Supplementary Materials for “The Effect of Legislature Size on Public Spending: A Meta-Analysis”

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A Search Criteria

The first step in our systematic review consisted in gathering a study sample. We started our data collection with a manual search based on a set of keywords we scouted from the distributive politics literature. This search produced a database with many entries that were unrelated to our subject of investigation. To reduce the number of false positives in our sample, we restricted our search to studies that cited Weingast, Shepsle and Johnsen's 1981 paper "*The Political Economy of Benefits and Costs: A Neoclassical Approach to Distributive Politics*", which is a seminal contribution to the field. Although Google Scholar reports the article has received 2,180 citations, our search resulted in 2,664 records on the 21st of November 2019.

We webscraped three large academic databases: Google Scholar (n = 1001); Microsoft Academic (n = 927); and Scopus (n = 736). The R script we wrote extracted the article title, abstract, authors, year, journal of publication, and database from which the record originated. Our code is available in section **??** below. We screened these results with an English language and article restriction, that is, we excluded all records written in other languages and all that were not academic papers, such as book chapters or doctoral theses. We set no restriction to unpublished articles. XXXX CATARINA AND HUZEYFE: FIX THIS

B Article Selection

The selection process was conducted by two authors in three phases. In the first round, we excluded all titles that were clearly unrelated to our topic of interest. For instance, we curiously found articles about car motors amidst our sample. We consider this a preliminary step, since we were not able to eliminate a large number of entries. Then, we read all abstracts. We chose to maintain those which indicated that either government expenditure or legislative structures were the main subject of the paper. For instance, if the paper sought to identify variables that increased government size, it was maintained. Abstracts that indicated the paper discussed or estimated the impacts of representative institutions, elections, or chamber dynamics were also included. This allowed us to significantly reduce our sample to 376 records.

In the second phase, we assessed full texts. To remain in our sample, the paper should (i) conduct a quantitative analysis, (ii) report data on the number of legislators, and (iii) also include data on public expenditure. If the publication had all three, it was maintained. Disagreements in this phase were discussed among the authors, and a third investigator was consulted when needed.

The third phase consisted of filling out tables for each of the remaining 47 articles to systematically evaluate their eligibility. Since authors use different measures for government spending and the number of lower/upper house members, we extracted all coefficients that provided this information. We decided which variables to keep by following the current practices of the literature. In this phase, we also collected information on whether or not the paper had been published, and if it explicitly discussed the *law of 1/n*. Upon choosing the variables, we excluded the non-conforming studies, arriving at our final sample of 31 articles.

B.1 Exclusion Analysis

We selected the final pool of articles based on two criteria regarding their reported coefficients:

1. Matched treatment variable:

- *N*: Number Legislators in the Lower House
- *logN*: Log Number Legislators in the Lower House
- *K*: Number Legislators in the Upper House

