC than any of the pooled models, implying that heterogeneity in the adjustment coefficients, which is not captured by any of the pooled models, is very important. Using the FE2 predictor, instead of the POLS predictor, the MLL only rose to 1582, with an extra 99

[7] While this could be interpreted as a two-step version of the iterative pooled mean group estimator of Pesaran, Shin and Smith (1999), which combines homogeneous long-run effects with heterogeneous short-run dynamics. Here the objective is rather different: to examine the explanatory power of the pooled predictions.

parameters, so the POLS predictor in the heterogeneous model would be preferred by both BIC and AIC.

Looking at the t statistics of λ_i using the POLS predictor, 10 have negative coefficients, though none are significantly negative. 20 have t statistics between zero and one, and 27 between one and two. Thus only 23 are significant at the conventional 5% level. Notice that the null hypothesis here, $\lambda_i = 0$, corresponds to the log share being a random walk with drift. Thus relative to a heterogeneous random walk with drift, the predicted values from the pooled regression significantly contribute to the explanation of the time-series variation in the share of military expenditure explanation around a quarter (28.75%) of the countries. Notice the average speed of adjustment here, 0.16, is lower than the 0.26 estimated by both dynamic fixed effects models. The range of estimates of λ_i is from -0.09 to 0.92.

Table A1 shows the estimates, there does not seem to be any pattern in the significance. The countries where the pooled predictions are most significant, with a t ratio greater than 3 are a heterogeneous group: Algeria, Burundi, Jordan, Nepal, Rwanda, UK and USA. Countries with more variation in predicted values tend to have higher t ratios, but the effect is not strong, the correlation between the standard deviation of the predicted values for each country and the t statistic is only 0.27.

A possible reason for the poor prediction is non-linearity in the relationships. There is some evidence of non-linearity in the cross-section relationship between the share and per-capita income. Dividing the observations into quartiles by per-capita income, the per capita income elasticity is negative for the bottom quartile, rises to a maximum for the third quartile then goes negative again. The population elasticity is always negative but tends to get less negative as one moves up to higher income quartiles. This pattern is very similar whether one constrains the other coefficients to be the same or not and they do not change their signs over quartiles. Non-linearity in cross-section may not correspond to non-linearity in time-series as Tasiran and Smith (2010) discuss for arms imports. One can check whether this effect is significant, by allowing the income coefficient to differ between countries, i.e. adding the level and change of income to the heterogeneous PAM above, removing the constraint of equality of income coefficients.

We have also assumed that the long-run coefficient of $\hat{s}_{it}$ is unity in the heterogeneous PAM, this restriction could be relaxed by including $s_{\mathrm{i,t-1}}$ in the equation. Similarly common factors and trends may have different impacts on different countries, this can be allowed for by including separate trends and the mean share of military expenditure and of GDP, following Pesaran (2006). A variety of such augmented models were tried. Summing over countries, the BIC would choose the most restricted model, the random walk with drift, the AIC the least restricted, of the form:

$$\Delta s_{it} = \alpha_i + \lambda_i(\hat{s}_{it} - s_{it-1}) + \beta_{1i}\mathrm{y}_{\mathrm{it}} + \beta_{2i}\Delta\mathrm{y}_{\mathrm{it}} + \beta_{3i}s_{\mathrm{i,t-1}} + \beta_{4i}t + \delta_{1\mathrm{i}}\overline{\mathrm{y}}_{\mathrm{t}} + \delta_{2\mathrm{i}}\overline{\mathrm{s}}_{\mathrm{t}} + \varepsilon_{it}$$

The estimates of λ_i were very dispersed, because the very few degrees of freedom, with a range from -49 to +110, with 9 out of the 80 coefficients significantly positive. These estimates could not be regarded as reliable.

