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The Effect of Military Expenditure on Growth: An Empirical Synthesis[1]

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Abstract

Using a sample of 243 meta-observations drawn from 42 primary studies, this paper conducts a metaanalysis of the empirical literature that examines the impact of military expenditure on economic growth. We find that existing studies indicate growth-retarding effects of military expenditure. The results from the meta-regression analysis suggest that the effect size estimate is strongly influenced by study variations. Specifically, we find that underlying theoretical models, econometric specifications, and data type as well as data period are relevant factors that explain the heterogeneity in the military expenditure-growth literature. Results also show that positive effects of military expenditure on growth are more pronounced for developed countries than less developed countries.

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1. Introduction

Though it is not always the case, economic development is often accompanied by a rise in military expenditure (hereafter ME). For instance, data from World Bank (World Development Indicators) shows that from 1988 to 2012, countries with the highest ME (as a proportion of GDP) have the highest economic development (5.96% in high income non-OECD and 2.57% in OECD), while countries with lower shares have lower economic development (2.08% in middle income countries and 2.05% in low income countries). What is the interaction between ME and economic development? Does ME promote economic growth? There are no clear-cut answers to these questions as complex interactions between ME and economic growth may occur.

Theoretically, ME can promote as well as hinder growth. ME may promote growth through the following channels. ME develops new technology that spills over to private sector, creates socioeconomic structure through spin-offs effects, provides public infrastructure and protections against threats, and increases aggregate demand and employment through the Keynesian multiplier effect. On the other hand, ME is harmful for growth through its opportunity costs. Through the gun-butter trade-off, ME crowds out investment or other productive activities. A rise in ME often comes with increased tax burden and government debt which may reduce growth. The net effect of ME on growth therefore will depend on the benefits versus the opportunity costs.

Although many studies have investigated the relationship between ME and growth, unfortunately, the empirical evidence that is currently available is inconclusive (Smith, 1980; Yildirim et al., 2005). Some studies show that ME is conducive to growth (see e.g., Benoit 1973, 1978; Weede, 1983; Biswas, 1993; Cohen et al., 1996; Yakovlev, 2007), some other studies however show that ME may retard growth (see e.g., Deger and Smith, 1983; Faini et al., 1984; Deger, 1986; Mintz and Huang, 1990, 1991; Heo, 1999; Ward and Davis, 1992; Pieroni, 2009a). There are also studies that show ME neither hinders nor boosts growth (see e.g., Biswas and Ram, 1986; Alexander, 1990).

According to Smith (1992), and Mintz and Stevenson (1995), theoretical and methodological limitations are possible reasons for the failure to reach a consensus in the literature. Furthermore, the heterogeneity in the reported findings has often been associated with the use of different samples, different theoretical and econometric specification, and different time periods (Chen et al., 2014).

Our goal in this paper is to provide a synthesis of the empirical literature that examines the effects of ME on growth using meta-analysis techniques. Based on 42 primary studies with 243 estimates, we formulate five hypotheses (H1-H5) to investigate the military expenditure-growth (hereafter ME-G), relationship: (H1) ME as a proportion of GDP reduces growth, (H2) ME as a proportion of GDP reduces growth in less developed countries (LDCs), (H3) ME as a proportion of GDP increases growth, (H4) The effect of ME as a proportion of GDP on growth is non-linear, and (H5) ME as a proportion of GDP increases growth in developed countries.

Our study re-examines and extends the work by Alptekin and Levine (2012), hereafter A-L, who conduct a meta-analysis of 32 studies on the ME-G relationship by formulating the first four hypotheses (H1)-(H4) mentioned earlier. Our study validates the results by A-L after using a subset of the 32 primary studies that they included in their meta-analysis. In addition, by using a larger set of primary studies, which includes newly published studies, we find that the general conclusion of A-L, that is the positive effect of ME on growth, is no longer valid.

Unlike A-L, we split our meta-observations into three country types – developed countries, LDCs and mixed countries, in order to thoroughly investigate the ME-G relationship listed in the hypotheses (H1)-(H5). A-L test (H2) by introducing a dummy which captures the effect of studies that report estimates on Africa. Beyond this approach, we run a separate meta-analysis for LDCs only. This enables us to determine the possible causes of heterogeneity in the literature that examines the ME-G effect for LDCs only. We use a similar approach to test (H5). In essence, we conduct a meta-analysis using 243 estimates to test (H1) and (H3), and also (H2), (H4) and (H5) (by introducing dummies). To explore (H2) and (H5) more thoroughly, we use the less-developed-countries sample only (147 estimates) to test (H2), and the developed-countries sample only (26 estimates) to test (H5).

This study makes a number of important contributions: first, we examine the 'genuine' effect of ME on growth beyond publication bias. Second, based on various sample clusters which capture country differences, we provide a generalized conclusion on the effects of ME on growth per development level. Third, we address issues of between and within study variations and explore possible causes of systematic heterogeneity in the ME-G literature. Thus, we control for study-to-study variations and provide an overall net ME-G effect. Lastly, our results lay a foundation and guide future studies into examining areas of particular importance.

2. Existing Theoretical and Empirical Perspectives

In this section, we provide a brief review of the theoretical foundations and various empirical findings for the effects of ME on growth.[3]

Theoretical arguments on the effects of ME on growth may come from three channels: the supply, the demand, and the security channels. The supply channel considers the opportunity cost of ME

[3] See Alptekin and Levine (2012) for an overview of the various econometric approaches that examine the ME-G relationship.

(such as the crowding-out effect, an adverse balance of payment, and distortions), and the spill-over or the spin-off effect of ME (such as the development of new technology and infrastructure by the military sector that benefits the private sector). On the other hand, the demand channel suggests that ME increases aggregate demand, employment and capital utilization through the Keynesian multiplier effect. The security channel stresses the role of ME in providing security for people and properties from internal and external threats. Theoretically, the net effect of ME on growth is uncertain and thus, how ME affects growth is ultimately an empirical issue.

Benoit's famous studies (1973, 1978) find that ME stimulates growth in a sample of 44 LDCs. According to Benoit, only a small part of income not spent on military is allocated to productive activities in LDCs. On the other hand, spending on military contributes to growth by providing education, medical care, technical training, and public infrastructure such as roads, airports and communication networks which could benefit the private sector. Military forces also engage in scientific and R&D activities which have positive spill-over effects to private production.

Numerous studies afterwards have focused on validating Benoit's (1973, 1978) finding. However, subsequent empirical studies show inconsistent results on the subject. The diversity of results largely comes from applying different models (such as neoclassical or endogenous growth models and Keynesian models), and using a variety of specifications, econometric estimators and types of sample in cross-section, time-series or panels (Dunne et al., 2005).[4]

Empirical studies such as Kennedy (1983), Weede (1983), Biswas (1993), Mueller and Atesoglu (1993), Cohen et al. (1996), Brumm (1997), Murdoch et al. (1997), and Yakovlev (2007) support Benoit's finding. In particular, Weede (1983), Deger and Sen (1983), Deger (1986), and Yakovlev (2007) find positive effects of ME on growth through human capital accumulation or spin-off technologies. Kennedy (1983), DeGrasse (1983), and Mueller and Atesoglu (1993), among others, find that ME helps growth through the process of enhancing infrastructure, increasing a Keynesian-type aggregate demand, and promoting full employment.