2. Matched outcome variable:

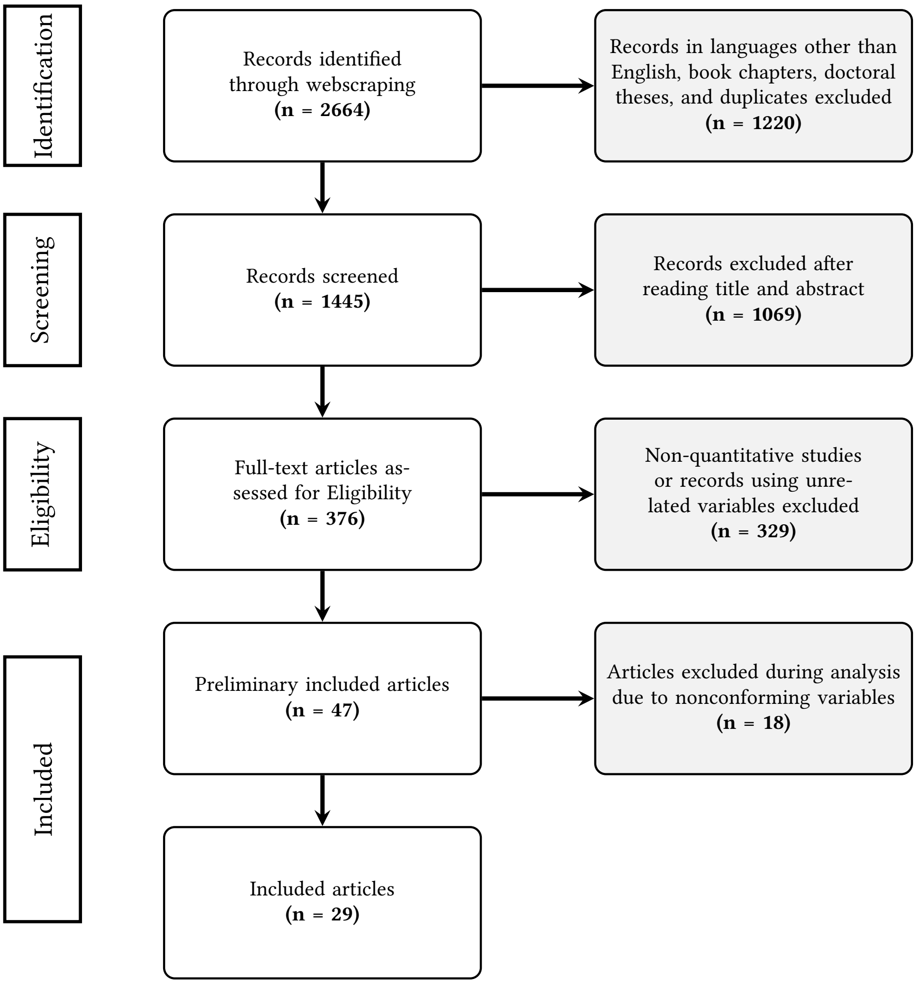
- *ExpPC*: Expenditure Per Capita
- *logExpPC*: Log Expenditure Per Capita
- *PCTGDP*: Percent GDP Public Expenditure

If a paper did not use a combination of these variables, we excluded it from the meta-analysis.

B.2 Flow Chart

The diagram below shows each step of our article selection process. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement to conduct our study[1]. The column to the right depicts the amount of articles excluded in each phase, and the one to the left shows the number of records evaluated.

[1] More information about the PRISMA statement is available at `http://www.prisma-statement.org`.



C Meta-Analysis Dataset

Our data are comprised of two datasets. The first dataset has the main coefficients reported in the studies. These data include only the most rigorous model from each paper, that is, those estimated with the largest sample size, most control variables, and fixed effects if the authors added them. If the article employed a regression discontinuity design, we chose the coefficient from the optimal bandwidth or from the intermediate one. This sample encompasses 44 estimates, as 13 articles analysed two dependent or independent variables of interest. Our second sample, in contrast, contains all the 148 effect sizes reported in the 31 papers.

In the main text, we focus on the results for our restricted sample as we consider them more robust, but the findings are very similar when we use the extended dataset. Here we present the results of all tests performed in both reduced and full samples.

D Descriptive Statistics

In this section, we show the descriptive statistics for our sample. We focus on the following paper characteristics: study year, whether the paper has been published or not, the electoral system of the country discussed in the original study, the data aggregation level, as well as the distribution of the dependent and independent variables of interest.

D.1 Study Year

For study year, we have an average of 2009.18, with standard deviation of 6.55. The oldest study included in the paper is from 1998, while the most recent paper was written in 2019. Therefore, we cover 21 years of tests of the *law of 1/n*.

