Does government spending affect income inequality? A meta-regression analysis

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Abstract

In this paper findings of a meta-regression analysis are presented exploring the effects of government spending on income inequality, with a particular focus on low and middle income countries. We find evidence that government spending can have a negative impact on income inequality, but only when considering certain types of spending. For the case of total government spending we find evidence of a moderate positive relationship with income inequality. However, when considering more disaggregated types of spending such as government social spending and government consumption spending we find evidence of a moderate negative relationship with income inequality. However, both the size and direction of the estimated relationship between government spending and income inequality is affected by a range of other factors, including the measure of inequality used, the control variables used, and the estimation method. We also find consistent evidence of publication bias, in that negative estimates of the relationship appear to be under-reported in the literature.

Keywords: Income inequality, Government Spending, Meta-regression

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http://r4d.dfid.gov.uk/pdf/outputs/SystematicReviews/Income_inequality_2014_Anderson_protocol.pdf; the full report is forthcoming. We are grateful for excellent research assistance in the literature search and screening process from Ines Afonso Roque Ferreira, Anthony Amoah, Victoria Zevallos Porles, and Paramita Muljono. We declare that we have no conflict of interest.

1. Introduction

The issue of inequality has been a key issue in international development for several decades now. Since the 1970s, a large literature has emerged which documents the many adverse effects of inequality on socio-economic outcomes, including investment and economic growth, poverty, health and well-being, crime, conflict and social cohesion – see for example Easterlin (1974), Williams (1984), Alesina and Perotti (1996), Ravallion (1997), Barber (2001), Luttmer (2005), Eibner and William (2005), Veenstra (2005), Subramanian and Kakawi (2006), Clark et al (2008), Gravelle and Sutton (2009), Wilkinson and Pickett (2009), Stiglitz (2013) and Ostry et al (2014). In addition, all societies share a basic, intrinsic concern for equity and justice, and high levels of inequality often conflict with those notions – as for example when life chances or opportunities differ significantly between groups defined by gender, inherited wealth, ethnicity or other accidents of birth (World Bank 2005).

Widespread concern about the adverse impacts of income inequality has generated significant interest in the question of what governments can to reduce inequality. The sorts of government policies which can affect income inequality are recognised to be broad, including fiscal policy, trade policy, minimum wages, interest rate controls, land reform, anti-discrimination legislation, affirmative action, and so on. Nevertheless, choices with regard to the level and composition of government spending are clearly one important way of addressing income inequality, and a large body of literature has emerged which investigates the effects of government spending on income inequality, much of it using cross-country econometrics.

In this paper we present the findings of a meta-regression analysis exploring the effects of government spending on income inequality, with a focus on low and middle income countries. We examine the results from the econometric literature, and identify a total of 87 separate studies containing over 900 estimates of the effect of one or more measures of spending on one or more measures of income inequality. We follow the MAER-Net reporting guidelines (Stanley et al, 2013:393) and adopt the following structure. The next section provides a review of the literature summarising the key evidence relating to the effects of government spending on income inequality in low and middle income countries. Section 3 outlines the search strategy and inclusion criteria; section 4 presents and discusses the meta-regression approach as well as findings. Section 5 concludes this paper.

2. Literature Review

There is much evidence to suggest that at least some types of government spending have tended to lower income inequality in many countries and regions of the world (e.g. Goni et al 2011; Lustig 2011, 2015; Lustig et al 2013; Martinez Vazquez et al 2012). However, it is also recognised that the relationship between government spending and inequality is complex, and many doubts have been raised about the effectiveness of government spending as a redistributive policy instrument, particularly in low and middle income countries.

For example, it is often argued that government spending on social transfers tends to reduce income inequality, However, the size of the effect can vary substantially, depending on the extent to which transfers are targeted on lower income groups; if most spending on transfers are captured by the middle class, for political economy reasons, the impact on inequality may be quite small (Milanovic 1994). The same applies to spending on indirect subsidies, which makes up a significant share of total government spending in many developing countries, but which often disproportionately benefits higher income groups (Rhee et al 2014). It has also been argued that government spending on health and education reduces income inequality, by producing a more equal distribution of human capital. However, the size of the effect again depends on how well such spending is targeted; there is evidence that much of the benefits of government health and education spending in developing countries are received by middle-income groups in urban areas (Tanzi 1974, Alesina 1998, Davoodi et al 2003).

One key issue in assessing the effects of government spending on income inequality is the distinction between short-run 'first-round' effects and longer-term 'second-round' effects (Chu et al 2000). For example, the immediate first-round effect of government transfers to lower income households will be to reduce inequality in household *disposable* ('post-fiscal') income, since transfers are included in the definition of disposable income. Over time however, government transfers can also have second-round effects on inequality in household *market* ('pre-fiscal') income, which may either reinforce or offset the first-round effects. The overall effects of government spending may differ therefore, depending on how income is measured (post-fiscal or pre-fiscal), and on the time period being considered. Some government spending, for example on primary education, may affect income inequality only after a fairly long time lag (ibid).

In addition, both spending and the financing of spending can affect income inequality, and the two effects could in theory either reinforce or counteract each other. It is often argued that the redistributive effect of taxation in developing countries has been limited, due for example to greater reliance on indirect taxes or widespread evasion of direct taxes (e.g. Tanzi 1974, Bird and Zolt 2005, Chu et al 2000, Goni et al 2011, Mahon 2012, Claus et al 2012). Nevertheless, there is evidence that higher inflation raises income inequality (e.g. Bulif 1998, Easterly and Fischer 1998), which could offset any redistributive impact of government spending, if spending is financed via monetary expansion. Thus the estimated effects of government spending may also differ depending on whether we are referring to the 'overall' effect of spending, including the way in which it is financed, or the 'pure' effect of spending, controlling for the way in which it is financed.

Another important issue is reverse causality. It has been argued that countries with higher levels of inequality in market income tend to engage in more redistributive activity (Meltzer and Richard 1981, Alesina and Rodrik 1994, Persson and Tabellini 1994). The idea is that when market incomes are unequal, governments face political pressures to redistribute income. In a democratic system for example, a larger share of the population will stand to gain from income taxes and transfers, and a political majority emerges in favour of redistribution. Even in a non-democratic system, similar effects may operate, e.g. through popular mass protest in support of redistributive political movements.[1] Thus the direction of causality between government spending and income inequality

[1] Some evidence in support of this argument has been found by Milanovic (2000) and Ostry et al (2014), although it has been challenged by other authors (e.g. Perotti 1996, Benabou 2000, de Mello and Tiongson 2006), who argue that governments in countries where inequality is high tend to redistribute less, because political power is firmly in control of higher income groups, who are able to resist any redistributive measures.

can run in both directions, and unless controlled for in some way, this could result in biased estimates of the causal impact of government spending on income inequality.

Despite widespread interest in the effects of government spending on income inequality, the results from the econometric literature appear so far to be inconclusive.[2] One widely cited study (Dollar and Kraay 2002) using a large cross-country dataset found no evidence of a statistically significant relationship between government spending on health and education and the share of the poorest 20 percent of households in national income, which is one common measure of income inequality. A recent update of this study, by Dollar et al (2013), found similar results. However, other recent studies have found evidence that certain types of government spending on social welfare, education and health does have a negative and statistically significant effect on income inequality (e.g. Martinez Vazquez et al 2012, Claus et al 2012).

There does therefore appear to be a role for meta-regression analysis in terms of synthesising these apparently conflicting research findings from the econometric literature, and in explaining why estimates of the effect of government spending on income inequality do tend to vary. There has to our knowledge been only one *systematic* review of the evidence on the determinants of income inequality. This is the study by Abdullah et al (2013), which compares the results of 64 mainly cross-country econometric studies looking at the effects of education on income inequality.[3] Their analysis showed that indicators of education do on average have a negative effect on income inequality, and that the heterogeneity of results can be explained – via meta-regression analysis – by a combination of differences in econometric specification, and differences in measures of inequality and education.

3. Search Strategy and Inclusion Criteria

Search strategy[4]

In order to select appropriate databases for this review we followed the Campbell Collaboration guide on key online databases for systematic reviews in International Development (Campbell Collaboration 2012). This list was complemented with additional databases and websites used by other systematic reviews on questions relevant to this review. We also reviewed relevant institutional websites of key institutions and conference proceedings. Each database was searched using a combination of the search terms indicated in Table 1. This shows three sets of concepts (A, B and C), each of them containing a list of associated terms or synonyms that were used in our search. When using foreign language databases, each of the terms was translated into the appropriate

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[2] Note that evidence on the effects of government spending on income inequality is not restricted to econometric evidence; a large body of evidence also comes from fiscal incidence analysis (e.g. Goni et al 2011; Lustig 2011, 2015). In this paper however we are concerned only with synthesising results from the econometric literature.

[3] There have, by contrast, been a number of systematic reviews of the evidence on the determinants of economic growth, including Doucouliagos and Paldam (2008, 2009, 2014) on the effects of foreign aid, and Josheski (2011) on the effects of infrastructure investment.