Studies that permit ME to affect growth through multiple channels such as Deger and Smith (1983), Faini et al. (1984), Deger (1986), Mintz and Huang (1990, 1991), and Ward and Davis (1992) find that the net effect of ME is negative. For example, Deger (1986) finds that while ME increases growth through demand and technological spin-off effects, ME reduces growth through the resource effects by reducing the savings rate. Many studies also find that ME reduces growth by crowding out private

[4] The neoclassical or endogenous growth models focus on the supply-side, while the Keynesian models focus on the demand-side.

investment and increasing tax burden (see e.g., Smith, 1980; Cappelen et al., 1984; Batchelor et al., 2000; Dunne et al., 2001). These studies imply that there is a substantial trade-off between ME and resource use (the gun-butter trade off). Higher ME often reduces expenditure that is essential to build future productive capacities such as investment in new capital stock, health and education.

The extent of the opportunity cost of ME (the gun-butter trade off) will depend on the size of ME as a proportion of GDP, how the increased ME is financed, the effectiveness of the military sector in providing security, and whether the country that increases ME is resource-constrained. For instance, distortionary taxes used to finance ME tend to distort saving decisions and lower growth when taxes are sufficiently large (Barro, 1990); resource-constrained countries that increase ME at the expense of cutting development programs such as education and health tend to reduce growth (see, e.g., Frederiksen and Looney, 1983).

Another group of studies such as Biswas and Ram (1986), Alexander (1990), Kinsella (1990), Payne and Ross (1992), Ward et al. (1992), and DeRouen (1994) show that there is no significant relationship between ME and growth. A more recent study by Pieroni (2009b) shows that there is no relationship between ME and growth in countries with low ME.

Thus, a priori, ME could have an insignificant, positive or negative effect on growth, as documented in previous surveys of the military-growth literature (see, e.g., Chan, 1987; Ram, 2003; Smaldone, 2006; Dunne and Uye, 2009).

3. Data and Methodology

Our meta-analysis methodology draws on guidelines proposed by the meta-analysis of economics research-network (MAER-NET), which reflects best practices and transparency in meta-analyses (Stanley et al., 2013). To collect relevant studies that examine the ME-G relationship, we search for journal articles and working papers in five electronic databases – JSTOR, Business Source Complete, EconLit, Google Scholar, and ProQuest, which in itself contains over 30 databases. We use various keywords for ME and growth.[5] We also check the references of related studies to ensure that no relevant studies are excluded from our meta-analysis.

We use the following criteria to select studies for inclusion in our meta-analysis. 1) We include only the empirical studies that examine the direct effect of ME on growth. 2) ME must be an

[5] Keywords for military expenditure include defence (defense) expenditure OR defence (defense) spending OR military spending OR military expenditure OR defense burden. Keywords for growth include economic growth OR economic development OR GDP OR gross domestic product.

independent variable and be measured as a share of GDP. 3) The growth rate of GDP is the dependent variable. We leave out studies that use the level of ME, the growth rate of ME and GDP level. We also include studies that adopt simultaneous equation models but we report only the direct effects as it is not possible to capture the net effect from these studies. (4) Given that partial correlation coefficients are calculated to allow for comparability of studies, we exclude studies that satisfy criteria (1) and (2) but do no report all relevant statistics to enable the calculation of partial correlation coefficients.

Following the above criteria, our meta-analysis therefore includes 42 relevant studies with 243 estimates. Table 1 presents an overview of these 42 studies in terms of the reported number of estimates, their simple means and fixed effects weighted means.

3.1. Partial Correlation Coefficients (PCCs)

To allow for comparability of studies and reported effect-size estimates, we first calculate partial correlation coefficients (PCCs), which measure the association between ME and per-capita GDP growth while all other independent variables are held constant. Given that PCCs are independent of the metrics used in measuring both dependent and independent variables, they are comparable across studies. However, given that PCCs are based on regression coefficients, there are limitations using PCCs especially when primary studies do not control for all relevant covariates. If a regression model is mis-specified, PCC will be biased because it is not based on a regression coefficient that is obtained after controlling for all relevant variables. Nonetheless, this does not make PCCs irrelevant. We later control for model specification (i.e., omitted variables) in our meta-regression to examine if the model specification has any systematic effect on PCCs. An alternative to PCCs is elasticities but primary studies usually do not report sufficient information for calculating elasticities. Thus, PCCs are very often used in meta-analysis (see, e.g., Alptekin and Levine, 2012; Ugur, 2013)

For each effect-size estimate reported by primary studies, we calculate a PCC and its associated standard error in accordance with equations (1) and (2) given below.

$$r_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \tag{1}$$

and

$$SE_{ri} = \sqrt{\frac{1 - r_i^2}{df_i}} \tag{2}$$

Here, r_i and SE_{ri} are PCC and standard errors associated with each effect-size estimate. SE_{ri} represents variation due to sampling error and its inverse is used as weight in the calculation of fixed-effect weighted averages for each study. t_i and df_i are t-value and degrees of freedom associated with estimates reported in primary studies.

3.2. Fixed Effect Weighted Means

We calculate fixed-effect weighted averages (hereafter, FEEs) for estimates reported in each study. We provide FEEs as a reliable overview of the ME-G evidence base as they are more reliable than simple means, and compared to random-effects weighted averages, they are less affected by publication bias (Henmi and Copas, 2010; Stanley, 2008; Stanley and Doucouliagos, 2014). FEEs are calculated using (3) below.

$$\bar{X}_{FEE} = \frac{\sum r_i \left(\frac{1}{SE_{ri}^2}\right)}{\sum \frac{1}{SE_{ri}^2}} \tag{3}$$

Here, $\bar{X}_{FEE}$ is the FEE and all other variables remain as explained before. FEEs assign higher weights to more precise estimates, and vice versa, thus, accounting for within-study variations.

Table 1 reports results from the study-based FEEs. First, based on a subset of our included studies, which consists of 32 studies included in A-L, we confirm the results presented by A-L to a large extent (except for very minor variations). FEEs provided by A-L for all 32 studies are consistent with what we find, except for slight variations in averages reported for Grobar and Porter (1989), and Lipow and Antinori (1995), where effect sizes are about 0.1 higher than those reported in A-L.

Based on the 42 studies included in this current study, we find that of the 243 reported estimates, 88 are insignificant, 80 are negative and significant, and 75 are positive and significant. The average FFE for all 243 estimates is -0.0401. Thus, based on our entire dataset, we conclude that ME has a negative effect on growth, in contrast to A-L who find a positive relationship. However, drawing on inferences made by Cohen (1988), our overall average FEE for the ME-G relationship is of no practical relevance.[6] Furthermore, the calculated FEE is valid only if there are no issues of publication selection bias. Thus, to investigate if the reported FEEs are fraught with issues of publication selection bias, we conduct various tests in the next subsection.

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[6] Cohen indicates that an effect size represents a small effect if its absolute value is less than 0.10, a medium effect if it is 0.25 and over, and a large effect if it is greater than 0.4.

3.3. Genuine Effects Beyond Bias

FEEs cannot be considered as 'genuine' measures of the effect of ME on growth, given that estimates reported by primary studies are subject to publication selection bias and/or affected by within-study dependence between reported coefficients (see De Dominicis et al., 2008; Ugur, 2013). Thus, in what follows, we conduct various tests to examine whether the reported effect-sizes are tainted with publication selection bias and whether they represent 'genuine effects'. First, we present a funnel plot to visually inspect the possibility of publication bias. A funnel plot is a scatter plot of the effect sizes against their precision ($1/SE_{ri}$). Figures 1 to 4 present funnel plots that examine the relationship between effects sizes and their precision. The funnel plots show less asymmetry considering our reference line. This suggests that there are no serious issues of publication selection bias.