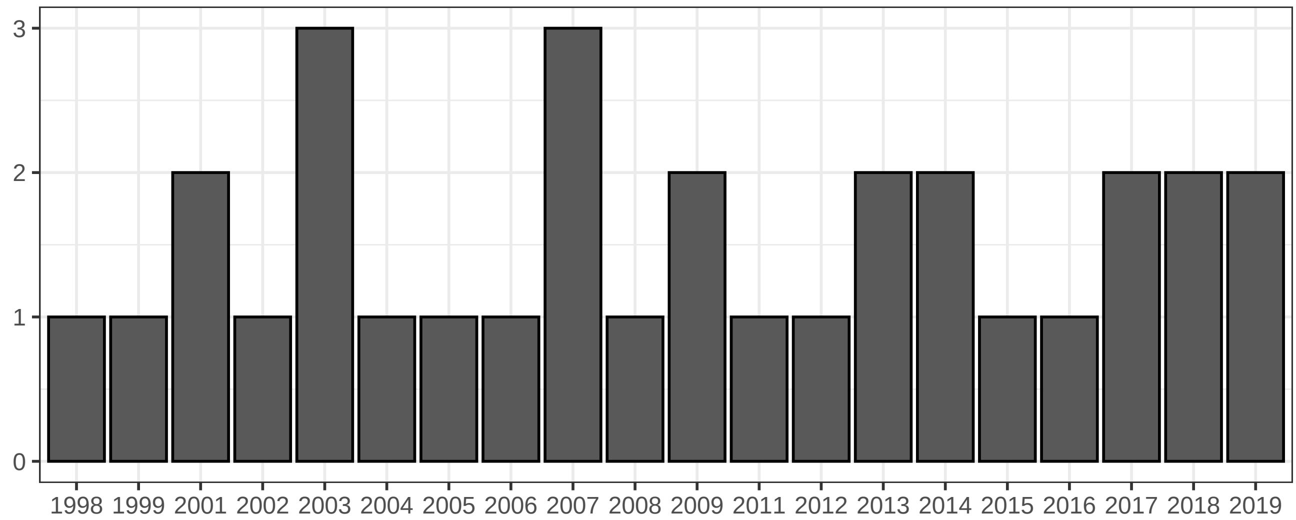


Figure 1: Study Year Frequencies

D.2 Frequency of Published Papers

Studies were included in our sample regardless of their publication status. From the 31 papers in the sample, 5 were published while 26 were not published.

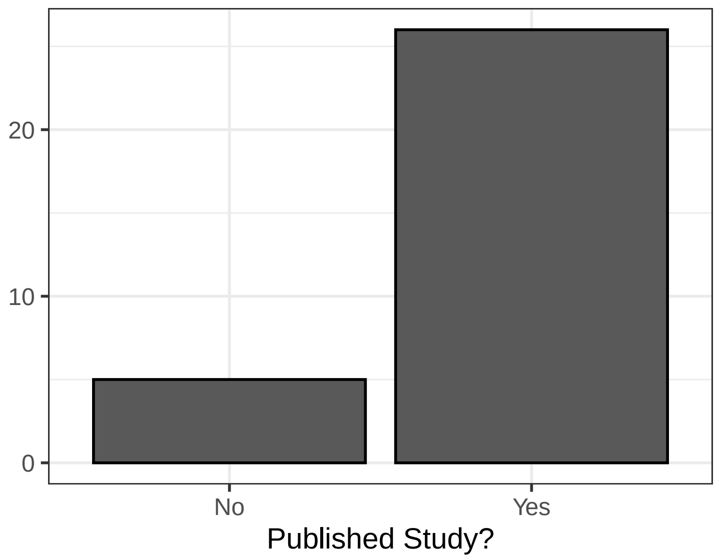


Figure 2: Was the study published?

D.3 Electoral System

Our sample differs considerably in regards to research design. One remarkable difference is that several authors apply the logics of the *law of 1/n*, which was built with majoritarian systems in mind, to non-majoritarian democracies. In the sample, 15 of the papers study *Majoritarian* systems while 16 study *Non-Majoritarian* electoral systems.[2]

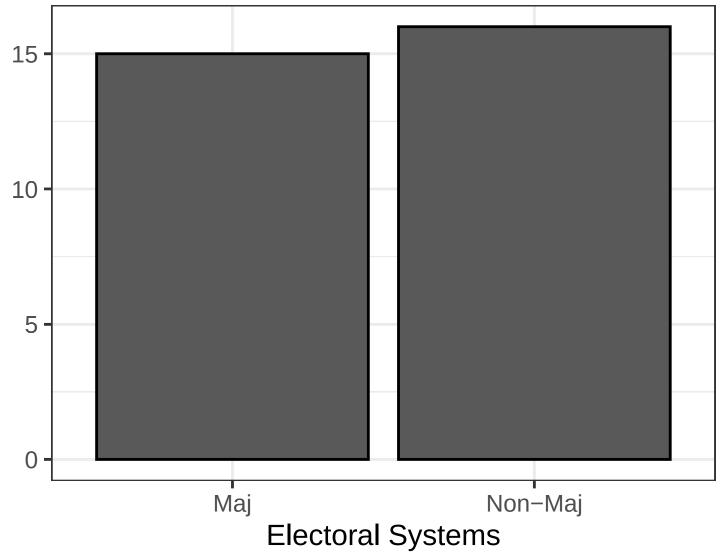


Figure 3: Electoral Systems

D.4 Dependent Variables

The outcome variables included in the paper are:

- 16 Per Capita Expenditure papers
- 8 Natural Log of Per Capita Expenditure papers
- 9 Expenditure as a Percentage of the GDP papers

[2]Note that for the *law of 1/n* to be valid in a non-majoritarian system, we need to assume that despite the fact that politicians are able to campaign in every place in the district, the votes are geographically concentrated. The concentration facilitates politicians to use pork-barrel projects to captivate their electoral supporters.

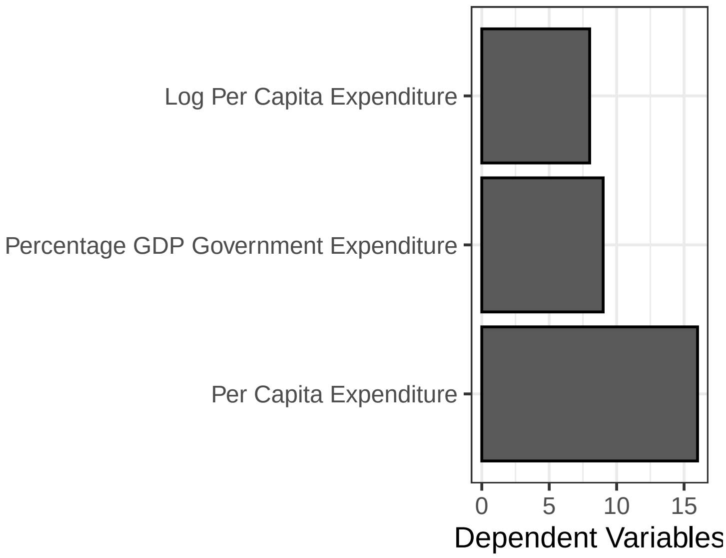


Figure 4: Dependent variables across the law of 1/n studies

D.5 Independent Variables

Most papers in our sample analyse the number of legislators in the lower house (7). The second most frequent independent variable is the number of legislators in the upper house (12). Finally, the minority of papers use the natural log of the number of legislators in the lower house as an independent variable (25). As we noted above, some papers had multiple coefficients, and thus the total number of coefficients is 44, while the number of papers is only 31.