[4] We should note that the search strategy outlined in this section was developed for the wider systematic review that was commissioned and funded by DFID (see footnote 2), which looked at all types of government policies and their link to income inequality. The focus was therefore on a broader range of policy interventions, not just government spending.

language, i.e., Portuguese or Spanish. Due to the fact that some search engines only allow a limited number of operators, two search query strings were used: a long version and a short version. The long version follows the equation:

A + (B W/n C)

Thus the terms within columns A, B or C in Table 1 were combined with 'OR'; columns B and C were combined with the proximity operator *W/n*, where *n* is the number of words that separate the terms from two columns; and column A was combined with the combination of B and C using the *AND* command.[5]

Table 1. Key terms for search strategy

A Policy	B Income	C Inequality
Polic* Intervention* Program* Instrument* Tool* Reform* Legislation* Govern*	Income* Expenditure*	*Equal* *Distribut* Disparit* Differen* Gap* *Equit* Share* Ratio* Gini

Notes: * is included as a truncation symbol to capture automatically conjugated forms of each word; thus *equal* captures "inequality" as well as "inequalities"; *distribut* captures "distribution" as well as "redistribution".

In addition to these electronic searches, we carried out some additional searches using hand-searching.

Inclusion Criteria

Our inclusion criteria follow standard procedures commonly used in the systematic review context. The studies included in our meta-regression satisfy the following criteria:

<u>Types of participants (population)</u>

The review is restricted to studies of low income countries (LICs) and middle income countries (MICs) at the time of the government intervention; studies which focus only on high income countries are excluded. The World Bank definitions of LICs and MICs are used in applying this criterion. Note however that many studies include countries from all income groups (low, middle and high) in the analysis; we include such studies, on the grounds that they typically contain a significant proportion of low and/or middle income countries. However, we exclude studies which focus predominantly on high income countries.

[5] Our strategy is to use n=1 to capture concepts such as 'distribution of income', 'inequality of income', as well as 'income distribution' and 'income inequality'.

Types of interventions

We require that the regression analysis includes one or more measure of government spending: examples include government spending on health, education, or social welfare, as a share of GDP.

Types of comparison groups

The control or comparison group for assessing the impact of government spending is constructed using an ex-post observational approach. The vast majority of studies involve comparisons of inequality across countries and over time, using panel data, although there are also some single-county studies using time series analysis. The analysis is restricted to studies focusing on income inequality at the national level.

Types of outcome measures

We include studies that focus on inequality in a comprehensive measure of income that includes income from all sources (e.g. wages and salaries, business profits, investment earnings, rental income, transfers. We also require that data on income or expenditure be drawn from a representative household survey covering all of the relevant population. We include studies that focus on market (pre-fiscal) or disposable (post-fiscal) income. We also include studies which focus on inequality in total consumption expenditure, since the latter is often considered to be a more reliable indicator when data on income are difficult to collect. Inequality may be measured using either a global or partial measure of inequality (e.g. the Gini coefficient, or the share of the poorest quintile in national income), measured across households or individuals.

Study designs

We include studies that use econometric analysis to estimate the effects of government policies on income inequality. They involve estimating a regression in which a measure of income inequality is the dependent variable and the explanatory variables include a measure of government spending. This can be written in general terms as:

$$I_{it} = \beta_0 + \beta_j X_{it} + \beta_k Z_{itk} + \varepsilon_{it}$$

where *I* is a valid measure of income inequality, *X* is a measure of government spending, *Z* is a vector of other explanatory variables, and ε is the error term, with subscripts *i* and *t* indicating country (or region within a country) and year respectively. Note that one exception occurs in the case of an approach first used by Dollar and Kraay (2002), and adopted since then by other researchers (e.g. Dollar et al 2013). This involves a regression of the average income of the poorest quintile(s) on the average per capita income for the population as a whole, as well as a measure of government spending and other explanatory variables. Although the dependent variable in this case is not a valid measure of inequality, the coefficients obtained from this type of regression are identical to those obtained from the above equation when the dependent variable is the share of the poorest quintile(s) in national income, which is a valid measure of inequality. Studies using this type of approach are therefore included in the review.

Publication status

We include published and unpublished studies, including refereed and non-refereed journal articles, working papers, conference proceedings, book chapters, government reports, NGO reports and other technical reports.

Timeframe

We restrict the review to studies published since 1990. This is mainly on the grounds that reliable, cross-country data on income inequality have only been available since the early 1990s, so that any studies before this date would not meet basic requirements in terms of data quality.

Language

We include studies published in English, Portuguese, and Spanish.

4. Meta-regression approach

We carry out a meta-regression analysis for government spending variables and their effect on inequality and follow the MAER-NET guidelines to report our findings (see Stanley et al, 2013:393). Our approach also follows Abdullah et al (2013) who examined the impact of education on income inequality using a meta-regression approach. Some of the studies that meet our inclusion criteria do not report sufficient information allowing us to calculate our chosen effect size measure (the partial correlation coefficient). Before presenting the meta-regression findings however, we first discuss the results of our risk of bias assessment, our effect size measure, our initial tests for publication bias, and our overall modelling approach.

Risk of bias assessment

We adapted the risk of bias tool developed by Duvendack et al (2011 and 2012) for the purpose of our risk of bias assessment. We began by categorising each study by its proclaimed research design and analytical method. Following Duvendack et al (2011 and 2012), each study was scored depending on its design and analytical approach. In a next step each of these scores was combined in an index. An arbitrary threshold of 2 was applied, i.e. a study with a score of equal or less than 2 was classified as low risk of bias while a study with a score above 2 was classified as medium risk of bias (Duvendack et al, 2011, 2012 and 2014).

The studies included in our analysis can be split into two dominant analytical approaches: 1) panel data techniques and 2) regression-based techniques; which formed the basis for adapting the risk of bias tool of Duvendack et al (2011 and 2012). Table 2 presents the results of our risk of bias assessment. Included studies are ranked by research design and analytical method using scores 1 – 3, where 1 implies low risk of bias and 3 high risk of bias.

Table 2. Distribution of studies by research design and analytical method

		Statistical Methods of Analysis		
		Panel data analysis (GMM, fixed and random effects), IV,PSM,2SLS/LIML,DID, RD	Regression-based approaches/OLS/ error correction models	Others (correlations)
Research Design	**Scores**	1	2	3
RCT	1	0	0	0
Pipeline	2	0	0	0
Panel (cross-country/time-series)	3	83	38	0

Legend	Low score	83	Medium score	38

Source: Duvendack et al (2011 & 2014, 2012 for an adaptation).

We are aware that the Duvendack et al tool is subjective (see Duvendack et al 2014, footnote 7 for an explanation) and the cut-off figures are arbitrary but at least an indication is given how well studies deal with risk of bias issues. We explored alternative risk of bias tools, for example, many Campbell Collaboration systematic reviews now use adaptations of the ICDG risk of bias tool (see for example Baird et al., 2013). However, the ICDG tool was developed with micro-econometric studies in mind (as was the Duvendack tool) and is a checklist approach which requires expert knowledge as well as a high degree of in depth information from the included studies. We felt that the implementation of the ICDG tool in our particular context will be as problematic as the tool we opted for.

Effect sizes

All regression-based estimates were converted into a comparable measure, the partial correlation coefficient which was the best choice given our particular context. The partial correlation measures the strength of association between income inequality and government spending, holding all other factors constant. It is calculated as follow:

$$r = \frac{t}{\sqrt{t^2 + df}}$$

where t is the t-statistic of the regression coefficient and df is the degrees of freedom from the t-statistic (Stanley and Doucouliagos, 2012).[6] If the t-statistic was not reported we calculated it by dividing the regression coefficient by its standard error. We had a few studies that did not report

[6] The t-statistic was multiplied by -1 when the variable referred to the income share of the poorest/bottom or the average income of the poor. This is because a rise in this income share means a fall in income inequality.

the t-statistic or the standard error but we had the exact p-value and the degrees of freedom. In these cases we used the TINV function in Excel which allowed us to calculate the t-statistic using the p-values as well as the degrees of freedom (see Stanley and Doucouliagos, 2012, footnote 45). In some cases we did not even have the exact p-value and only the levels of statistical significance were given such as * (for 10%), ** (for 5%) and *** (for 1%). Stanley and Doucouliagos (2012) argue that in such cases the analyst will have to decide whether or not the estimates should be included. We decided to include them and followed the simplest approach Stanley and Doucouliagos (2012:31) suggested, namely to assume that the p-value is 0.01 if the significance level is given as ***, 0.05 if the significance level is given as ** and so on. We then used these p-values as well as the degrees of freedom to calculate the t-statistic using the TINV function in Excel again. We excluded any study that did not report any of the above statistics and therefore did not enable us to calculate the partial correlation coefficient.

We should note that a number of effect size measures exist in the meta-analytical context such as standardised mean differences, odds and risk ratios as well as partial correlation coefficients. We narrowed down the list of possible effect size calculations closely looking at the data reported in the studies we included in our meta-regression approach. The vast majority of the included studies reported regression coefficients, t-statistics and standard errors. Hence, we chose the partial correlation coefficient as it can be calculated easily from regression output requiring only limited information. It is a unitless measure allowing comparisons within and between studies as well as comparisons involving variables using different scales such as Gini coefficients and income shares (Stanley and Doucouliagos, 2012; Abdullah et al, 2013). It is often argued that the partial correlation coefficient should be converted into Fisher's z scale as the partial correlation coefficient is truncated at -1 and +1 which can cause problems. These problems can be overcome by running the meta-regression on the Fisher's z transformations, though Hunter and Schmidt (2004) cast doubts about using this transformation. Despite these doubts we used the command corrci in STATA to transform our partial correlation coefficients to Fisher's z scale but this made little difference to our results which is not surprising if one follows the arguments set out by (Stanley and Doucouliagos, 2012) and Abdullah et al (2013).