Although funnel plots are useful in inspecting publication bias visually, they cannot be precise in determining the magnitude and significance of selection bias. Thus, to thoroughly inspect the issues of publication selection bias, we conduct the precision effect test (PET) and funnel asymmetry test (FAT), which involve the estimation of a bivariate weighted least square (WLS) model (Egger et al., 1997; Stanley, 2008). Equation (4) has been shown to be effective in testing for both FAT (publication selection bias) and PET (genuine effect beyond bias) (Stanley, 2008), and is widely used in the meta-analysis literature.

$$t_{ij} = \alpha_0 + \beta_0\left(\frac{1}{SE_{rij}}\right) + \varepsilon_{ij} \tag{4}$$

Here, t_{ij} is the t-statistic associated with estimate i of study j, and SE_{rij} is the corresponding standard error calculated from (2) above. We test α_0 and β_0 to examine if they are statistically different from zero. The FAT test $\alpha_0 = 0$, and PET tests $\beta_0 = 0$. At conventional levels, there is evidence of publication bias, if α_0 is statistically different from zero, and in that case, α_0 determines the magnitude and the direction of bias. Further, 'genuine' exists if β_0 is statistically different from zero at conventional levels.

Stanley and Doucouliagos (2007) demonstrate that there is a nonlinear relationship between reported estimates and their associated standard errors, given that results from the PET/FAT analysis indicate the co-existence of both genuine effect and selection bias. In such cases, they propose the use of equation (5), a precision effect estimate with standard errors (PEESE) model to estimate a corrected β_0.

$$t_{ij} = \beta_0\left(\frac{1}{SE_{rij}}\right) + \alpha_0\left(SE_{rij}\right) + v_{ij} \tag{5}$$

We estimate the PET-FAT-PEESE models for our entire dataset, and also on the basis of three country types included in primary studies– developed countries, LDCs, and a sample that mixes data for both developed and LDCs (mixed countries).

PET/FAT results are presented in Table 2A. We report estimates for weighted least square (WLS), clustered data analysis (CDA) and multilevel linear (ML) model regressions. The CDA controls for within study dependence, while the ML model (Goldstein, 1995) controls for both within and between study dependence. Thus, the ML is our preferred model. Based on the PET/FAT results presented in Table 2A, we find that for all 243 estimates (the entire sample), there is a negative association between ME and growth with evidence of publication bias. The bias appears to be substantial as the absolute value of the constant term is greater than one in magnitude. This result is robust to controlling for within study dependence (panel 1 column 2) but not both within and between study dependence (panel 1 column 3). For developed countries, we find a positive effect of ME on growth with no evidence of publication bias. This result is robust to controlling for within study dependence, and also both within and within study dependence. For LDCs, we find a negative association between ME and growth with evidence of bias, and this result is robust to controlling for within study dependence but not to both within and between study dependence. Lastly, for the mixed-countries sample, there is evidence of a negative relationship between ME and growth across all estimation types.

Given that there is evidence of publication bias in estimates reported for the entire dataset (WLS and CDA models), LDCs (WLS only), and mixed countries (WLS and ML models), we run PEESE estimates to take into account the nonlinear relationship between the reported PCCs and their standard errors. As shown in Table 2B, the PEESE results are consistent with the PET/FAT results. We find that the negative relationship between ME and growth is maintained though there is evidence of a weaker effect across data samples. For the entire sample, the effect size from the WLS and CDA drops from -0.1109 to -0.0598; for LDCs, the effect size drops from -0.0985 to -0.0428 (WLS model only); and for mixed countries, the effect size from the WLS drops from -0.1283 to -0.1056, and the ML model drops from -0.1328 to -0.0917. Thus, based on Cohen's criterion, the effect of ME on growth for the entire dataset, LDCs, and mixed countries is negative and significant but of no practical significance. This weak relationship is consistent with the findings from the FEEs.

3.4. Multivariate Meta-regression Analysis (MRA)

PET/FAT and PEESE estimates are effective in making inferences about the existence or absence of genuine effect. However, they do not include moderator variables because they assume that moderator variables related to primary study characteristics are equal to their sample means and independent of the standard error. As a result, they do not account for potential sources of heterogeneity. Thus, we conduct a multivariate meta-regression analysis (MRA) to examine if the association between ME and growth is robust to the inclusion of moderator variables, and also to examine the effect of study characteristics on the reported effect-sizes. Exploring the issues of heterogeneity is relevant to understand the variations that exist in the reported empirical findings.

Given that primary studies often report more than one effect size estimate, issues of estimates dependency can emerge (De Dominicis et al., 2008). Thus, we estimate equation (6) assuming study-level fixed-effect (Stanley and Doucouliagos, 2012). We use the multi-level linear model as our preferred model, to account for data dependency and the multi-level structure of our data.

$$t_{ji} = \alpha_0 + \beta_0\left(\frac{1}{SE_{jri}}\right) + \sum \beta_k \frac{(Z_{ki})}{SE_{jri}} + \epsilon_j + u_{ji} \tag{6}$$

Here, t_{ji} is the ith t-value from the jth study and k is the number of regressors or moderator variables. Z_{ki} is a vector of moderator variables that may account for variation in the ME-G relationship evidence base, and ϵ_j is the study-specific error term. Both error terms ϵ_j and u_{ji} are normally distributed around the PCCs' mean values such that $\epsilon_i \sim N(0, SE_{ri}^2)$, where SE_{ri}^2 is the square of the standard errors associated with each of the derived PCC, and $u_i \sim N(0, \tau^2)$, where τ^2 is the estimated between-study variance.

We estimate MRA model (6) with WLS, CDA and ML regressions for the entire sample, and also for all three country types noted earlier. We report results on two estimation types – general and specific. The more general specification includes all relevant dimensions. However, the inclusion of a large number of moderator variables may lead to the issues of multicollinearity and over-determination. Thus, we also estimate a general-to-specific model to reduce model complexity. This process involves the removal of highly insignificant variables (i.e. variables with high p-values) one at a time in order to attain significance for included variables.[7] Unless otherwise indicated, all interpretations presented here refer to the general specification. The general-to-specific results are presented for comparison and this estimation is not performed for all country types due to data limitations.

MRA results are presented in Tables 3A to 3D. The moderator variables used are informed by the empirical and theoretical dimensions of primary studies, as well as other factors that are likely to affect the estimates reported in primary studies. Thus, we introduce three main sets of moderator variables that are likely to affect the ME-G relationship. The first dimension of variables relates to the

[7] See Campos et al. (2005) for a review of the literature on general-to-specific modelling.

characteristics of data included in primary studies. The second relates to the underlying theoretical models and econometric specifications used in primary studies. The third dimension of variables captures publication characteristics. Depending on estimation, specification and sample type, results reported in Tables 3A to 3D suggest that the included moderator variables account for about 54% to 74% of the variations in the reported estimates. Table A1 presents a list and description of the moderator variables included in our MRA.

3.4.1. Data Characteristics

We first consider the effects of the number of observations regressions reported, and also the number of years of data (data period) that are included in the regressions. A-L argue that the variations in the series of ME are reduced in the long-run. Thus, majority of the existing studies prefer to use cross-country data that covers a short period of time. Therefore, it is worthwhile to see if the data period used in primary studies affects the reported estimates. For the entire dataset (Table 3A), we find that across all estimation types of the general model (columns 1, 3, 5), sample size is insignificant. This is also the case for the mixed-countries sample (Table 3D). The data time-period variable is mainly insignificant except for a positive and significant in the CDA. For LDCs, results across all estimation and specification types suggest that the sample size variable is positive and significant. This suggests that studies that consider LDCs and use larger samples tend to report more positive relationships. Based on the results of the general-to-specific model, we also find that the length of data period has a positive effect on the reported estimates for LDCs.