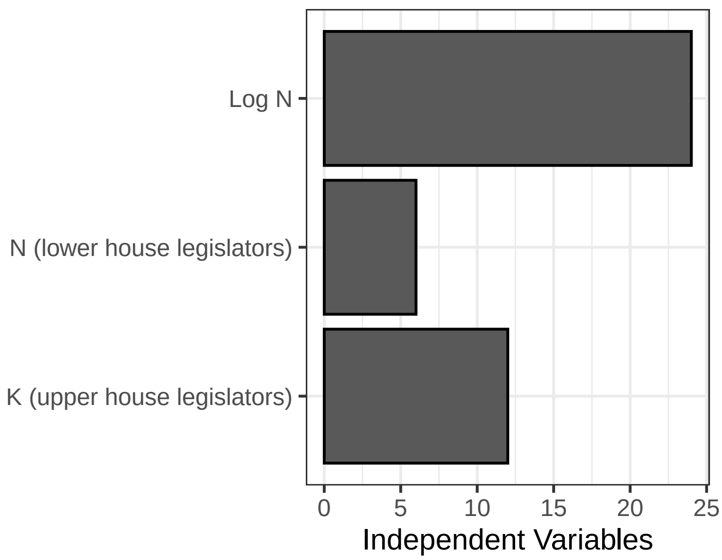
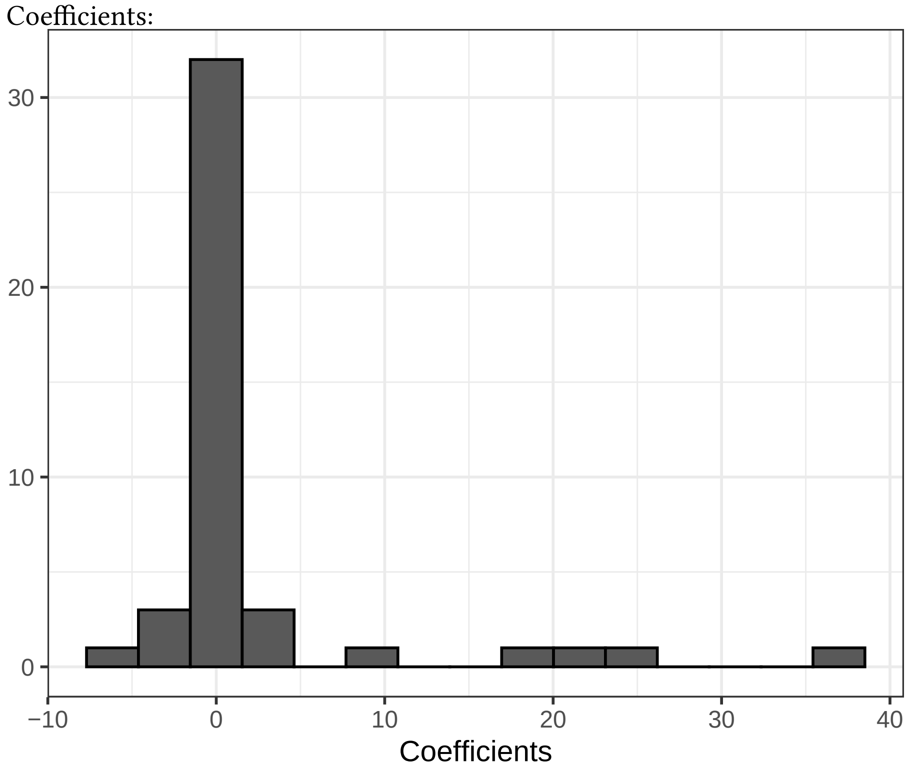


Figure 5: Independent variables across the law of 1/n studies

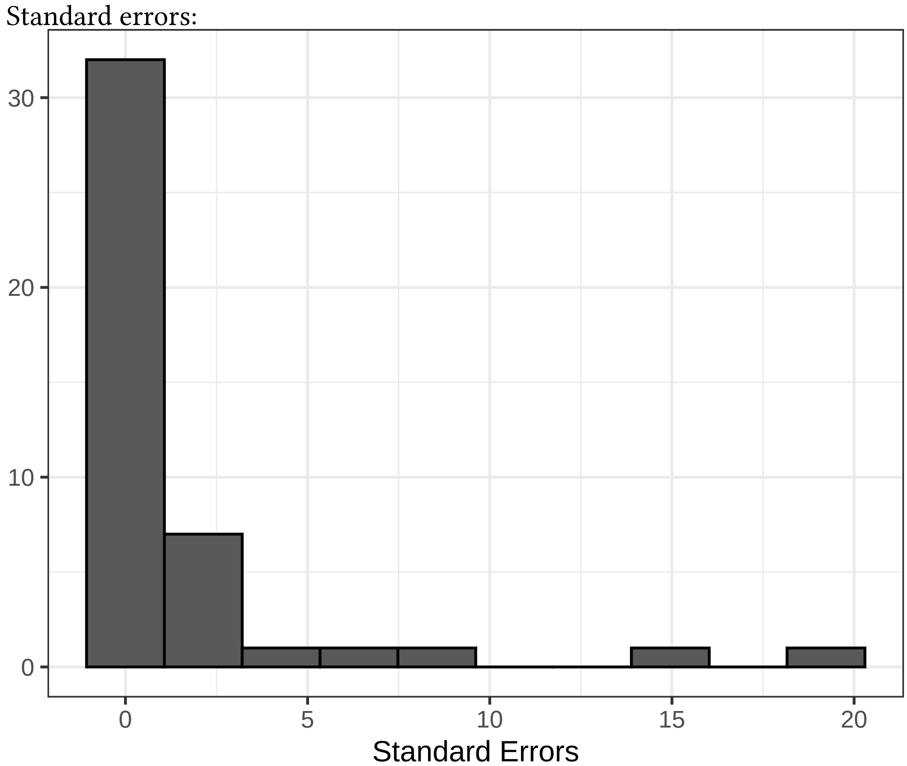
D.6 Histogram of the Coefficients and the Standard Errors

The coefficients in the papers vary considerably. In this section, we plot a histogram of the coefficients for all measurements included in the meta-analytic dataset.