Table 3 provides an overall description of the sample of included studies as well as the distribution of their results. For the government spending variables, we were able to extract 987 estimates of the partial correlation coefficient, from 87 studies. Of these, 521 recorded positive partial correlations between a government spending variable and income inequality, with 243 of these being statistically significant. On the other hand, 466 of the estimates recorded negative partial correlations with 180 of these being statistically significant.

Table 3. Description of the sample

	Government spending
Number of studies	87
Number of estimates	987
Distribution of results	
Positive	521
Of which statistically significant	*243*
Negative	466
Of which statistically significant	*180*
Total	987

Publication bias

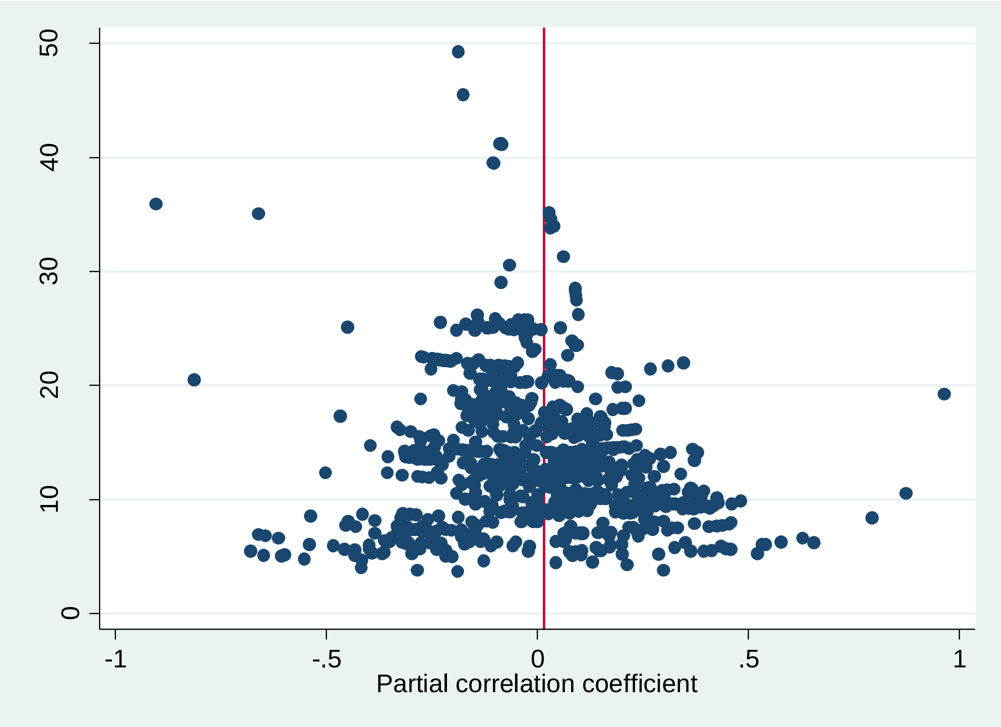
Publication bias is a serious issue in particular in the context of systematic reviews as it can introduce serious biases in the meta-analytical results. It is argued that studies reporting statistically significant findings are more likely to be published in peer-reviewed journals than studies reporting statistically non-significant findings. This bias in the literature will then also be reflected in the meta-analysis as published studies are more likely to be included in a meta-analysis (Borenstein et al 2009).

The funnel plot is one of the most common methods to illustrate the presence of publication bias (see for example Egger et al 1997). Figure 1 illustrates a funnel plot which plots the effect size on the x-axis, here the partial correlation coefficient between measures of government spending and income inequality, and precision (or the inverse of the standard error of the partial correlation coefficient) on the y axis. At the bottom of the graph we find the estimates with less precision, i.e. with the larger standard errors, while the estimates with more precision, i.e. smaller standard errors, are more towards the top of the funnel plot. There is no publication bias present when the studies are distributed symmetrically. In this case a visual inspection of the funnel plot suggests symmetry as both positive and negative estimates are evenly distributed around the mean value of the partial correlation coefficient (0.016), indicated by the solid vertical line.

Note that Figure 1 indicates the presence of outliers, particularly in the upper left corner. These estimates were double checked to ensure they had been correctly reported and coded. In Appendix Figure A1 we present the funnel plot removing the main outliers, but we cannot observe any substantial differences between the funnel plots with and without outliers.

However, visual inspections of this nature can be subjective (Borenstein et al, 2009; Abdullah et al, 2013) and thus Stanley (2005, 2008) suggests the use of the FAT-PET (Funnel-Asymmetry Precision-Effect) regression as an empirical test to check more reliably for any publication bias. We carry out this test as part of our meta-regression analysis.

Figure 1. Funnel Plot, Partial Correlations of Government Spending and Income Inequality (n=987)



Note: Precision is calculated as 1/standard error of the partial correlation coefficient. The weighted mean of the partial correlation coefficient is marked with a red line with the value of 0.016 (s.e. = 0.005).

Modeling heterogeneity

We mentioned above that we suspect that a certain degree of heterogeneity remains in the studies we included in this synthesis. This view is confirmed by the funnel plot we presented in Figure 1 as the reported estimates are rather spread out. To better understand what drives this heterogeneity we follow Abdullah et al (2013) and adopt the following meta-regression model to explore heterogeneity in the reported estimates:

$$r_{ij} = \beta_1 + \sum \beta_k Z_{ki} + \beta_0 SE_{ij} + \varepsilon_{ij}$$

where *r* is the partial correlation coefficient expressing the link between a measure of government spending and income inequality, of the *i*th estimate from the *j*th study. **Z** is a vector of variables that capture differences in the effect between the policy variable and income inequality. *SE* is the standard error of the partial correlation coefficient and ε_{ij} is the error term. The standard error of the partial correlation coefficient is calculated as follows:[7]

$$SE = \frac{r}{t}$$

The following variables are included in the **Z** vector (see Table 4):

[7] Note that the standard error of the partial correlation coefficient if different from the standard error of the individual regression coefficients.

Measures of the dependent variable: Our variable of interest is income inequality. We included any study that used a recognized measure of income inequality. While most of the estimates use the Gini coefficient, a substantial proportion use income shares or other measures of inequality.

Measures of government spending: Government spending was coded into 10 different categories: total, health, education, health & education, social safety net, military, housing, social general, consumption spending and others (see Table 4).[8] Our meta-regression model aims to test the differential impact of these different types of government spending measures on the reported results.

Country composition: The main geographical areas covered include Sub-Saharan Africa, Latin America and South Asia. Although our main focus is on low and middle income countries, over half of the estimates include data from high income countries.

Data: Most estimates use a non-OLS method, e.g. dynamic panel estimators such as generalised method of moments (GMM), more traditional panel data analysis using random and/or fixed effects, other econometric approaches such as instrumental variables, 2 or 3-stage least squares, propensity score matching, differences-in-differences or similar. The average year of the data used was included to account for different time periods and spans, as the relationship between government spending or taxation and income inequality may vary over time. However it was transformed as follows: Yr= Year data- average year data (1987).

Other explanatory variables: Most studies include a range of explanatory variables in their regressions. In our MRA we include variables corresponding to whether any of the six broad control variables were included: trade, tax, inflation, governance, education and population. The variables are coded 1 if they are included in the regressions as explanatory variables and 0 if otherwise. These specific variables were chosen after careful reviewing all included studies and counting the variables that appear more frequently. The trade category incorporates all variables that were considered valid policy variables like import tariffs, export duties, non-tariff barriers and trade policy indices. Tax includes all tax-related variables in particular tax revenue, direct and indirect taxes and other measures of tax progressivity. The governance category was included to reflect all democracy and institutional aspects as proxied by voice and accountability, corruption, etc. Education variables include years of education and schooling-related variables like educational attainment, enrolment rates or human capital. Population and inflation appeared frequently in the specifications and it was decided to include them as well.

Publication: The standard error of the partial correlation coefficient is included to account for publication bias. We also account for the differences between published and unpublished studies.

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[8]Social safety net includes components such as pensions, social security, social protection, welfare spending. Coefficients fall into the social general category when disaggregation into subgroups such as (health, education, housing) was not provided in the study. Total government spending is used if the study refers to "total government spending", or just "government spending" or "government size". Government consumption is used if the study refers specifically to government "consumption" expenditure. If the study refers to categories of government spending not covered by the other codes, (e.g. government investment spending or wage bill) it was coded under government spending others.

More detailed descriptive information for each variable, including their mean values and standard deviations, is reported in Appendix Table A2.

We should note that we decided to run our meta-regression analysis with and without the outliers. The results including outliers are presented in the main text, while the findings excluding outliers are presented in Appendix Table A3. It is not clear which of these findings should be preferred, comparing the results of the regressions with and without outliers we typically only observe very small differences. Where the results do differ we comment further below on the few cases in which they do differ.

Estimations are carried out using a regression procedure with a weighted least squares (WLS) routine that Stanley and Doucouliagos (2013 and 2015) advocate in a recent set of papers. They demonstrate how an unrestricted WLS-MRA is likely to be as good as and often better than both random-effects and fixed-effect meta-analysis and meta-regression analysis in practical applications (using the command metareg in STATA). The majority of the studies we included reported more than one result that could be used to calculate the partial correlation coefficient, none of the studies specified a preferred result, and thus we were faced with multiple dependent estimates per study. This needs to be dealt with appropriately to avoid bias due to data dependency (Lipsey and Wilson, 2001: 105, 125). The literature suggests a number of approaches to dealing with multiples estimates per study (see for example Lipsey and Wilson, 2001; Borenstein et al, 2009:230) and there is no consensus on the preferred approach. Thus, in Appendix Table A4, we explore different approaches to dealing with multiple dependent estimates per study as robustness checks. We find that irrespective of the approaches we adopted our findings hold. Following Abdullah et al (2013), our preferred approach to accounting for multiple estimates per study is to use precision squared (inverse variance or 1/standard error squared) as weights with study level clustered standard errors.