So clearly, heterogeneity is important in the dynamics. Indeed, for most countries, the share of military expenditure seems close to a random walk with drift, while the predictions from the pooled regression, which gives equal weight to the cross-section and time series variation, only help predict the share of military expenditure in about a quarter of the countries. There is further evidence that spillover effects are not important, with common factor proxies, time effects and year means, not having significant influences.

7. Conclusions

This paper is a contribution to the growing literature on the determinants of military spending in the international community. After reviewing the empirical analyses undertaken so far, it has taken up a number of the issues raised by the increasing use of pooled time series and cross section data and attempts to introduce economic and strategic factors into the analysis. A range of available estimators were used to estimate a standard model of the determination of the share of military expenditure in GDP, using data for 80 countries from 1988 to 2008.

Most of the results for the political variables were as one might expect: more democratic governments spend less on the military, countries at war spend more, higher military expenditure by rivals and countries within the countries security web increase military expenditure as does membership of NATO or the Warsaw Pact. The effect of the economic variables was less clear. The cross-section dimension suggested that per-capita income had a positive effect on the share and population a negative effect, time series estimates the reverse.

Heterogeneity across countries is found to be important, particularly in the dynamic adjustment processes. For most countries, the share of military expenditure seems close to a random walk with drift and the predictions from the pooled regression, which gives equal weight to the cross-section and time series variation only help predict the share of military expenditure in about a quarter of the countries. Spillover effects do not seem that important, with the coefficients on the Rivals and Web variables being quite small and common factor proxies, time effects and year means, do not seem important.

These results have implications for future work as they suggest that there is considerable cross country heterogeneity that needs to be taken account of, both in terms of the impact of strategic and economic variables and in the dynamic specification. This means that developing longer data series that would allow the application of large N large T panel data methods such as the mean group estimator to a comprehensive demand function would be of considerable value. At present this is difficult as the main consistent long run series on military spending provided by SIPRI only starts at 1988. The clear difference between time-series and cross-section estimates of the determinants of military expenditure, also makes attempts to develop theories that could distinguish what is being measured in the two dimensions very worthwhile.

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Table A1 Estimates of $\Delta s_{it} = \alpha_i + \lambda_i(\hat{s}_{it} - s_{it-1}) + \varepsilon_{it}$

Significant positive estimates of lambda in bold.