We further examine if the ME-G association is time variant. To do this, we capture the effects of data time periods by including five dummy variables in our MRA: 1950s (D50), 1960s (D60), 1980s (D80), 1990s (D90), and 2000s (D00). Each dummy represents the studies that use data which includes a sample from the year in question. For instance, D50 suggests that primary study includes data from the 1950s. We use 1970s as the base. Our results from all estimation, sample and specification types indicate that the ME-G effect changes over time. For instance, studies that include data from 1950s and 90s tend to report more positively, while those from 2000s report negatively on the ME-G relationship.

In addition, various studies have argued that the ME-G relationship for developed countries, differs from LDCs. We examine this relationship more thoroughly by separating estimates for developed and LDCs. However, it is worthwhile to include a dummy for country type in the entire sample (243 observations) estimation to ensure the inclusion of all relevant dimensions that are likely to affect the reported estimates. Concerning country types, we include a dummy for developed countries and another dummy for studies that report estimates on Africa. Our results across all estimation types report no significant effect for the developed countries dummy. However, the dummy for Africa is negative and significant, suggesting that studies using samples from Africa usually report a negative relationship. These results are consistent across all estimation types (WLS, CDA, ML) and specification types (general and specific).

Similarly, we include dummy variables to capture the type of data used in primary studies (i.e., whether time series, panel or cross-section). The type of data used in determining the ME-G relationship has been discussed in the existing literature as a factor that affects reported estimates. Thus, to examine this, we include dummies for studies that use data on only one country (time series data) and those that use panel datasets in their analysis. Using cross-section data as the reference point, we find that the dummy for panel data is mainly insignificant across all estimation types (Tables 3A, 3B). However, the single-country dummy is negative for the entire sample (Table 3A), but is positive for the developed-countries sample (Table 3C), and insignificant for the LDCs sample (Table 3B). This lends support to the existing discussions that suggest that data type affects the nature of the ME-G relationship.

Lastly, the data on ME used by primary studies comes from different sources. Evidence suggests that the data source could affect the ME-G relationship. For instance, Deger and Smith (1983) find that data from the United States Arms Control and Disarmament Agency (ACDA) gives negative effects of ME on growth, while data from the Stockholm International Peace Research Institute (SIPRI) gives positive effects. Other sources of data used in the literature include International Monetary Fund (IMF) and World Bank. To capture the effect of data source on the reported effect sizes, we include ACDA and SIPRI in our MRA and leave out other data sources as the base. In general, we find that the use of different data sources does not affect the ME-G relationship.

3.4.2. Theoretical Models and Econometric Specification

As discussed earlier, primary studies base their econometric model specification on specific theoretical models. These differences in the underlying theoretical models have been argued to affect the ME-G relationship. Thus, we include dummy variables to capture this dimension. Similar to A-L, we include two variables in our MRA, excluding one as the base. We control for 'growth models', that is, if the study used either an endogenous or a neoclassical growth model. We also introduce a dummy to capture the effect of studies that adopt a simultaneous equation model (SEM) or a Keynesian demand-supply model. We exclude the dummy for studies that use models other than the two described as the base. CDA results for the general specification (Table 3A column 3) indicate that studies that use one form or the other of the growth model report negative effects of ME on growth. This is also the case for the developed-countries sample using ML and WLS estimations (Table 3B).

The first dimension of econometric specification relates to the length of period over which the independent and dependent variables are averaged. Primary studies have presented various arguments to support the length of time over which variables are averaged. Thus, we control for time horizon to verify if the effect of ME on growth is affected by the averaging period. A popular trend in the literature is to use a 5-year averaging of growth. Therefore, we control for studies that use 5-years averaging, using other averaging periods as base. We find that the coefficient of the 5-year average dummy is negative and significant across all sample, estimation and specification types. Thus, quite robustly, our results suggest that the use of 5-year growth averages is associated with a negative ME-G effect. The 5-year growth average may be considered long enough to capture the long-run effect of ME on growth compared to other average time period less than 5-year average. The variations in ME, however, may be greatly reduced for the average time period longer than 5-year average.

Another dimension related to econometric specification that is likely to affect the reported effect sizes is the set of control variables used in primary studies. In fact, it is well known that the inclusion or exclusion of certain control variables in growth regressions can affect the nature of the reported effects. Thus, it is necessary to consider the effect of control variables included in primary studies. For instance, Levine and Renelt (1992) indicate that the key growth determinants include average investment share of GDP, human capital, initial GDP per capita and average growth rate of population. Thus, in our MRA, we include dummies to capture studies that include these variables in their model specifications.

The dummy for human capital is consistently insignificant across sample and estimation types. For the entire sample (Table 3A), the investment dummy is mostly insignificant across estimation types. However, quite robustly, a negative and significant effect is observed for LDCs sample while a positive and significant coefficient is observed for the developed-countries sample. This suggests that studies that use a sample of developed countries with investment as a control variable in the specified model tend to report positive ME-G effect. However, the opposite happens for LDCs. We also find positive and negative effects for the initial GDP and population dummies, respectively. This suggests that investment share of GDP, initial GDP per capita, and population growth rate are important determinants of growth. Thus, the exclusion of such variables from the ME-G model specification may lead to biased results.

Specific to the ME-G literature, we also include a dummy for studies that control for war, and also a nonlinear term of ME. The war dummy is mostly negative and significant across sample, estimation and specification types. This relationship is expected given that in the presence of war, ME increases significantly which in turn affects growth negatively (military burden). The nonlinear effect of ME is generally insignificant but is positive for the mixed-countries sample (Table 3D) in the WLS, CDA and ML.

3.4.3. Publication Characteristics

First, we control for publication type, and examine whether journal articles tend to report different estimates in comparison to working papers. Controlling for publication type makes it possible to determine whether there is a predisposition to publish studies with statistically significant results, congruent with theory to justify model selection. Thus, we include a dummy for journal articles in our MRA, and leave out working papers as base. Overall, our results suggest that the effect of ME on growth is more adverse for journal publications, and this is consistent across all sample, estimation and specification types. In addition, we examine if the ME-G effect reported by primary studies varies with the publication outlet used. Therefore, we control for high-ranked journals to determine if publication outlet used affects reported effect sizes.[8] For the entire sample (Table 3A), our results suggest that the publication outlet used does not affect the ME-G effect. However, when we consider the samples of less developed and developed countries, we find that high-ranked journals tend to report more negatively on the ME-G relationship.

Next, we control for publication year. Controlling for publication year is necessary to verify if reported effect sizes on the ME-G relationship change overtime as more studies emerge to challenge the status quo with newer econometric techniques and richer datasets. Also, given that A-L consist only 32 studies out of 42 studies included in our study, we include a dummy variable to capture newer studies which have not been included in their study. This would enable us to determine the effects of newer studies on the ME-G relationship and also to examine if the inclusion of these new studies contributes to our finding that shows a negative effect of ME on growth. In general, consistent with our expectations, we find that studies not included in the meta-analysis of A-L (PD_08) tend to report negatively on the effects of ME on growth. We also include dummies for studies that were published in the 1970s and 80s (PD7_80), and also in 1990s (PD90) in our MRA. We use other studies which do not fall in any of the three categories as the base. In general, our results indicate that the period of

[8] The Australian Business Dean's Council (ABDC) and the Australian Research Council (ARC) present classifications for journal quality. Journals are ranked in descending order of quality as A*, A, B and C. Thus, we introduce a dummy for A* and A ranked journals (high quality) in our MRA, and use other ranks as base.

publication presents variations in the reported estimates in that more recent studies (PD_08, PD90) report negatively on the ME-G nexus.