Finally, the data used for the meta-regression analysis as well as the corresponding STATA do files are available from the authors on request.

Table 4. Meta-regression variable definitions

Variable name	Variable description
Inequality measure	
Gini	BD=1: Gini coefficient (used as the base)
Income Share Bottom	BD=1: Income share of the bottom quintile
Income Share Top	BD=1: Income share of the top quintile
Income Share Other	BD=1: Income share other (e.g. income ratios, average income of the poorest quintile)
Income Inequality Other	BD=1: Other inequality measures (e.g. Theil, Atkinson)
Government spending measure	
Total spending	BD=1: Total government spending (used as the base)
Health spending	BD=1: Health government spending
Education spending	BD=1: Education government spending
Health & Education spending	BD=1: Health &Education government spending
Social net government spending	BD=1: Social net government spending
Military government spending	BD=1: Military government spending
Housing government spending	BD=1: Housing government spending
General social spending	BD=1: Social government spending
Consumption spending	BD=1: Government spending (consumption)
Other types of spending	BD=1: Government spending (any/not specified/other)
Country composition	
Sub-Saharan Africa (SSA)	BD=1: Countries in Sub-Saharan Africa included in samples
Latin America (LAC)	BD=1: Countries in Latin America included in samples
South Asia (SA)	BD=1: Countries in South Asia included in samples
Developed	BD=1: Developed countries included in samples
Data	
OLS	BD=1: OLS estimator used
Year data	Average year of data used in each study minus average year data of the sample
Other explanatory variables	
Tax	BD=1: Tax included as explanatory variable
Trade	BD=1: Trade included as explanatory variable
Education	BD=1: Education variables included as explanatory variable
Inflation	BD=1: Inflation included as explanatory variable
Population	BD=1: Population included as explanatory variable
Governance	BD=1: Governance variables included as explanatory variable
Publication	
Standard error	Standard error of the partial correlation coefficient
Unpublished	BD=1: Study is unpublished

Notes: * BD means binary dummy with a value of 1 if condition if fulfilled and zero otherwise.

Main meta-regression findings

We present the main findings of our meta-regression in Table 5 where we establish whether there is a relationship between government spending and income inequality. Regression 1 reports the FAT-PET results where the standard error of the partial correlation coefficient is regressed on the partial correlation coefficient. Recall that the FAT-PET regression is an empirical check to explore publication bias. The results indicate that there is some publication bias as the coefficient for the standard error is statistically significant. This finding holds across all estimations presented in Table 5. This implies that the visual inspection of the funnel plot might have been misleading as it indicated no publication bias. In addition, the coefficient for the standard error is positive, indicating that the estimated partial correlation coefficients are skewed towards positive values; negative effects are being under-reported in the literature.

To get an indication of the magnitude of this bias, recall from Figure 1 that the average reported correlation coefficient across all 987 observations is slightly positive, at 0.016. The constant in regression 1 quantifies the overall or average relationship between government spending and income inequality, after correcting for publication bias. This takes the value of -0.134, which is statistically significant at a 1% significance level, implying a statistically significant negative relationship between government spending and income inequality. Adjusting for publication bias therefore turns a small positive relationship into a larger negative (and statistically significant) relationship.[9]

In regression 2 additional dummy variables are added representing different income inequality measures, to explore whether the relationship differs depending on the income inequality measure that has been adopted. Only the values for *income share other* and *income inequality other* are positive and statistically significant at 5% and 1% respectively. A positive effect for a moderator variable means that the variable results in a larger positive (or smaller negative) relationship between government spending and income inequality. Thus the results in Regression 2 indicate that in the case of using the *Gini* coefficient there is an average relationship of -0.13 (significant at 1%) between government spending and income inequality, after correcting for publication bias. On the other hand, the relationship is slightly positive when *income share other* (0.021) and *income inequality other* (0.064) are used.[10]

Regression 3 is our main model as it includes all potentially relevant explanatory variables described above. Of the moderator variables for the control variables (tax, trade, governance, inflation, education and population), *governance* is positive and statistically significant at the 5% level. This implies that studies which control for governance indicators report a smaller negative (or larger positive) relationship between government spending and income inequality, other things being equal. By contrast, the coefficient for inflation is negative and statistically significant (at the 5% level), indicating that studies that control for inflation report a larger negative (or smaller positive) relationship between government spending and income inequality. In terms of the variables for sample coverage, the variable for SA is positive and significant at the 10% level, indicating that studies including South Asian countries in the sample find a smaller negative (or larger positive) relationship. None of the other moderator variables for control variables or sample coverage are statistically significant however.

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[9] Another way to control for publication bias is to focus on the 10 per cent of the most precise reported estimates (Stanley and Doucouliagos 2012: 56). The average correlation coefficient among the 10 per cent most precise estimates in our sample is -0.051 (s.e.=0.008). Thus again controlling for publication bias turns a small positive relationship into a negative relationship.

[10] This value was calculated by adding the coefficient on *income share other* to the constant, i.e. -0.13 +0.151. The same logic applies for the calculations we present for the other income inequality measures presented in regressions 3-5.

We are particularly interested in the results for the disaggregated measures of government spending. Surprisingly, the coefficients for *health and education spending* and *social spending* are both positive and statistically significant. This indicates that studies that use these measures of government spending find on average a larger positive (or smaller negative) relationship between spending and inequality than studies using *total government spending*. This is surprising since of all the categories of spending, we would most expect health, education and social spending (which includes cash transfers), to have a negative relationship with income inequality, other things being equal. However, it is consistent with evidence from studies such as Tanzi (1974), Alesina (1998) and Davoodi et al (2003) suggesting that much of the benefits of government spending on health and education in developing countries are received by middle-income groups in urban areas, which can end up raising inequality.

We are also particularly interested in the results for the *OLS* variable, which captures the different analytical approaches used. The coefficient for this variable is negative and statistically significant at the 5% level. This implies that studies using *OLS* as an estimation method report, on average, larger negative (or smaller positive) correlations between government spending and income inequality, holding all other MRA variables constant.

In regression 4 we follow Leonard, Stanley and Doucouliagos (2014) and employ a general-to-specific modelling strategy, removing the variable that has the largest p-value until all p-values are <0.05. The rationale for employing a general-to-specific approach can be found in Stanley and Doucouliagos (2012) who argue that they prefer a more specific model as it makes the underlying associations clearer. In the specific model (regression 4) we observe that *income inequality other, OLS, governance, health and education government spending* and *government spending others* are statistically significant and positive (except *OLS*) as already seen in regression 3. In addition *tax is* negative and significant at 5%.

Finally in regression 5 we report the estimates from a robust regression which strengthen our findings further. We should note that six of the variables in regression 3, i.e. *income share other, OLS, governance, health and education government spending, social net government spending* and *government spending others*, are statistically significant across most of the estimations we present in Table 5. In addition, when we compare the results in Table 5 with those in Appendix Table A3 (which exclude outliers), we typically only observe very small differences. The main differences can be found on the variables *LAC* and *Trade* that appear consistently significant throughout the regressions with no outliers, which is not the case in Table 5. The standard error is not significant in one out of five regressions with no outliers. However, removing the outliers does not seem to change our main results: *income inequality other, OLS, governance, inflation* and the three measures of government spending *(health & education, social net and government others)* are statistically significant in both tables.

Table 5. MRA of the effects of government spending on income inequality (dependent variable=partial correlation)

	(1) FAT PET WLS	(2) WLS	(3) WLS general	(4) WLS specific	(5) Robust
Standard error	1.778***	1.532***	1.496**	1.748***	0.433**
	(0.530)	(0.482)	(0.724)	(0.482)	(0.169)
Income Share Bottom		0.055	0.057		-0.015
		(0.072)	(0.081)		(0.018)
Income Share Top		-0.068	-0.055		-0.124***
		(0.061)	(0.055)		(0.024)
Income Share Other		0.151**	0.153*		0.162***
		(0.059)	(0.089)		(0.022)
Income Inequality Other		0.194***	0.208**	0.205***	0.087
		(0.031)	(0.087)	(0.030)	(0.062)
Developed			0.004		0.001
			(0.038)		(0.014)
Unpublished			-0.029		-0.062***
			(0.033)		(0.013)
Year data			0.001		-0.002**
			(0.004)		(0.001)
OLS			-0.097**	-0.124***	-0.101***
			(0.041)	(0.033)	(0.016)
LAC			-0.071		-0.106***
			(0.048)		(0.022)
SSA			-0.084		0.026
			(0.080)		(0.034)
SA			0.139*		0.024
			(0.077)		(0.031)
TAX			-0.059	-0.079**	-0.032
			(0.053)	(0.038)	(0.027)
TRADE			0.049		0.195***
			(0.105)		(0.020)
Governance			0.077**	0.088**	0.084***
			(0.036)	(0.034)	(0.012)
Inflation			-0.067**		-0.052***
			(0.028)		(0.012)
Population			-0.006		-0.034**
			(0.039)		(0.015)
Education			-0.041		0.007
			(0.035)		(0.013)
Health government spending			-0.052		0.070**
			(0.100)		(0.034)
Education government spending			0.075		0.074***
			(0.054)		(0.020)
Health & Education government spending			0.276***	0.119***	0.259***
			(0.066)	(0.033)	(0.067)
Social net government spending			0.145***	0.079**	0.102***
			(0.046)	(0.032)	(0.021)
Military government spending			0.000		0.101**
			(0.080)		(0.046)
Housing government spending			-0.012		0.090
			(0.066)		(0.068)
Social general government spending			0.001		-0.054
			(0.093)		(0.046)