Uses POLS fit regr;lhs=dlsm;rhs=dlsmer,one$

Country	lam	alpha	T(lam)	Se(lam)	Se(alph)	MLL	SER	R2
Algeria	0.29289	-0.1294	**3.5241**	0.08311	0.05416	12.5432	0.13623	0.40827
Argentina	0.05927	-0.0447	0.53769	0.11024	0.03223	20.3137	0.09237	0.01581
Australia	0.02962	-0.0051	0.36026	0.08221	0.0229	40.4988	0.03367	0.00716
Austria	0.15692	-0.0264	1.84038	0.08527	0.01216	32.2801	0.05078	0.15837
Bahrain	-0.0951	0.00097	-0.4734	0.20092	0.07036	19.9181	0.09422	0.0123
Bangladesh	0.01714	0.00264	0.49845	0.03439	0.01477	27.8993	0.06321	0.01362
Belgium	0.08047	-0.0587	1.98401	0.04056	0.01438	31.1327	0.05378	0.17944
Botswana	0.19345	0.12004	1.54513	0.1252	0.09861	22.324	0.08354	0.1171
Brazil	0.30399	0.10008	1.7305	0.17567	0.07686	8.84596	0.16389	0.14264
Burkina Faso	0.11249	-0.052	0.79807	0.14095	0.06457	14.2415	0.12514	0.03417
Burundi	0.1941	0.18799	**3.0346**	0.06396	0.06353	15.3534	0.11837	0.33845
Cambodia	0.38431	-0.1408	**2.8726**	0.13379	0.06781	2.73778	0.22243	0.31433
Cameroon	0.257	-0.1942	1.83446	0.14009	0.11067	27.9476	0.06306	0.15751
Canada	0.11389	-0.1213	**2.0634**	0.0552	0.05059	26.7699	0.06689	0.19129
Chile	-0.0226	-0.0373	-0.2023	0.11146	0.09743	27.5257	0.06441	0.00227
Colombia	0.15535	0.06637	0.95657	0.16241	0.05478	13.8563	0.12757	0.04838
Cyprus	0.1518	-0.0237	1.17073	0.12967	0.06592	-1.8899	0.28034	0.07076
Denmark	0.06254	-0.0371	0.83	0.07534	0.01936	32.4592	0.05033	0.03686
Djibouti	0.11691	0.02343	0.79762	0.14657	0.07844	12.0698	0.13949	0.03414
Dominican Rep.	0.4847	-0.2439	**2.2537**	0.21506	0.11626	2.49998	0.22509	0.22008
Ecuador	0.42973	0.09427	**2.4528**	0.1752	0.0459	10.7509	0.149	0.25051
Egypt	0.13554	-0.0127	**2.5885**	0.05236	0.02113	30.7039	0.05494	0.27126
El Salvador	0.14361	-0.1453	1.98251	0.07244	0.0364	16.4963	0.1118	0.17922
Ethiopia	0.41912	0.1872	**2.8448**	0.14733	0.11891	-3.8841	0.30973	0.31016
Fiji	0.12931	-0.0124	1.3265	0.09749	0.03363	11.5848	0.14292	0.08905
Finland	0.18132	-0.0628	1.42185	0.12752	0.04162	21.7294	0.08606	0.10097
France	0.03877	-0.0008	0.88417	0.04385	0.02554	40.9722	0.03288	0.04162
Germany	0.11985	-0.0232	**2.5925**	0.04623	0.01352	31.4329	0.05298	0.27188
Ghana	0.19569	-0.1288	**2.0631**	0.09485	0.08669	6.26894	0.18643	0.19125
Greece	0.19538	-0.0299	1.81064	0.10791	0.01728	25.6049	0.0709	0.15407
Guatemala	0.2401	-0.2583	1.83607	0.13077	0.11458	9.61948	0.15767	0.15774
Hungary	0.06475	-0.0378	1.25033	0.05179	0.02859	17.471	0.10648	0.07991
India	0.04988	-0.0056	0.60193	0.08287	0.02657	33.3696	0.04809	0.01973
Indonesia	-0.0005	-0.0345	-0.0052	0.08924	0.03937	15.8223	0.11563	1.5E-06
Ireland	0.01977	-0.04	0.3444	0.0574	0.02611	19.8865	0.09437	0.00655
Israel	0.23295	0.1694	**2.2606**	0.10305	0.09226	18.4136	0.10158	0.22112
Italy	0.22477	0.0441	1.97782	0.11365	0.03018	34.9618	0.04441	0.17852
Japan	0.04061	-0.0387	0.28911	0.14045	0.11601	35.8142	0.04255	0.00462
Jordan	0.91972	0.56343	**4.4412**	0.20709	0.13504	14.2377	0.12516	0.52286
Kenya	-0.0025	-0.0241	-0.0368	0.0693	0.02372	18.291	0.1022	7.5E-05
Korea, South	0.14369	-0.0098	**3.0609**	0.04695	0.0097	38.0305	0.03809	0.34232
Kuwait	0.24404	0.09831	1.63163	0.14957	0.15631	-16.13	0.57136	0.12885
Lesotho	0.13828	0.05002	1.0974	0.12601	0.07164	12.289	0.13797	0.06271
Madagascar	0.20223	0.07028	1.35082	0.14971	0.07022	7.4659	0.1756	0.09204
Malaysia	0.25429	0.05829	1.48279	0.1715	0.05634	10.7707	0.14885	0.10885
Malta	0.11022	-0.0877	1.29615	0.08504	0.04393	25.3493	0.07181	0.08537
Mauritius	0.17809	-0.2648	1.28696	0.13838	0.20881	9.50439	0.15858	0.08426

