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# Random coefficients models of arms imports[☆,☆☆]

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ABSTRACT

This paper uses a large panel of data with up to 19 time-series observations for almost 150 countries to estimate models of arms imports. Qualitative evidence suggests a non-linear relationship. As income and military expenditure grow, the propensity to import first rises and then falls as a domestic arms industry develops. We face the difficulty that there is virtually no data on domestic arms procurement or production capability. We respond to this difficulty by adopting a random coefficient approach in order to identify any systematic influences on import propensity, through the impact of military expenditure, size of the armed forces or income on unobserved domestic production capability. While a clear non-linear pattern is apparent in the cross-section relationship, once one allows for parameter heterogeneity such a pattern is not apparent in the time-series.



## 1. Introduction

The random coefficient model, RCM introduced by Swamy (1970), has been widely used in panels where one has data over units, such as countries, $i=1,2,...,N$, for a fairly large number of time periods $t=1,2,...,T$. The RCM estimator can be calculated as a weighted average of the coefficients estimated for each unit and has the advantage that it introduces a focus on coefficient heterogeneity at the initial stage of modelling. Heterogeneity is important, since tests regularly reject homogeneity, and the heterogeneity can make standard pooled estimators misleading, particularly in dynamic models. In static models, if all the heterogeneous parameters (including the intercept) are distributed independently of the exogenous regressors, all the usual pooled or averaged estimators are unbiased. This is not the case for pooled estimators of models that include a lagged dependent variable. For instance, the bias in heterogeneous dynamic fixed effect models does not decline as $T$ increases, as it does in homogeneous dynamic fixed effect models (Pesaran and Smith 1995). Averaged estimators, such as the Swamy RCM or the mean group estimator of Pesaran and Smith (1995), are not subject to this heterogeneity bias.

The empirical experience with large $T$ panels is that the dispersion of coefficient estimates over units is not only often large, but sometimes implausibly large, as noted by Baltagi and Griffin (1997), among many others. Using a panel of $N=57$ countries with $T=31$ annual observations (Boyd and Smith 2002) estimate purchasing power parity equations where one would expect the elasticity of the exchange rate to price differentials to be close to unity. They find a range from $-0.40$ to 2.47 in static levels regression and from $-2.21$ to 7.93 for long-run coefficients in a first order dynamic model. The larger heterogeneity of the long-run coefficients may reflect the fact that the estimator has no finite sample moments, since the estimated coefficient of the lagged dependent variable can equal unity. Boyd and Smith interpret the heterogeneity in terms of omitted variables, unobserved factors which bias the coefficient for any particular unit. However, since the correlation between the included and omitted variables is not structural, it averages to zero over time and units, producing reasonable estimates for the average effect.

Omitted variables are only one possible form of misspecification. As Swamy has emphasised in subsequent work, e.g. in Hall et al. (2009), there are also measurement errors, endogeneity problems, structural breaks and non-linearities which could cause coefficients to differ over countries in a way that is not independent of the regressors. For instance, the effect of the non-linearity, which will be one focus of our concern, is that different units, observed at different values of the explanatory variables, provide different linear approximations to an underlying non-linear function. The procedure Hall et al. (2009) suggest 'is to first estimate a model with coefficients that are allowed to vary as a result of the fundamental misspecifications in the model, and, then, to identify the specification biases that are occurring in the underlying coefficients and remove them.' They

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focus on coefficient instability over time, in this paper we follow a similar procedure, but focus on coefficient instability over units in a large panel.

Misspecification seems likely in the example we examine. The aim is to explain arms imports in a large panel of countries as a function of the countries military expenditures and other variables. The data are very 'noisy', with missing values, zeros and severe problems of measurement error, non-linearity and omitted variables. The data are bad partly because there are strong incentives, both on the demand and the supply side, to misreport weapons transfers and many transfers, particularly of small arms and light weapons, are illicit and unrecorded. Even where there is no intention to deceive, there are problems in defining arms imports, particularly for dual use items that can have military or civil uses. For instance, Iceland has no armed forces or military expenditures but has recorded arms imports, because suppliers regard some of the equipment supplied, e.g. for the coast guard, as military. Contracts can be complex involving spares, training and facilities as well as the systems themselves; there is often little information on prices or payments which may involve bribes and other corrupt practices and countertrade (barter). The contracts often include offsets, promises by the exporter to set up production facilities in the importing country. In the estimated equations, there are almost certainly omitted explanatory variables such as domestic arms production capability and geostrategic factors, both of which are difficult to measure.

There is also likely to be a fundamental non-linearity in the relationship. Poor countries tend not to import major weapons systems, since they cannot afford them and the conflicts they are involved in, primarily civil wars, usually involve small arms, which are of low value and often domestically produced. Donors and international financial institutions also disapprove of expensive arms imports by poor countries.[1] As countries become richer and increase military expenditure, they import more major weapons systems; but beyond a certain size they are likely to establish a domestic arms industry which they protect for strategic reasons, thus reducing imports. The US, the biggest military spender, imports relatively little. Thus one might expect an inverted U shape relationship, as the elasticity of arms imports rises and then falls with the level of military expenditure or income. While one might expect non-linearity, previous work has not revealed a clear pattern. The non-linearity is apparent in cross-section estimates, e.g. in Levine et al. (1998), but not in the panels examined in our earlier paper, Smith and Tasiran (2005), referred to as ST below.