Turning to the net effect of ME on growth after controlling for all relevant moderator variables, we find that the coefficient of precision ($1/SE_{ri}$) across all estimations of the specific model is negative and significant. Specifically, using the ML (Table 3A column 6) as our preferred estimation type, we find that the coefficient of precision is -0.067. This is the measure of genuine empirical effect which takes into account the selection bias and moderator variables. Based on Cohen's guidelines, we conclude that this effect is weak and of no practical significance. With regard to developed countries, the preferred ML model (Table 3C column 3) shows that the coefficient of precision is 0.3020. This suggests that for developed countries, the effect of ME on growth is positive. This result is quite robust across all estimation types. For LDCs, CDA model (Table 3B column 4) indicates that the coefficient of precision is -0.3510. This supports the hypothesis that ME is detrimental to growth in LDCs. Lastly, the results from the mixed-countries sample mainly indicate that the coefficient of precision is insignificant.

4. Discussions and Conclusion

Based on 243 estimates drawn from 42 primary studies, we conduct a meta-analysis that examines the following five hypotheses: (H1) Military expenditure (ME) as a proportion of GDP reduces growth, (H2) ME as a proportion of GDP reduces growth in less developed countries (LDCs), (H3) ME as a proportion of GDP increases growth, (H4) The effect of ME as a proportion of GDP on growth is non-linear, and (H5) ME as a proportion of GDP increases growth in developed countries. The following major conclusions emerge.

Using only the sample of 32 studies included in A-L, that is Alptekin and Levine (2012), we confirm their results. However, with the addition of newer studies, mostly with newer datasets, their general conclusion on the military expenditure-growth (ME-G) relationship, which indicates a positive association, is no longer valid. The new conclusion (negative effect of ME on growth) could be as a result of the increasing levels of ME recorded over time. Data shows that global ME has consistently increased since 1998 except for a slight decline (about 0.5%) in 2011. This is also consistent with MRA results, where we find that studies that include data from the 2000s report stronger negative effects of ME on growth. Another possible reason for a negative effect of ME on growth is government corruption. Mauro (1998) finds that corruption may induce more government spending on ME.

The results from fixed effects weighted averages, bivariate precision effect and funnel assymetry tests (PET/FAT), and multivariate meta-regression analysis (MRA) all indicate that the ME-G effect is negative and is estimated to be between -0.0401 and -0.0790 depending on whether publication selection bias and/or moderator variables have been controlled for. Based on these results, it is obvious that (H1) is supported but (H3) is rejected. Although negative, these results are practically negligible according to Cohen's guidelines. However, based on the guidelines recently introduced by Doucouliagos (2011), this effect is not trivial. Doucouliagos (2011) indicates that the application of Cohen's guidelines to partial correlation coefficients understates the economic significance of empirical effect.

Our results also support (H2), that is ME is detrimental to growth in LDCs. This is inconsistent with the findings presented by A-L. Additionally, by considering the coefficient of the precision for LDCs only, both MRA (Table 3B column 4) and PET/FAT results (Table 2A panel 3) show a negative ME-G effect. Thus, quite robustly, we can conclude that ME is detrimental to growth in LDCs.

The negative military effect on growth in LDCs may be due to the following reasons. LDCs in general have lower government quality and more corrupt governments than developed countries (see e.g., La Porta at al., 1999). Rent-seeking in the military sector increases the cost of military activities and together with inefficient operations and high regulatory costs, ME tends to reduce growth in LDCs. Moreover, raising taxes in LDCs may be difficult and thus, higher ME may be financed by higher seigniorage which could lead to higher inflation and thus, lower savings.

LDCs also tend to suffer from political tensions, security threats or economic constraints. Examples of political tensions in LDCs are interstate tensions in the Middle-East, Eastern Europe, South Asia, the East China Sea and the South China Sea. Examples of security threats coming from intrastate conflicts in LDCs include insurgencies, terrorism and other civil conflicts.[9] It is a widely held view that political tensions and associated high levels of ME tend to retard growth.

The opportunity cost of ME may be sufficiently large in insecure regions where as a net effect, high ME may aggravate distortions, reduce the efficiency of resource allocation, and crowd out productive activities such as R&D, and investment in physical and human capital in these regions.[10] Insecure regions tend to devote a disproportionate share of the scarce resources to military which may adversely affect the composition of government expenditure.[11] ME may also worsen the balance of

[9] According to Dahal et al. (2003), all nine countries in South Asia have experienced internal conflict in the last two decades. Moreover, more of the conflicts have been in the poorer regions of those countries than elsewhere since 2001 (Iyer, 2009).

[10] Knight et al. (1996) find that ME reduces growth through crowding-out and distortion effects.

[11] LDCs such as Saudi Arabia and Russia have increased their ME as a proportion of GDP from 8.1% to 9.3% and from 3.5% to 4.1%, respectively, between 2004 and 2013 (IMF, 2013). Devarajan et al. (1996) show that the change in the composition of government spending affects a country's economic growth.

payment for LDCs because most of these countries import military armaments from developed countries (see, e.g., Knight et al., 1996).

MRA and PET/FAT results for the developed-countries sample consistently lend support to the finding of A-L which suggests that (H3) is supported for developed countries. In essence, (H5) is also supported. For our prefered specification, PET/FAT and MRA results show that the coefficient of precision is 0.1564 and 0.3020, respectively. One explanation offered by A-L which supports (H5) is that relative to LDCs, most developed countries record low levels of ME and thus, the benefits outweigh the opportunity cost of ME. However, based on the recent data from World Bank (World Development Indicators), ME as a share of GDP remains lower for LDCs relative to develop countries. Thus, there may be other reasons why ME promotes growth in developed countries.

One possible explanation for (H5) is that developed countries tend to be arms exporters (see the information from the Stockholm International Peace Research Institute, for instance), while LDCs tend to be arms importers. Countries that increase miliatary expenditure tend to face less balance of payment difficulties when they increase military exports at the same time. Arms exporters are more likely to enjoy the "Keynesian effect" whereby increases in ME generates effective demand, leading to growth. Furthermore, considering the high levels of military related R&D in developed countries, the civilian sector is likely to experience positive externalities. It is also possible that ME in developed countries tend to provide security and respect internationally, while ME in LDCs are more likely to increase their dependency on aid and increase political conflict. Additionally, our results do not support (H4) as the dummy for studies that formulate a nonlinear ME-G relationship is insignificant.

With regard to systematic heterogeneity in the ME-G literature, we find that differences in primary studies that contribute to variations in the reported effect sizes include data period, data type, data source, period of data averaging and control variables included in econometric specifications. These results confirm those presented by A-L, and also conclusions drawn by earlier surveys such as Dunne (1996).

Overall, our findings show that meta-analysis is effective in sythesizing evidence when the evidence base is broad and is accompanied by a high level of heterogeneity. This study has derived verifiable conclusions about the effects of miliatary expenditure on growth, and has accounted for about 54% to 74% of the variations in the evidence base. We identify a number of shortcomings which are relevant to guide future research. First, given that our result on the nonlinear effect of ME contradicts that of A-L, it would be useful to futher explore this relationship in future research. Particularly, as our results suggest that higher levels of ME are associaited with lower economic performance, future research can focus on determining a threshold beyond which further increments in ME become detrimental to growth. Additionally, given the hypothesized relationship between corruption and ME (see, e.g., Mauro, 1998), it would be worthwhile for future studies to explore this relationship more thoroughly. As it stands, only few studies control for corruption in their ME-G models.