	(1)	(2)	(3)	(4)	(5)
Government spending (consumption)			0.053		0.063***
			(0.048)		(0.016)
Government spending others			0.238***	0.137***	0.171***
			(0.051)	(0.038)	(0.041)
Constant	-0.134***	-0.130***	-0.119	-0.158***	-0.016
	(0.034)	(0.033)	(0.080)	(0.033)	(0.026)
N	987	987	974	987	974
R^2	0.076	0.125	0.298	0.198	0.399

Notes: Columns report estimates variants of regression 2. Regressions 1, 2 and 4 use 987 estimates from 87 studies; while regressions 3 and 5 use 974 estimates from 85 studies. Standard errors are reported in parentheses. All regressions use cluster standard errors to adjust for data dependence, i.e. multiple estimates per study. All columns use weighted least squares, except for regression 5 that uses robust regression. In regression 4 we employed a general-to-specific modelling strategy, removing the variable that had the largest p-value until all p-values are <0.05. For definitions of variables see Table 4. Total government spending is used as the base category for the government spending variable. GINI is used as a base in the inequality variable. In order to test for multicollinearity we use the Variance Inflation Factor (VIF) for both the general (3) and specific regressions (4); the mean VIF is 2.65 and 1.36, respectively, which is not a case for concern. According to Hosmer and Lemeshow (2000) values of VIF exceeding 10 are often regarded as indicating multicollinearity and should be investigated.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness checks – what do subgroup analyses tell us?

To check the robustness of our findings we conduct a range of subgroup analyses. In Table 6 we explore how our findings differ by the different categories of government spending, focusing on the four measures of government spending where we had sufficient number of observations. For the remaining government spending variables most of the variables of interest were omitted due to the low number of observations and hence we felt there is not much value in presenting them here. Regression 1 shows the results for total government spending, Regression 2 the results for government education spending, Regression 3 the results for government social spending, and Regression 4 the results for government consumption spending, respectively.

The findings in Table 6 show some interesting differences between the results for different spending measures. In regression 3 for example, the coefficients of the *income share top* and *income share bottom* are both negative and statistically significant. This indicates that, compared to studies that use the Gini coefficient, studies that use these measures find a larger negative (or smaller positive) relationship between social spending and inequality, ceteris paribus. On the other hand, the coefficients on *income share bottom* and *income share other* in regression 4 are positive and statistical significant. This suggests that compared with the *Gini* coefficient, studies that use either of these measures report a larger positive (or smaller negative) relationship between consumption spending and income inequality, ceteris paribus.

The results for the *average year of the data* used also differ somewhat between spending measures. This variable is included in order to explore whether the relationship between government spending and inequality varies with time. The coefficient is positive and statistically significant in regressions 2 and 4, i.e., when education government spending and consumption government spending are used. This suggests that, holding all else constant, studies that use more recent data find a smaller negative (or larger positive) relationship between education spending and income inequality, and between consumption spending and income inequality, in comparison with studies using older data.

Particularly interesting are the results for the regional variables. For example, consider the results for Latin America (*LAC*). The negative coefficient for this variable in regressions 1 and 2 (statistically significant at the 1% level and 5% respectively) suggests that studies including Latin American countries in the sample find a larger negative (or smaller positive) relationship between total government spending and income inequality. By contrast, the positive coefficient for Sub-Saharan Africa (SSA) in the same regressions indicates that studies including countries from this region find a less negative (or larger positive) relationship between total spending and income inequality. One possible explanation for these results is that government spending has a greater effect in reducing income inequality in Latin America than in Sub-Saharan Africa. Note however that the results for consumption government spending in Regression 4 shows larger negative (smaller positive) relationship with income inequality for studies including countries from Sub-Saharan Africa.

As in Table 5, the sub-group analysis in Table 6 suggests that the inclusion of different control variables in econometric models (*trade, governance, inflation, population and education*) influences the partial correlation between government spending and income inequality. Studies that control for *trade* find a smaller negative (or larger positive) relationship between total government spending and inequality. The same applies for studies that control for *governance,* which find a smaller negative (or larger positive) relationship between total government spending and income inequality, and social spending and income inequality. The *education* variable is statistically significant across three out of four subgroups, implying that the inclusion of this control variable in studies of the relationship between government spending and income inequality is particularly appropriate.

In Table 7 we conduct a series of other subgroup analyses with the objective to explore additional aspects in the data and to check the robustness of our main findings (note also that Appendix Table A4 presents further robustness checks). We were particularly interested to explore how our findings might differ by region (Latin America, Sub-Saharan Africa) and check whether the inclusion of developed countries in the sample makes a difference.

The results from Table 7 strengthen our previous discussion and results. In regressions 3-5 (i.e. studies including developed countries, Latin America and Sub-Saharan African countries in the sample) two measures government spending are consistently positive and statistically significant (*social net and government spending others)* indicating that these categories of government spending report smaller negative (or larger positive) partial correlations with income inequality. By contrast, in Regression 5 (studies including the Sub-Saharan Africa region in the sample) *health spending* has a negative and statistically significant value, meaning that the relationship with inequality is on average more negative (less positive) for this measure of spending. *Health & education government spending* is highly significant and positive in samples that include Latin America countries. These results are consistent with the hypothesis that the relationship between government spending and income inequality varies significantly across regions. However, we are unable to test this hypothesis directly, since most of the studies included in our review focus on more than one region, and only rarely provide separate results for different regions.

Table 6. Subgroup analysis for government spending variables (dependent variable=partial correlation)

	(1) Total government spending	(2) Education government spending	(3) Social net government spending	(4) Government spending (consumption)
Standard error	0.114	-2.216	-0.456	4.899**
	(0.806)	(1.345)	(1.389)	(2.168)
Income Share Bottom	0.004	-0.007	-0.385**	0.220**
	(0.108)	(0.077)	(0.138)	(0.104)
Income Share Top	-0.108***	-0.042	-0.406**	0.076
	(0.029)	(0.185)	(0.159)	(0.092)
Income Share Other	-0.127***	-0.153*	.	0.342***
	(0.041)	(0.075)		(0.067)
Income Ineq other	-0.059	.	.	.
	(0.068)			
Developed	-0.072	-0.100**	0.142	0.127*
	(0.047)	(0.046)	(0.156)	(0.068)
Unpublished	-0.048	0.018	-0.078	-0.066
	(0.031)	(0.091)	(0.080)	(0.070)
Year data	-0.002	0.015**	-0.008	0.016***
	(0.004)	(0.007)	(0.006)	(0.005)
OLS	-0.086**	-0.023	0.000	-0.161
	(0.037)	(0.044)	(0.071)	(0.101)
LAC	-0.278***	-0.638**	-0.045	0.091
	(0.060)	(0.250)	(0.207)	(0.069)
SSA	0.597***	0.612*	0.015	-0.313***
	(0.086)	(0.303)	(0.266)	(0.094)
SA	-0.408***	-0.298	-0.264	0.490***
	(0.060)	(0.188)	(0.272)	(0.113)
TAX	.	-0.123	-0.084	.
		(0.135)	(0.082)	
TRADE	0.196***	.	0.040	-0.045
	(0.052)		(0.104)	(0.134)
Governance	0.093***	0.005	0.050	0.064
	(0.031)	(0.042)	(0.081)	(0.063)
Inflation	-0.135***	-0.061	0.009	0.001
	(0.035)	(0.076)	(0.044)	(0.099)
Population	0.046	-0.024	-0.021	-0.247**
	(0.049)	(0.091)	(0.063)	(0.106)
Education	0.134***	-0.214**	-0.190*	-0.159*
	(0.045)	(0.093)	(0.106)	(0.088)
Constant	0.079	0.820**	0.391	-0.648**
	(0.079)	(0.295)	(0.257)	(0.303)
N	277	96	110	392
R^2	0.411	0.735	0.699	0.514

Notes: Standard errors are reported in parentheses. All regressions use cluster standard errors to adjust for data dependence, i.e. multiple estimates per study. All columns use weighted least squares.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Subgroup analysis for selected non-government variables (dependent variable=partial correlation)