Mexico	0.29694	-0.3144	**2.3554**	0.12607	0.13292	10.9622	0.14743	0.2356
Morocco	0.36839	0.00288	**2.1924**	0.16804	0.03218	11.7492	0.14175	0.21075
Mozambique	0.3868	-0.0693	**2.5503**	0.15167	0.05674	0.41358	0.24984	0.26542
Nepal	0.16361	0.03059	**3.8225**	0.0428	0.02105	19.9622	0.09401	0.44805
Netherlands	0.07093	-0.0313	1.81397	0.0391	0.00883	37.7521	0.03862	0.15455
New Zealand	0.0728	-0.0509	1.64483	0.04426	0.01619	34.8746	0.0446	0.13066
Nigeria	0.2886	-0.2448	1.69024	0.17075	0.15332	-6.7207	0.35693	0.13698
Norway	0.00368	-0.04	0.03978	0.09261	0.02192	19.2084	0.09762	8.8E-05
Oman	-0.0052	-0.0492	-0.0296	0.17619	0.15557	18.3775	0.10176	4.9E-05
Pakistan	-0.0093	-0.0384	-0.4455	0.02096	0.01554	29.4135	0.05861	0.0109
Papua New Guinea	0.07191	-0.1135	0.61475	0.11698	0.09829	6.02859	0.18868	0.02056
Philippines	-0.0089	-0.0274	-0.129	0.06871	0.03409	29.4949	0.05837	0.00092
Poland	0.09033	0.00453	1.37009	0.06593	0.03037	14.1334	0.12582	0.09444
Portugal	0.05105	-5E-05	0.7967	0.06408	0.0207	37.5511	0.03901	0.03406
Romania	0.05599	-0.0047	0.98037	0.05712	0.05695	13.4093	0.13046	0.05069
Rwanda	0.56236	0.035	**3.1333**	0.17948	0.04724	4.45866	0.20409	0.35292
Saudi Arabia	0.10091	0.03181	0.87645	0.11514	0.07786	12.3106	0.13782	0.04093
Senegal	0.02665	-0.0113	0.31811	0.08378	0.0207	20.269	0.09258	0.00559
Singapore	0.20266	0.05413	1.14499	0.177	0.05636	25.959	0.06965	0.06789
South Africa	0.15283	0.02237	**2.2316**	0.06848	0.04113	22.7152	0.08192	0.21671
Spain	0.07994	-0.0382	0.99688	0.08019	0.02155	23.7552	0.07777	0.05232
Sri Lanka	0.27361	0.07169	**2.6187**	0.10449	0.04212	8.78784	0.16437	0.27587
Sweden	-0.0388	-0.0356	-0.8441	0.04598	0.00963	35.7194	0.04276	0.03808
Switzerland	0.00979	-0.0369	0.1925	0.05086	0.01379	29.3563	0.05877	0.00205
Syria	0.16173	-0.0042	0.76756	0.2107	0.05519	11.0203	0.14701	0.03169
Taiwan	0.1192	-0.0072	1.73983	0.06851	0.024	21.0963	0.08883	0.14396
Thailand	0.07112	-0.0211	**2.1844**	0.03256	0.0179	23.866	0.07734	0.20954
Tunisia	0.00418	-0.0302	0.05176	0.08068	0.03411	29.0484	0.05968	0.00015
Turkey	0.07171	-0.0485	0.64594	0.11102	0.05915	16.7153	0.11058	0.02265
Uganda	0.25057	-0.0703	1.86666	0.13423	0.0408	15.9148	0.11509	0.16218
UK	0.07567	0.00012	**3.5303**	0.02143	0.01046	41.4859	0.03205	0.40911
Uruguay	0.20386	-0.001	1.40906	0.14468	0.04876	5.8688	0.1902	0.09934
USA	0.12017	0.07491	**3.8763**	0.031	0.02558	33.5654	0.04762	0.45497