In conclusion, ME is an important aspect of fiscal policy-growth relationship and has received considerable attention from researchers and policy analysts. Our findings offer a useful policy implication on whether ME is the component of government expenditure to adjust in order to promote growth in a context of limited economic resources and fiscal constraints.

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Table 1
(Overview of Evidence Base per Study - Simple & Fixed Effect Weighted Means)

Paper	No. of Estimates	Simple Mean	Weighted Mean	Significance	Confidence Interval
Aizenman and Glick (2006)	9	-0.1451	-0.1667	Yes	(-0.2998, -0.0335)
Antonakis (1997)	2	-0.4592	-0.4594	Yes	(-0.6228, -0.2960)
Benoit (1978)	3	0.3676	0.3851	No	(-0.0355, 0.8057)
Biswas and Ram (1986)	6	0.1323	0.1949	Yes	(0.0620, 0.3278)
Blomberg (1996)	1	-0.0419	-0.0419		
Bose et al. (2007)	4	0.2509	0.2690	Yes	(0.0528, 0.4852)
Brumm (1997)	2	0.3056	0.3170	No	(-1.2011, 1.8351)
Cappelen et al. (1984)	8	0.0325	0.0276	No	(-0.2427, 0.2978)
Chan (1988)	3	0.0919	0.0926	No	(-0.1219, 0.3070)
Cooray (2009)	5	0.0388	0.0388	Yes	(0.0016, 0.0759)
Deger (1986)	5	0.3275	0.3279	Yes	(0.2960, 0.3599)
Deger and Sen (1983)	1	0.1462	0.1462		
Deger and Smith (1983)	5	0.0089	0.0691	No	(-0.2649, 0.4032)
DeRouen (2000)	1	0.1969	0.1969		
Dunne and Mohammed (1995)	3	0.0295	0.0306	No	(-0.3118, 0.2506)
Dunne and Tian (2013)	27	-0.1188	-0.1183	Yes	(-0.1278, -0.1087)
Faini et al. (1984)	1	0.0601	0.0601		
Galvin (2003)	9	-0.1412	-0.1438	Yes	(-0.2366, -0.0511)
Grobar and Porter (1989)	5	0.2160	0.2517	No	(-0.0692, 0.5727)
Gyimah-Brempong (1989)	2	0.0580	0.0581	No	(-0.2219, 0.3380)
Heo and DeRouen (1998)	5	-0.1307	-0.1356	No	(-0.3011, 0.0300)
Hou and Chen (2013)	6	-0.0824	-0.0829	Yes	(-0.1510, -0.0148)
Kalaitzidakis and Tzouvelekas (2011)	1	0.0720	0.0720		
Kelly (1997)	8	0.0612	0.0610	No	(-0.0240, 0.1460)
Knight et al. (1996)	4	-0.0538	-0.0550	No	(-0.2409, 0.1310)
Kollias et al. (2007)	2	0.1557	0.1567	No	(-0.5586, 0.8720)
Landau (1986)	12	-0.0587	-0.0003	No	(-0.0425, 0.0419)
Landau (1994)	30	0.1894	0.1872	Yes	(0.1567, 0.2177)
Landau (1996)	11	0.2849	0.2860	Yes	(0.1429, 0.4291)
Lebovic and Ishaq (1987)	4	-0.0969	-0.1022	No	(-0.3302, 0.1259)
Lim (1983)	9	-0.0478	0.0647	No	(-0.2296, 0.3591)
Lipow and Antinori (1995)	2	0.2786	0.2991	No	(-1.9812, 2.5793)
Looney (1989)	2	-0.0505	-0.2718	No	(-5.7252, 5.1817)
Looney and McNab (2008)	4	-0.1071	-0.0893	No	(-0.3917, 0.2131)
Miller and Russek (1997)	6	-0.1333	-0.1632	Yes	(-0.2640, -0.0624)
Myo (2013)	5	0.1505	0.2058	Yes	(0.1033, 0.3083)
Na and Bo (2013)	3	-0.4245	-0.4961	No	(-1.1954, 0.2031)
Stroup and Heckelman (2001)	5	0.2416	0.2330	Yes	(0.1239, 0.3421)
Yakovlev (2007)	10	-0.1459	-0.1563	Yes	(-0.2210, -0.0916)
d’Agostino et al. (2010)	2	-0.2110	-0.2112	No	(-0.4511, 0.0286)
d'Agostino et al. (2013)	10	-0.1365	-0.1349	Yes	(-0.1665, -0.1034)
Total	243	0.0164	-0.0401		

Table 2A – PET/FAT Results

	Panel 1 Entire Dataset			Panel 2 Developed Countries			Panel 3 LDCs			Panel 4 Mixed Countries		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	WLS	CDA	ML	WLS	CDA	ML	WLS	CDA	ML	WLS	CDA	ML
Precision (β_0)	-0.1109***	-0.1109**	-0.0264	0.1594**	0.1594**	0.1564**	-0.0985***	-0.0985*	0.0323	-0.1283***	-0.1283***	-0.1328***
	(0.0179)	(0.0430)	(0.0205)	(0.0688)	(0.0460)	(0.0756)	(0.0254)	(0.0567)	(0.0276)	(0.0259)	(0.0301)	(0.0359)
Bias (α_0)	1.2108***	1.2108**	0.3580	-0.1277	-0.1277	-0.5022	1.1474***	1.1474	-0.3161	0.9379**	0.9379	1.8730***
	(0.2595)	(0.5319)	(0.3735)	(0.7157)	(0.8823)	(0.9508)	(0.3398)	(0.6754)	(0.4828)	(0.4593)	(0.6430)	(0.7198)
Observations	243			26			147			70		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2B – PEESE Results

	(1)	(2)	(3)	(4)	(5)
VARIABLES	WLS	CDA	WLS	WLS	ML
Precision (β_0)	-0.0598***	-0.0598*	-0.0428***	-0.1056***	-0.0917***
	(0.0112)	(0.0347)	(0.0154)	(0.0165)	(0.0255)
Standard Error (α_0)	4.1462***	4.1462*	3.2283**	7.2517**	15.0302***
	(1.1999)	(2.0961)	(1.3872)	(3.2662)	(5.3717)
Observations	243		147	70	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3A – MRA for Entire Dataset