When confronted with such noisy panels, applied investigators have a number of choices in selecting the sample used for estimation. One route is to choose to ignore some of the data, working with a balanced panel using a smaller sample of better quality data. A second route is to use all the data, imputing observations for missing values; and trying to allow for the sample selection bias that comes from ignoring missing or zero values and the coefficient heterogeneity that comes from misspecification. In ST, we chose the first route, considering a small balanced panel of better quality data with 19 time-series observations for each of 52 countries, ignoring the data for almost a hundred other countries. This paper examines the implications of choosing the second route: using all the data, trying to model the coefficient heterogeneity, and investigating the possible non-linearity within a random coefficient framework.

In Section 2, we discuss the random coefficient models. In Section 3 we provide some background on the arms trade and the two data sources, SIPRI and WMEAT. We have imputed data for cases where there are data from one source but not the other, details of how this is done is given in Tasiran and Smith (2009). We then adopt two quite different approaches to the data. In Section 4, we follow ST and estimate demand functions for arms imports on this larger data set allowing for possible sample selection bias, but assuming quite a lot of coefficient homogeneity. As long as country fixed effects are included in both the selection and regression equations, sample selection bias does not appear to be a serious problem. However, the results for the whole sample of countries were rather different from those from the smaller balanced sample of countries. In Section 5 we estimate simpler random coefficient models allowing for considerable coefficient heterogeneity to explore the extent to which the differences in coefficients can be explained by non-linearity. Section 6 contains some concluding remarks.

## 2. Random coefficient models

Hsiao and Pesaran (2008) provide a review of random coefficients models: here we consider some aspects that are relevant for our investigation. Consider a heterogeneous panel model:

$$\mathbf{y}_i = \mathbf{W}_i \delta_i + \mathbf{u}_i, \tag{1}$$

where $\mathbf{y}_i$ is a $T\times 1$ vector, and $\mathbf{W}_i$ is a $T\times k$ vector of strictly exogenous variables, including the intercept. We assume, that $\delta_i = \delta + \eta_i$ where $E(\eta_i) = 0$ and $E(\eta_i \eta_j') = \Omega$, if $i = j$, $E(\eta_i \eta_j') = 0$ otherwise, and that the $\eta_i$ are independent of $\mathbf{W}_i$. As Pesaran et al. (2000) emphasise this assumption of the independence of the randomly varying parameters from the regressors is crucial and we return to it. Because of the relatively small value of $T$, we just consider static models in this application. There are a large number of estimators for $\delta \equiv \mathbf{E}(\delta_i)$, the expected value of the random coefficients. The simplest is to compute the OLS estimates for each group[2]:

$$\hat{\delta}_i = (\mathbf{W}_i' \mathbf{W}_i)^{-1} \mathbf{W}_i' \mathbf{y}_i \tag{2}$$

and then construct the average $\bar{\delta} = \sum_i \hat{\delta}_i / N$, estimating the $k\times k$ covariance matrix $\Omega$ by

$$\hat{\Omega} = \sum_i \left(\hat{\delta}_i - \bar{\delta}\right)\left(\hat{\delta}_i - \bar{\delta}\right)' / (N-1). \tag{3}$$

Pesaran and Smith (1995) call $\bar{\delta}$ the Mean Group, MG, estimator. Its estimated covariance matrix is $V(\bar{\delta}) = \hat{\Omega}/N$.

Swamy (1970) suggests a feasible generalised least squares, GLS, estimator, which is equivalent to using a weighted average of the individual OLS estimates $\hat{\delta}_i$ instead of the MG unweighted average. Using the residuals and the unbiased estimate of the variance

$$\hat{\mathbf{u}}_i = \mathbf{y}_i - \mathbf{W}_i \hat{\delta}_i; \quad s_i^2 = \hat{\mathbf{u}}_i' \hat{\mathbf{u}}_i / (T-k),$$

respectively, the estimated covariance of $\hat{\delta}_i$ is

$$V\left(\hat{\delta}_i\right) = s_i^2 (\mathbf{W}_i' \mathbf{W}_i)^{-1}.$$

Swamy suggests estimating $\Omega$ by the unbiased estimator

$$\tilde{\Omega} = \hat{\Omega} - \sum_i V\left(\hat{\delta}_i\right) / N. \tag{4}$$

However, $\tilde{\Omega}$ need not be positive definite, and in practice it often is not. In this case, Swamy suggests setting the last term to zero and using $\hat{\Omega}$, from (3) as the estimator instead. Notice that although $\hat{\Omega}$ ignores the correction for the sampling error of $\hat{\delta}_i$, it is consistent as $T$

[1] The negative response by the World Bank and others to the Tanzanian purchase of an expensive UK military air traffic control system from BAE is illustrative in this respect.

[2] There are also a range of simulation based, parametric, random coefficient models which involve assuming some distribution for the coefficients but do not require estimating the coefficient for each group. We do not consider these, since we have little prior knowledge of the appropriate distribution in our case.