	(1) FAT PET WLS	(2) WLS general	(3) Developed, yes=1	(4) Latin America, n=1	(5) Sub-Saharan Africa, yes=1
Standard error	1.778***	1.496**	2.146**	1.678**	2.343**
	(0.530)	(0.724)	(0.933)	(0.812)	(0.884)
Income Share Bottom		0.057	0.106	0.077	0.075
		(0.081)	(0.088)	(0.090)	(0.088)
Income Share Top		-0.055	-0.073	-0.059	-0.077
		(0.055)	(0.060)	(0.060)	(0.059)
Income Share Other		0.153*	0.141	0.162*	0.162*
		(0.089)	(0.105)	(0.091)	(0.092)
Income Ineq other		0.208**	0.281	0.219	0.197
		(0.087)	(0.180)	(0.146)	(0.152)
Developed		0.004		0.008	0.009
		(0.038)		(0.039)	(0.036)
Unpublished		-0.029	-0.036	-0.038	-0.076
		(0.033)	(0.052)	(0.039)	(0.047)
Year data		0.001	-0.002	-0.000	-0.002
		(0.004)	(0.005)	(0.004)	(0.004)
OLS		-0.097**	-0.178***	-0.102**	-0.207***
		(0.041)	(0.064)	(0.046)	(0.062)
LAC		-0.071	-0.321		-0.161
		(0.048)	(0.212)		(0.101)
SSA		-0.084	0.174	0.028	
		(0.080)	(0.199)	(0.057)	
SA		0.139*	0.074	.	.
		(0.077)	(0.072)		
TAX		-0.059	-0.088	-0.055	-0.041
		(0.053)	(0.079)	(0.055)	(0.070)
TRADE		0.049	-0.034	0.045	0.047
		(0.105)	(0.147)	(0.117)	(0.127)
Governance		0.077**	0.036	0.061	0.059
		(0.036)	(0.046)	(0.038)	(0.043)
Inflation		-0.067**	-0.059	-0.070*	-0.062
		(0.028)	(0.046)	(0.035)	(0.039)
Population		-0.006	0.000	0.001	-0.011
		(0.039)	(0.059)	(0.041)	(0.039)
Education		-0.041	-0.042	-0.043	-0.024
		(0.035)	(0.043)	(0.036)	(0.040)
Health government spending		-0.052	-0.132	-0.079	-0.235**
		(0.100)	(0.124)	(0.123)	(0.102)
Education government spending		0.075	0.072	0.077	0.053
		(0.054)	(0.066)	(0.061)	(0.068)
Health & Education government spending		0.276***	.	0.284***	.
		(0.066)		(0.074)	
Social net government spending		0.145***	0.146**	0.161***	0.117*
		(0.046)	(0.070)	(0.049)	(0.063)
Military government spending		0.000	0.119	0.090	0.083
		(0.080)	(0.094)	(0.084)	(0.093)

Housing government spending		-0.012	0.003	-0.059	-0.095
		(0.066)	(0.079)	(0.078)	(0.073)
Social general government spending		0.001	0.044	0.010	-0.146
		(0.093)	(0.122)	(0.100)	(0.145)
Government spending (consumption)		0.053	0.034	0.047	0.011
		(0.048)	(0.074)	(0.056)	(0.064)
Government spending others		0.238***	0.254***	0.244***	0.228***
		(0.051)	(0.070)	(0.055)	(0.062)
Constant	-0.134***	-0.119	-0.070	-0.174**	0.002
	(0.034)	(0.080)	(0.100)	(0.073)	(0.108)
N	987	974	569	810	736
R^2	0.076	0.298	0.312	0.284	0.345

Notes: Standard errors are reported in parentheses. All regressions use cluster standard errors to adjust for data dependence, i.e. multiple estimates per study. All columns use weighted least squares.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, there are some similarities between the regressions presented in Table 5 and some of the subgroup analyses presented in Table 7. For example, using *income share other* yields significant results on the effect of government spending on income inequality (however the results are only significant at the 10% level). *Government spending others* is positive and significant across all subgroup analyses and thus confirming the trends outlined in Table 5. This implies that this more varied category of spending will tend to yield a smaller negative (or larger positive) relationship with inequality, as might be expected. The same applies to *social net spending* that is consistently positive and significant. Similarly, *OLS* is consistently negative and significant implying that studies using this estimation method are, on average, reporting a larger negative (or smaller positive) relationship between government spending and income inequality. This finding is quite important because according to the risk of bias tool developed previously, most of the studies identified as having a medium risk of bias use *OLS* as an estimation method.

As mentioned above, we also conducted further robustness checks using different approaches to addressing multiple dependent estimates per study. Appendix Table A4 presents the results of the different weighting schemes that are often used to deal with biases due to data dependence.

Is there an association between government spending and income inequality?

The results in Tables 5-7 show that both the size and direction of the estimated relationship between government spending and income inequality are affected by a range of factors, including the country composition of the sample, the control variables included in the analysis, the analytical approach used, and the measure of government spending used. This makes it difficult to answer the question of whether or not there is – on average – a strong association between government spending and income inequality. However, we are able to make some progress towards this question by calculating the average (or predicted) relationship between government spending and income inequality implied by the results in Tables 5-7, for a certain set of values of the moderator variables. This is done in Table 8.

Panel A of Table 8 shows the average relationship between government spending and the different measures of inequality predicted by the results in Regression 3 of Table 5. Here we consider a study that is published, uses a more robust non-OLS analytical approach, includes all developing country regions but not developed countries in the sample, uses a period of time centred on 1987, includes all six control variables in the analysis (e.g. governance, inflation, education), and focuses on total government spending. At least for this case, the average relationship when including outliers is negative for the *Gini* coefficient (-0.182), the *income share of the poorest* (-0.125), and the *income share of the richest* (-0.238). However, only the results for the income share of the richest quintile is statistically significant (at the 10% level); in addition, the results when excluding outliers are all statistically insignificant. For the other measures of inequality, the average relationship is slightly positive, but not statistically significant.

Panel B of Table 8 then shows the average relationship between each measure of government spending and income inequality, predicted by the results in Regressions 1-4 of Table 6.[11] We again consider a study that is published, uses a more robust non-OLS analytical approach, includes all developing country regions but not developed countries in the analysis, uses a sample coverage centred on 1987, and includes all six control variables in the analysis (e.g. governance, inflation, education). For this case, the predicted relationship is positive for total government spending, across all inequality measures; the results are statistically significant at the 10% level or below. For *education spending*, the results are mixed and not statistically significant. In contrast however, the predicted relationship is negative for both government *social spending* and *consumption spending*, across all inequality measures except the Gini coefficient for social spending.

These results in Table 8 refer of course only to one particular set of moderator variables. Nevertheless, the results do show at least some evidence of a statistically significant negative relationship between government social spending and inequality, and between government consumption spending and income inequality. In terms of the strength of association, it has been suggested that a partial correlation coefficient of less than 0.07 in absolute terms can be considered small, with 0.17 or above considered to be moderate, and 0.33 or above large (Doucouliagos 2011, Abdullah et al 2013). This is in line with what Cohen (1988: 115) suggests who argues that for partial correlation coefficients, the effects are considered to be small when r = 0.1, medium when r = 0.3 and large when r = 0.5. Judging by these guidelines therefore, the results in Table 8 imply a potentially large negative relationship between government social spending and government consumption spending and income inequality.

[11] The results of the pooled analysis in Table 5 are based on a strong assumption – that the effect of each moderator variable on the partial correlation between government spending and income inequality is the same across all measures of spending. The fact that the results of the sub-group analysis in Tables 6-7 differ from the pooled analysis suggests that this assumption is not well supported by the data, which in turn implies that the sub-group results are more reliable, despite the smaller sample size.

Table 8. Predicted (average) relationship between government spending and income inequality

	Gini	Income share bottom	Income share top	Other income share measure	Other inequality measure
A. Pooled analysis ~					
Including outliers	-0.182	-0.125	-0.238*	-0.030	0.025
Excluding outliers	-0.049	-0.019	-0.105	0.089	0.074
B. Sub-group analysis, including outliers#					
Total spending	0.324***	0.328**	0.216**	0.197*	0.265***
Education spending	0.079	0.072	0.037	-0.074	.
Social spending	-0.099	-0.484*	-0.506*	.	.
Consumption spending	-0.765***	-0.545**	-0.688***	-0.423*	.
C. Sub-group analysis, excluding outliers$					
Total spending	0.330***	0.335**	0.223**	0.202*	0.270***
Consumption spending	-0.496***	-0.340***	-0.430***	-0.120	.

Notes: ~Based on regression 3 from Table 5; # based on regressions 1-4 in Table 6; $underlying regressions not reported but available from authors on request. The following values of each moderator variable are assumed: standard error=0; developed=0; unpublished=0; year=0; OLS=0; LAC, SSA, SA all equal to 1; Tax, Trade, Governance, Inflation, Population, Education all equal to 1. In Panel A, the spending measures are all equal to 0, so the results refer to total government spending (base case). In Panel B, for total spending the variables for SA and TAX are set to 0 by default; the same applies to the variable Trade for Education spending and Tax for social spending. Only the results for total and consumption spending are shown excluding outliers because the results for education and social spending are identical in this case.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion

The issue of inequality has been a key issue in international development for several decades now. Since the 1970s, a large literature has emerged which documents the many adverse effects of inequality. Moreover, income inequality remains high in a large number of developing countries. Over 50 low and middle income countries have Gini coefficients of income inequality exceeding 40, above which the potential to undermine progress in key development outcomes, and/or to conflict with basic notions of equity and fairness, is considered significantly greater. For this reason, there is a clear demand from policy-makers in national governments and international organisations for accurate, reliable and up-to-date evidence as regards which policies and interventions can be used to reduce income inequality, and also which policies and interventions may (in the absence of complementary, offsetting measures) raise income inequality.

Overall, the results show that both the size and direction of the relationship between government spending and income inequality are affected by a range of factors.

First, we find some evidence that studies using measures of inequality other than the Gini coefficient, the income share of the poorest 20%, or the income share of the richest 20%, find a smaller negative (or larger positive) relationship between government spending and income inequality. This is an important finding because although the majority of studies do use the Gini coefficient or income shares, these are not necessarily the best measures of inequality, nor are they necessarily the most relevant from a policy perspective. It would be better in future if each econometric study reported the results for a wider range of inequality measures.