VARIABLES	(1) WLS	(2) WLS	(3) CDA	(4) CDA	(5) ML	(6) ML
Precision	0.1557	-0.0790***	0.1557	-0.0790***	0.1505	-0.0607*
	(0.2275)	(0.0221)	(0.1919)	(0.0263)	(0.2017)	(0.0351)
lnObs	0.0109		0.0109		0.0118	
	(0.0226)		(0.0218)		(0.0228)	
lnYear	0.0750		0.0750*		0.0481	
	(0.0620)		(0.0425)		(0.0536)	
Developed Countries	0.0320		0.0320		0.0277	
	(0.0484)		(0.0485)		(0.0501)	
Single Country	-0.2902***	-0.2916***	-0.2902**	-0.2916**	-0.2714*	-0.3019*
	(0.1093)	(0.0681)	(0.1274)	(0.1164)	(0.1542)	(0.1554)
Africa	-0.0509**	-0.0893***	-0.0509*	-0.0893***	-0.0661**	-0.0684***
	(0.0207)	(0.0179)	(0.0277)	(0.0204)	(0.0262)	(0.0231)
Panel Data	-0.0863		-0.0863		-0.0303	
	(0.1216)		(0.0649)		(0.0802)	
Growth Model	-0.0880		-0.0880*		-0.0864	
	(0.0702)		(0.0485)		(0.0647)	
SEM	-0.0175	0.0515	-0.0175	0.0515	0.0276	0.0800*
	(0.0748)	(0.0444)	(0.0627)	(0.0373)	(0.0782)	(0.0481)
SIPRI	0.0260	0.1130***	0.0260	0.1130***	0.0417	0.0831**
	(0.0491)	(0.0225)	(0.0394)	(0.0246)	(0.0505)	(0.0342)
ACDA	-0.0106	-0.0245	-0.0106	-0.0245	-0.0413	-0.0850*
	(0.0991)	(0.0287)	(0.0755)	(0.0433)	(0.0894)	(0.0489)
5-yr Average	-0.0782***	-0.0876***	-0.0782***	-0.0876***	-0.0736***	-0.0657**
	(0.0275)	(0.0218)	(0.0298)	(0.0256)	(0.0285)	(0.0273)
D50	0.1455	0.1956***	0.1455**	0.1956***	0.1833**	0.2484***
	(0.0949)	(0.0551)	(0.0703)	(0.0514)	(0.0904)	(0.0868)
D60	-0.1070		-0.1070**		-0.0325	
	(0.0783)		(0.0518)		(0.0631)	
D80	-0.0157		-0.0157		-0.0381	
	(0.1145)		(0.0905)		(0.1117)	
D90	0.1331***	0.0816***	0.1331***	0.0816***	0.1414***	0.1179***
	(0.0475)	(0.0217)	(0.0400)	(0.0218)	(0.0514)	(0.0306)
D00	-0.1198		-0.1198**		-0.1229*	
	(0.0823)		(0.0531)		(0.0659)	
War	-0.1079*		-0.1079**		-0.0687	
	(0.0629)		(0.0437)		(0.0552)	
Non-Linear	0.0702		0.0702		0.0009	
	(0.1137)		(0.0842)		(0.1078)	
Investment	-0.0974		-0.0974*		-0.0092	
	(0.0775)		(0.0537)		(0.0615)	
Human Capital	0.0008		0.0008		-0.0202	
	(0.0874)		(0.0585)		(0.0704)	
Population	-0.0838***	-0.1472***	-0.0838***	-0.1472***	-0.1626***	-0.1749***
	(0.0246)	(0.0161)	(0.0293)	(0.0180)	(0.0440)	(0.0314)
Initial GDP	0.1731**	0.1323***	0.1731***	0.1323***	0.1864***	0.1137***
	(0.0836)	(0.0216)	(0.0471)	(0.0216)	(0.0584)	(0.0334)
Journal Rank	0.1122		0.1122		0.0610	
	(0.1050)		(0.0753)		(0.0953)	
Journal	-0.2367***		-0.2367***		-0.2586***	
	(0.0857)		(0.0620)		(0.0734)	
PD7_80	-0.1471		-0.1471		-0.0979	

	(0.1280)		(0.0950)		(0.1268)	
PD90	-0.1624		-0.1624*		-0.0878	
	(0.1111)		(0.0878)		(0.1095)	
PD_08	-0.1181*		-0.1181**		-0.1033	
	(0.0626)		(0.0562)		(0.0745)	
Constant	0.0506	0.0233	0.0506	0.0233	-0.0018	-0.1889
	(0.5191)	(0.2451)	(0.5487)	(0.2411)	(0.5707)	(0.3293)
Observations			243			
R-squared	0.6240	0.5357	0.6240	0.5357		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3B – MRA for LDCs

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	WLS	WLS	CDA	CDA	ML	ML
Precision	-0.0482	-0.3510	-0.0482	-0.3510*	-0.0482	-0.0929
	(0.3404)	(0.2629)	(0.2133)	(0.1866)	(0.1982)	(0.2093)
lnObs	0.0612*	0.0793**	0.0612**	0.0793***	0.0612**	0.0492*
	(0.0335)	(0.0358)	(0.0285)	(0.0259)	(0.0265)	(0.0284)
lnYear	0.0291	0.0803***	0.0291	0.0803***	0.0291	0.0718**
	(0.0597)	(0.0187)	(0.0477)	(0.0240)	(0.0443)	(0.0339)
Single Country	0.0241		0.0241		0.0241	
	(0.1435)		(0.1820)		(0.1692)	
Africa	0.0135		0.0135		0.0135	
	(0.0296)		(0.0361)		(0.0336)	
Panel Data	0.0674		0.0674		0.0674	
	(0.0941)		(0.0852)		(0.0792)	
SEM	0.1713***	0.1983***	0.1713***	0.1983***	0.1713***	0.2026***
	(0.0496)	(0.0479)	(0.0528)	(0.0445)	(0.0491)	(0.0578)
SIPRI	-0.0348		-0.0348		-0.0348	
	(0.1209)		(0.0571)		(0.0531)	
5-yr Average	-0.0601***	-0.0794***	-0.0601*	-0.0794***	-0.0601**	-0.0622**
	(0.0180)	(0.0205)	(0.0321)	(0.0286)	(0.0298)	(0.0280)
D50	0.2414	0.2864***	0.2414*	0.2864***	0.2414*	0.3064***
	(0.2692)	(0.1005)	(0.1373)	(0.0839)	(0.1276)	(0.1180)
D80	-0.0333		-0.0333		-0.0333	
	(0.1321)		(0.0840)		(0.0781)	
D90	0.1836		0.1836**		0.1836**	
	(0.2679)		(0.0922)		(0.0857)	
War	-0.3097***	-0.1722***	-0.3097***	-0.1722***	-0.3097***	-0.1914***
	(0.1135)	(0.0339)	(0.0662)	(0.0305)	(0.0615)	(0.0451)
Investment	-0.1211		-0.1211**		-0.1211**	
	(0.0849)		(0.0602)		(0.0560)	
Population	-0.0274	-0.0658***	-0.0274	-0.0658**	-0.0274	-0.0962**
	(0.0212)	(0.0183)	(0.0311)	(0.0260)	(0.0289)	(0.0427)
Journal Rank	-0.3446	-0.2754***	-0.3446**	-0.2754***	-0.3446***	-0.2552***
	(0.2226)	(0.0483)	(0.1392)	(0.0557)	(0.1294)	(0.0784)
PD7_80	0.1660		0.1660		0.1660	
	(0.3033)		(0.1730)		(0.1608)	
PD90	-0.2229	-0.2086***	-0.2229	-0.2086***	-0.2229	-0.2392***
	(0.1426)	(0.0514)	(0.1483)	(0.0578)	(0.1379)	(0.0797)
PD_08	-0.4496**	-0.3373***	-0.4496***	-0.3373***	-0.4496***	-0.3355***

	(0.1882)	(0.0451)	(0.1321)	(0.0590)	(0.1228)	(0.0829)
Constant	0.1625	0.8270	0.1625	0.8270	0.1625	-0.0316
	(0.7266)	(0.7128)	(0.6171)	(0.5729)	(0.5735)	(0.6551)
Observations			147			
R-squared	0.6479	0.6029	0.6479	0.6029		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3C – MRA for Developed-Countries Sample