Coefficients:



Standard errors:



D.7 Sign Coefficients

One simple statistic that we can compute to assess the validity of the *law of 1/n* is the frequency of positive and negative estimates in the study sample. Below we plot the frequency for all the papers included in the meta-analytic dataset.

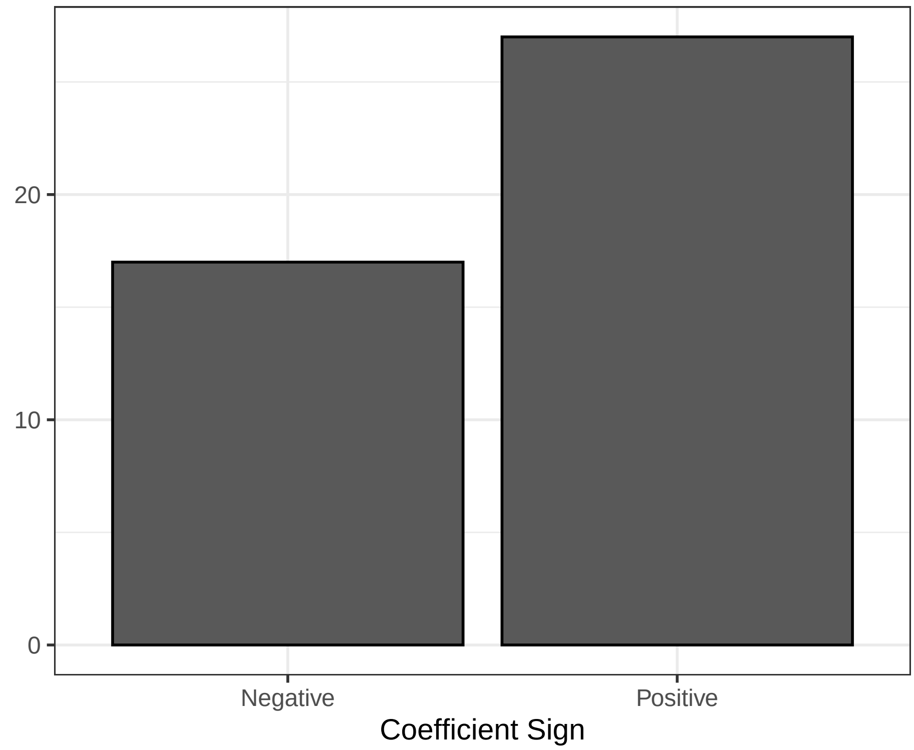


Figure 6: Coefficient Sign

E Descriptive Statistics of Moderators

We chose a set of moderators that frequently appear in the literature and may help us interpret our results. We included them in our meta-regressions alongside an indicator for the type of independent variable used in the original study (n, $\log(n)$, or k). The additional moderators are: 1) electoral system; 2) data aggregation level; 3) estimation method; 4) publication year; 5) paper publication in an academic journal. The table below presents descriptive statistics for these moderators in our selection of articles.

Table 1: Descriptive Statistics of Moderators

	[ALL]	Other Coefficients	Main Coefficients
	N=148	N=104	N=44
Independent Variables:			
K	45 (30.4%)	33 (31.7%)	12 (27.3%)
logN	22 (14.9%)	15 (14.4%)	7 (15.9%)
N	81 (54.7%)	56 (53.8%)	25 (56.8%)
Year	2008 (6.04)	2008 (5.81)	2009 (6.55)
Published work:			
No	15 (10.1%)	8 (7.69%)	7 (15.9%)
Yes	133 (89.9%)	96 (92.3%)	37 (84.1%)