Second, we find little evidence that the inclusion of developed countries in the samples used for estimation affects the results. This is an important finding because many econometric studies do include both developed and developing countries in the sample, in the interests of increasing sample size. Our results on the whole provide no indication that this generates bias.

With regard to the regional coverage of the samples used for estimation, the results are more mixed with fewer consistent patterns. The majority of studies include countries from all regions, and there are very few studies focusing on one region only. This means that direct comparisons of the relationship between government spending and inequality in different regions are not generally possible. There is some evidence that *not* including Latin American countries in the sample leads to a smaller negative (or larger positive) relationship between government spending and inequality; a possible explanation being that government spending has a more redistributive effect in Latin America than in other regions. But in the absence of more direct comparisons across regions, this conclusion remains tentative.

Third, we find little evidence that the period of time covered by the sample makes a big difference to the results. This is important because econometric studies typically use the largest possible time period, again in the interests of increasing sample size; our results on the whole provide no indication that this affects the results substantially. The only exceptions are for education spending and consumption spending, where the use of more recent data leads to a less negative (more positive) relationship with inequality. One possible explanation is a general tendency for expenditure in these areas to become less progressive (or more regressive) over time, thus lowering their negative (raising their positive) impact on inequality. Another possible explanation is diminishing returns to government spending; i.e., the higher the overall level of spending, the lower the effect of additional spending on the reduction of income inequality.

Fourth, we find fairly consistent evidence that studies using ordinary least squares (OLS) as an estimation method find a larger negative (or smaller positive) relationship between government spending and income inequality. This is an important finding because according to the risk of bias tool developed previously, most of the studies identified as having a medium risk of bias use OLS as an estimation method. It indicates the importance of using more robust analytical approaches with lower risk of bias, such as panel data methods and instrumental variables (IV) estimation. Studies relying on OLS appear to have had a tendency to overestimate the contribution of government spending to the reduction of inequality, compared with more robust analytical approaches.

Fifth, we also find consistent evidence that the control variables used in the analysis makes a difference to the results. This is an important finding because researchers tend to differ in terms of precisely which control variables they include in their analysis. Our results show that these choices affect the estimated results, sometimes quite substantially – and therefore highlight the importance of very careful consideration by researchers of the control variables included in their analysis. Although a large set of control variables is not always possible (due to lack of data), our results suggest that failing to control for measures of governance and inflation could lead to biased estimates of the relationship between government spending and inequality.

Sixth, we find consistent evidence of publication bias. This is an important finding, because unless corrected for in some way, publication bias can lead to significant errors in attempts to summarise empirical knowledge on a given issue. Stanley and Doucouliagos (2012) for instance discuss how the existence of publication bias in the estimated effect of minimum wages on employment can lead researchers to overestimate the negative effect of minimum wages on employment by a factor of 5 or more. Publication bias is common in the literature, and has been observed in a number of different contexts. Stanley and Doucouliagos (2012, Table 4.1) for instance provide evidence of publication bias in estimates of the employment effect of minimum wages; in this case, positive estimates appear to be under-reported. Similarly, Doucouliagos and Paldam (2008, 2009, 2014) have found evidence of publication bias in estimates of the relationship between foreign aid and economic growth, with negative estimates being under-reported.

In our case, it appears that negative estimates are being under-reported in the literature. It is difficult to say precisely what might be driving this however. One possible explanation is that it is due to 'polishing' – in other words, the tendency for researchers and editors to report and publish results that are statistically significant (Doucouliagos and Paldam 2008). Another possible explanation is that researchers themselves are reluctant to report negative relationships, perhaps because of ideological persuasion (e.g. a belief in limited government involvement in the economy), or because they work for or are funded by institutions which have are pre-disposed towards this view.[12] We are not able to disentangle these different possible explanations for publication bias. Nevertheless, we can at least correct for publication bias when determining whether or not there really is a relationship between government spending and inequality.

Finally, in terms of our central question – is there a strong association between measures of government spending and income inequality – we find that the answer depends very much on the type of spending being considered. When considering *total* government spending, we find evidence of a moderate positive relationship with income inequality. However, when considering more disaggregated types of spending, we find evidence of a moderate negative relationship between government *social* spending and income inequality, and between government *consumption* spending and inequality. It is important to recognize however that both the size and direction of the estimated relationship between government spending and income inequality is affected by a range of factors. For example, we have seen that studies using measures of inequality other than the Gini coefficient or income shares tend to find a smaller negative relationship between government spending and income inequality. This makes it difficult to say whether or not there is on average a

[12] This is in fact the explanation favoured by Doucouliagos and Paldam (2008, 2009) to explain the evidence of publication bias in the aid effectiveness literature. They argue that the research community is reluctant to publish negative estimates of this relationship, partly because of researchers desire to be seen as supporting the 'do-good' activity of foreign aid, and partly because research is often funded by aid organisations.

strong association between any particular type of government spending and income inequality.

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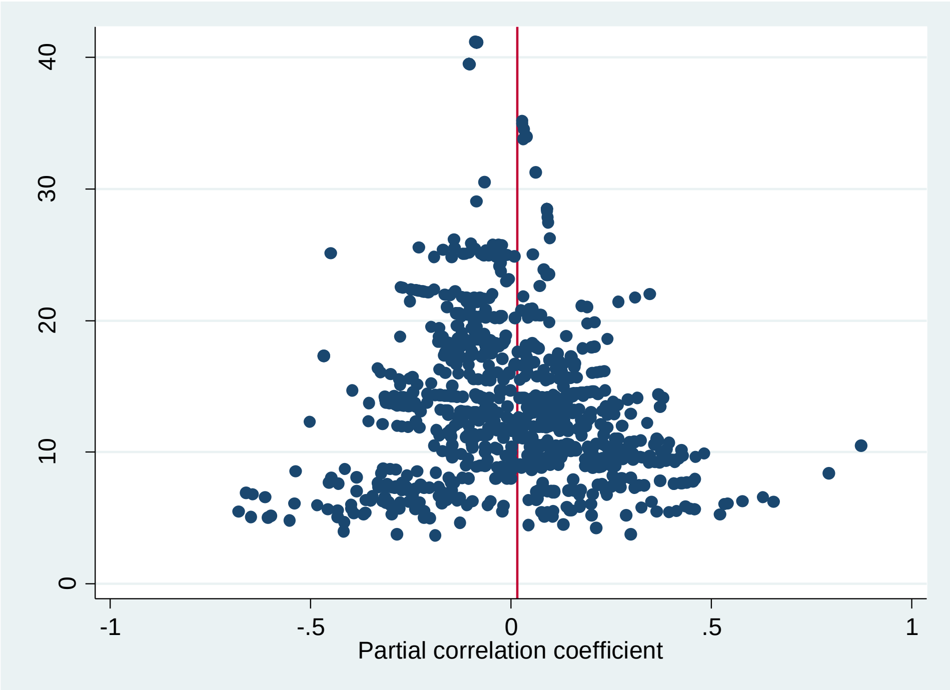
Appendix

Figure A1. Partial Correlations of Government Spending and Income Inequality (n=987) after removing the main outliers



Note: Precision is calculated as 1/standard error of the partial correlation coefficient.
The weighted mean of the partial correlation coefficient is marked with a red line with the value of 0.016

Table A2. Descriptive statistics

		n=987	
Variable name	Variable description	Mean	Standard deviation
Partial correlation	Partial correlation of the effect of government spending variables on income inequality. This is the dependent variable in the meta-regression.	0.011[13]	0.215
Inequality measure			
Gini	BD=1: Gini coefficient (used as the base)	0.741	0.439
Income Share Bottom	BD=1: Income share of the bottom quintile	0.137	0.344
Income Share Top	BD=1: Income share of the top quintile	0.045	0.206
Income Share Other	BD=1: Income Share other (ratio, growth of the poor, etc)	0.068	0.252
Income Inequality Other	BD=1: Other income inequality measure (Theil, Atkinson, EHHI)	0.010	0.100
Government spending measure			
Total government spending	BD=1: Total government spending included as explanatory variables (used as the base)	0.281	0.450
Health government spending	BD=1: Health government spending included as explanatory variables	0.025	0.157
Education government spending	BD=1: Education government spending included as explanatory variables	0.109	0.312
Health & Education government spending	BD=1: Health &Education government spending included as explanatory variables	0.006	0.078
Social net government spending	BD=1: Social net government spending included as explanatory variables	0.112	0.316
Military government spending	BD=1: Military government spending included as explanatory variables	0.019	0.137
Housing government spending	BD=1: Housing government spending included as explanatory variables	0.006	0.078
Social general government spending	BD=1: Social government spending included as explanatory variables	0.015	0.122
Government spending consumption	BD=1: Government spending (consumption) included as explanatory variables	0.397	0.490
Government spending others	BD=1: Government spending (any/not specified/other) included as explanatory variables	0.028	0.166
Country composition			
Sub-Saharan Africa (SSA)	BD=1: Countries in Sub-Saharan Africa region included in samples	0.746	0.436
Latin America (LAC)	BD=1: Countries in Latin America region included in samples	0.821	0.384
South Asia (SA)	BD=1: Countries in South Asia region included in samples	0.799	0.401
Developed*	BD=1: Developed countries included in samples	0.584	0.493

[13] The weighted mean of the partial correlation coefficient by study is 0.016.