	(1)	(2)	(3)
VARIABLES	WLS	CDA	ML
Precision	0.3020**	0.3020*	0.3020**
	(0.1262)	(0.1734)	(0.1442)
Single Country	0.4114***	0.4114	0.4114*
	(0.0992)	(0.2919)	(0.2428)
Growth Model	-0.2283**	-0.2283	-0.2283**
	(0.0993)	(0.1371)	(0.1141)
SIPRI	-0.1419	-0.1419	-0.1419
	(0.1037)	(0.1270)	(0.1057)
War	-0.7963***	-0.7963**	-0.7963***
	(0.0985)	(0.3438)	(0.2860)
Investment	0.4850***	0.4850**	0.4850***
	(0.1189)	(0.1933)	(0.1608)
Journal Rank	-0.3527***	-0.3527	-0.3527*
	(0.0670)	(0.2192)	(0.1824)
Constant	-0.1286	-0.1286	-0.1286
	(0.7947)	(1.3123)	(1.0919)
Observations		26	
R-squared	0.6543	0.6543	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

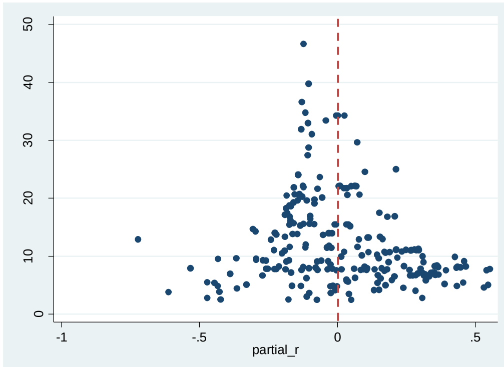
Table 3D – MRA for Mixed-Countries Sample

VARIABLES	(1) WLS	(2) CDA	(3) ML
Precision	0.1971	0.1971	0.1971
	(0.6271)	(0.6002)	(0.5173)
lnObs	0.0346	0.0346	0.0346
	(0.0295)	(0.0390)	(0.0336)
lnYear	-0.4465**	-0.4465**	-0.4465***
	(0.1837)	(0.2010)	(0.1733)
Panel Data	-0.1925***	-0.1925***	-0.1925***
	(0.2927)	(0.3245)	(0.2797)
Growth Model	0.5565**	0.5565***	0.5565***
	(0.2119)	(0.1983)	(0.1709)
SIPRI	0.5248**	0.5248**	0.5248**
	(0.2080)	(0.2490)	(0.2146)
5-yr Average	-0.9838***	-0.9838***	-0.9838***
	(0.2720)	(0.2640)	(0.2275)
D70	0.4609	0.4609	0.4609
	(0.3041)	(0.3255)	(0.2806)
D80	0.2134***	0.2134***	0.2134***
	(0.2591)	(0.2472)	(0.2131)
D90	0.4406**	0.4406*	0.4406**
	(0.2030)	(0.2460)	(0.2121)
War	0.5593**	0.5593***	0.5593***
	(0.2103)	(0.1971)	(0.1699)
Non-linear	0.3779**	0.3779**	0.3779**
	(0.1636)	(0.1846)	(0.1591)
Human Capital	-0.1317	-0.1317	-0.1317
	(0.1785)	(0.1395)	(0.1202)
Population	-0.4275**	-0.4275**	-0.4275**
	(0.1799)	(0.2087)	(0.1799)
Journal Rank	-0.0418***	-0.0418***	-0.0418***
	(0.3455)	(0.3877)	(0.3342)
Journal	0.8048***	0.8048**	0.8048***
	(0.2977)	(0.3155)	(0.2719)
PD_08	0.2964**	0.2964***	0.2964***
	(0.1152)	(0.1093)	(0.0942)
Constant	2.8762*	2.8762	2.8762*
	(1.6488)	(1.7265)	(1.4880)
Observations		70	
R-squared	0.7449	0.7449	

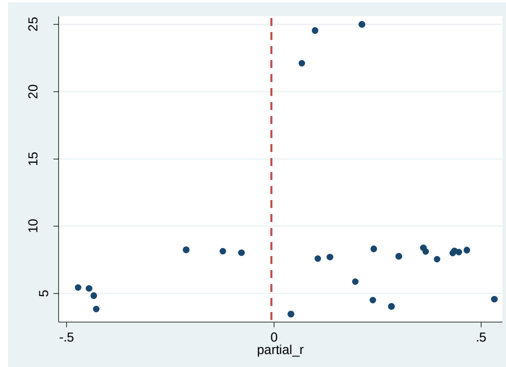
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figures 1 - 4

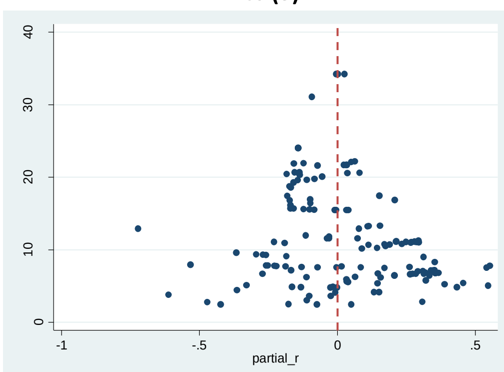
Entire Dataset (1)



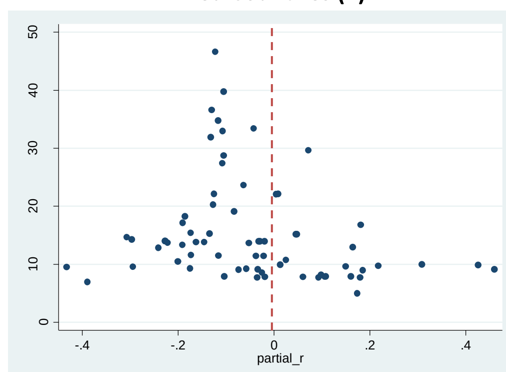
Developed Countries (2)



LDCs (3)



Mixed Countries (4)



Appendix Table A1 (MRA Variables)

Variables	Definition
lnObs	Natural logarithm of number of observation in PS
lnYear	Natural logarithm of number of years in PS
Developed Countries	1 if the PS data is for developed countries, otherwise 0
Single Country Study	1 if a single time series analysis of a country is done, otherwise 0
Africa	1 if only African countries data is used, otherwise 0
Panel Data	1 if panel data is used in PS, otherwise 0.
Growth Model	1 if the model is based on growth model, otherwise 0.
SEM	1 if estimation method is simultaneous equations approach, otherwise 0
SIPRI	1 if data used in PS comes from SIPRI, otherwise 0
ACDA	1 if data used in PS comes from ACDA, otherwise 0
5-yr Average	1 if PS uses 5-year data averaging, otherwise 0
D50	1 if PS includes data from 1950s, otherwise 0
D60	1 if PS includes data from 1960s, otherwise 0
D80	1 if PS includes data from 1980s, otherwise 0
D90	1 if PS includes data from 1990s, otherwise 0
D00	1 if PS includes data from 2000s, otherwise 0
War	1 if PS control for instability or war, otherwise 0
Non-Linear	1 if PS control for non-linear, otherwise 0
Investment	1 if PS control for investment, otherwise 0
Human Capital	1 if PS control for human capital, otherwise 0
Population	1 if PS control for population, otherwise 0
Initial GDP	1 if PS control for initial GDP, otherwise 0
Journal Rank	1 if PS is published in high-ranked journal, otherwise 0
Journal	1 if PS is a journal paper, otherwise 0
PD7_80	1 if PS is published in the 1970s or 80s, otherwise 0
PD90	1 if PS is published in the 1990s, otherwise 0
PD_08	1 if PS is not included in Alptekin and Levine (2012), otherwise 0

*All variables are divided by SE_{ri}

* PS refers to primary study