Data			
OLS	BD=1: OLS estimator used	0.196	0.397
Year data	Average year of data used in each study – Average year data of the sample (Yr=Avg-1987)	-0.283	7.610
Other specification variables			
Tax	BD=1: Tax included as explanatory variable	0.102	0.303
Trade	BD=1: Trade included as explanatory variable	0.124	0.329
Education	BD=1: Education variables included as explanatory variable	0.475	0.500
Inflation	BD=1: Inflation included as explanatory variable	0.503	0.500
Population	BD=1: Population included as explanatory variable	0.188	0.391
Governance	BD=1: Governance variables included as explanatory variable	0.435	0.496
Publication			
Standard error	Standard error of the partial correlation coefficient. Used to correct for publication bias.	0.088	0.041
Unpublished	BD=1: Study is unpublished	0.479	0.500

Notes: *This variable has n=974. BD means binary dummy with a value of 1 if condition if fulfilled and zero otherwise.

Table A3. Results excluding outliers

MRA of the effects of government spending on income inequality after removing the outliers (dependent variable=partial correlation)

	(1) FAT PET WLS	(2) WLS	(3) WLS General	(4) WLS specific	(5) Robust
Standard error	1.395***	1.109**	0.690	0.877**	0.412**
	(0.509)	(0.457)	(0.416)	(0.424)	(0.169)
Income Share Bottom		0.074	0.030		-0.015
		(0.061)	(0.052)		(0.018)
Income Share Top		-0.070	-0.056		-0.126***
		(0.061)	(0.053)		(0.024)
Income Share Other		0.152**	0.138	0.139**	0.161***
		(0.059)	(0.086)	(0.068)	(0.022)
Income Ineq other		0.186***	0.123**	0.159**	0.087
		(0.035)	(0.049)	(0.071)	(0.061)
Developed			-0.011		-0.000
			(0.031)		(0.014)
Unpublished			-0.024		-0.062***
			(0.026)		(0.013)
Year data			-0.001		-0.002**
			(0.003)		(0.001)
OLS			-0.081**	-0.068**	-0.100***
			(0.037)	(0.034)	(0.016)
LAC			-0.100**	-0.066**	-0.110***
			(0.042)	(0.032)	(0.021)
SSA			-0.001		0.031
			(0.067)		(0.034)
SA			0.067	0.059**	0.021
			(0.068)	(0.027)	(0.031)
TAX			-0.053	-0.071**	-0.030
			(0.038)	(0.028)	(0.027)
TRADE			0.133***	0.107**	0.196***
			(0.047)	(0.043)	(0.020)
Governance			0.055*	0.075**	0.084***
			(0.028)	(0.029)	(0.012)
Inflation			-0.074***		-0.055***
			(0.028)		(0.012)
Population			-0.006		-0.036**
			(0.034)		(0.015)
Education			-0.028		0.007
			(0.033)		(0.013)
Health government spending			0.069		0.070**
			(0.047)		(0.035)
Education government spending			0.100**		0.075***
			(0.050)		(0.020)
Health & Education government			0.282***	0.147***	0.262***
spending			(0.054)	(0.035)	(0.067)
Social net government spending			0.131***	0.075**	0.101***
			(0.042)	(0.029)	(0.021)
Military government spending			0.078		0.099**
			(0.050)		(0.046)
Housing government spending			-0.005		0.093
			(0.076)		(0.068)

Social general government spending			0.041		-0.045
			(0.069)		(0.046)
Government spending (consumption)			0.074*		0.063***
			(0.041)		(0.016)
Government spending others			0.211***	0.123***	0.170***
			(0.046)	(0.029)	(0.040)
Constant	-0.102***	-0.098***	-0.042	-0.104***	-0.010
	(0.031)	(0.030)	(0.060)	(0.033)	(0.026)
N	981	981	968	981	968
R^2	0.063	0.136	0.329	0.268	0.403

Notes: This table reports the same regressions as table 5 after removing 6 outliers that were identified through visual inspection of the funnel plot. Columns report estimates variants of regression 2. Regressions 1, 2 and 3 use 981 estimates from 87 studies; while regressions 3 and 5 use 968 estimates from 85 studies. Standard errors are reported in parentheses. All regressions use cluster standard errors to adjust for data dependence, i.e. multiple estimates per study. All columns use weighted least squares, except for regression 5 that uses robust regression. For definitions of variables see Table 4. Total government spending is used as the base category for the government spending variable. GINI is used as a base in the inequality variable.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4. Robustness checks

Robustness checks using different weights (dependent variable=partial correlation) for government spending variables

	(1) FAT PET WLS	(2) WLS general	(3) WLS weights1	(4) WLS weights2	(5) WLS weights3	(6) WLS weights4
Standard error	1.778***	1.496**	0.659*	-2.220*#	0.401	-1.033#
	(0.530)	(0.724)	(0.383)	(1.208)	(0.323)	(0.788)
Income Share Bottom		0.057	0.056	0.061	0.001	0.013
		(0.081)	(0.065)	(0.064)	(0.062)	(0.024)
Income Share Top		-0.055	-0.033	-0.021	0.016	0.001
		(0.055)	(0.067)	(0.068)	(0.101)	(0.019)
Income Share Other		0.153*	0.212**	0.222**	0.175***	0.006
		(0.089)	(0.104)	(0.101)	(0.066)	(0.023)
Income Ineq other		0.208**	0.139**	0.141*	0.130*	0.130***
		(0.087)	(0.068)	(0.082)	(0.067)	(0.038)
Developed		0.004	-0.010	-0.025	0.014	-0.009
		(0.038)	(0.024)	(0.021)	(0.031)	(0.012)
Unpublished		-0.029	-0.025	-0.011	-0.003	0.030
		(0.033)	(0.031)	(0.031)	(0.036)	(0.021)
Year data		0.001	-0.003	-0.005	-0.002	-0.004***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
OLS		-0.097**	-0.071*	-0.029	-0.117**	-0.006
		(0.041)	(0.041)	(0.035)	(0.046)	(0.016)
LAC		-0.071	-0.151**	-0.201***	-0.074	-0.108***
		(0.048)	(0.058)	(0.056)	(0.053)	(0.037)
SSA		-0.084	-0.060	-0.046	-0.148	-0.049
		(0.080)	(0.100)	(0.102)	(0.101)	(0.060)
SA		0.139*	0.146*	0.146	0.198**	0.088
		(0.077)	(0.088)	(0.093)	(0.088)	(0.056)
TAX		-0.059	-0.062	-0.073**	-0.080	-0.061**
		(0.053)	(0.038)	(0.034)	(0.064)	(0.029)
TRADE		0.049	0.140**	0.141**	0.142**	0.053
		(0.105)	(0.057)	(0.057)	(0.059)	(0.033)
Governance		0.077**	0.090**	0.097***	0.114***	0.035**
		(0.036)	(0.035)	(0.034)	(0.032)	(0.017)
Inflation		-0.067**	-0.080***	-0.094***	-0.048	-0.045**
		(0.028)	(0.029)	(0.030)	(0.039)	(0.021)
Population		-0.006	-0.029	-0.024	-0.062*	-0.046*
		(0.039)	(0.034)	(0.033)	(0.035)	(0.026)
Education		-0.041	-0.068	-0.087*	-0.046	-0.035*
		(0.035)	(0.043)	(0.044)	(0.045)	(0.018)
Health government spending		-0.052	0.101	0.121*	0.087	0.049
		(0.100)	(0.070)	(0.068)	(0.058)	(0.033)
Education government		0.075	0.123**	0.159***	0.074	0.088***
spending		(0.054)	(0.051)	(0.053)	(0.061)	(0.025)
Health & Education		0.276***	0.351***	0.385***	0.284***	0.173***
government spending		(0.066)	(0.060)	(0.063)	(0.060)	(0.038)
Social net government		0.145***	0.183***	0.211***	0.141**	0.101***
spending		(0.046)	(0.061)	(0.062)	(0.069)	(0.025)
Military government		0.000	0.063	0.104	0.126*	-0.005
spending		(0.080)	(0.081)	(0.091)	(0.068)	(0.038)
Housing government		-0.012	0.082	0.112*	0.076	0.009
spending		(0.066)	(0.062)	(0.061)	(0.071)	(0.044)

Social general government		0.001	0.082	0.166***	0.006	0.143***
spending		(0.093)	(0.066)	(0.052)	(0.083)	(0.026)
Government spending		0.053	0.104**	0.139***	0.091*	0.062**
(consumption)		(0.048)	(0.045)	(0.046)	(0.049)	(0.025)
Government spending others		0.238***	0.283***	0.309***	0.225***	0.105***
		(0.051)	(0.064)	(0.064)	(0.070)	(0.026)
Constant	-0.134***	-0.119	-0.025	0.071	-0.077	0.053
	(0.034)	(0.080)	(0.069)	(0.064)	(0.065)	(0.039)
N	987	974	974	974	974	974
R^2	0.076	0.298	0.498	0.497	0.462	0.506

Notes: Standard errors are reported in parentheses. All regressions use cluster standard errors to adjust for data dependence, i.e. multiple estimates per study. All columns use weighted least squares. # The standard error of the mean of the partial correlation coefficient is reported instead of the standard error of the partial correlation coefficient Regression 3 uses the sum of precision squared (or inverse variance) for each study as weights. Regression 4 uses the sum of precision squared (or inverse variance) for each study as weights and the standard error of the mean of the partial correlation coefficient instead of the standard error of the partial correlation coefficient. Regression 5 uses 1/n as weights where n is number of estimates per study. Regression 6 uses the weighted mean of the partial correlation, the sum of precision squared (or inverse variance) for each study as weights and the standard error of the mean of the partial correlation.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.