Table 1: Descriptive Statistics of Moderators *(continued)*

	[ALL]	Other Coefficients	Main Coefficients
Electoral system:			
Maj	72 (48.6%)	49 (47.1%)	23 (52.3%)
Non-Maj	76 (51.4%)	55 (52.9%)	21 (47.7%)
Estimation method:			
OLS	47 (31.8%)	36 (34.6%)	11 (25.0%)
PANEL	78 (52.7%)	54 (51.9%)	24 (54.5%)
IV	12 (8.11%)	7 (6.73%)	5 (11.4%)
RDD	11 (7.43%)	7 (6.73%)	4 (9.09%)

F Binomial Tests for Coefficient Signs

The *law of 1/n* posits that we should expect a positive influence of legislature size on public expenditures. A general test of the theory could investigate whether the papers tend to find a higher frequency of positive coefficients in their estimations. In statistical terms, consider a random variable representing the coefficient sign for the papers. As each sign of the paper is a Bernoulli trial, the aggregate result for all papers follows a Binomial distribution with parameters n equals the number of papers, and p the chance of a positive sign. The *law of 1/n* can be reformulated as the chance of $p > 0.5$, which facilitates the testing of the theory. The null hypothesis for such a test is that:

- H_0: the proportion of positive and negative signs are indistinguishable ($p = 0.5$).

As we are taking an agnostic approach, we acknowledge that either the *law of 1/n* ($p > 0.5$), or the *reverse law of 1/n* ($p < 0.5$) could be true. In this case, the alternative hypothesis is $p \neq 0.5$. To perform this test, we run binomial tests in `R`, using the function `binom.test(.)`.

This test has two advantages. First, it is robust to the design of the paper. This is an important feature as papers analyse different countries, samples, and have distinct characteristics, such as whether they were published or not. All these factors increase the levels of study heterogeneity. The binomial test ignores the design discrepancies and focuses on the overall reported effect. Second, this test has the advantage of being straightforward and easy to interpret. It requires very few assumption and has a direct statistical formulation. The disadvantage is that we can extract more information from the articles with meta-regressions, as we see in the next sections.

For the number of legislators in the lower house (N), the results follow below.

method	alternative	estimate	p.value
Exact binomial test	two.sided	0.44	0.69

Under the null hypothesis of $p = 0.5$, we find that 11 studies, out of 25, had a positive sign. The chance of a distribution with $p = 0.5$ generate this sample is equal to p-value = 0.69. Therefore, we reject the hypothesis that $p \neq 0.5$.

For the log of the number of legislators in the lower house ($\log(N)$), the results follow below.

method	alternative	estimate	p.value
Exact binomial test	two.sided	0.8571	0.125

Out of 7, 6 had a positive sign. The chance of a distribution with $p = 0.5$ generate this sample is equal to p-value = 0.125. So we reject the hypothesis that $p \neq 0.5$.

Finally, for the number of legislators in the upper house (K), the results are:

method	alternative	estimate	p.value
Exact binomial test	two.sided	0.8333	0.03857

Here we see that 10 out of 12 had a positive sign. The p-value for this test is 0.039. Therefore, we accept the hypothesis that $p \neq 0.5$. This is the only test that presents evidence of an association between the legislature size and expenditure.

G Meta-Analysis

G.1 Estimation Method

In general terms, there are two main ways to conduct a meta-analysis, either by using fixed effects or by employing random effects models. The fixed effects model assumes that there exists only one true effect, and that all estimates are an attempt to uncover this effect. The random effects model, in contrast, assumes that there is a distribution of true effects, and that the coefficients vary based on sampling and tests characteristics.

In this paper, we a random-effects model. The empirical papers testing the *law of 1/n* are very diverse. We tried to capture some of this diversity by considering the main dependent and independent variables separately, but they have at least three other important sources of dispersion:

1. **Subjects**: Counties, Municipalities, States, Provinces, Countries.

2. **Electoral systems**: Majoritarian, PR, Mixed.
3. **Modelling strategies**: Panel data, Standard OLS, IV, RDD.

These sources of heterogeneity have two implications. First, they make our estimates notably disperse. All but one of our heterogeneity tests are significant. When the sample sizes are large enough, we removed more heterogeneous studies, but we still had considerable dispersion in our estimates. Second, the amount of heterogeneity makes fixed effects estimates unrealistic and biased. Thus, we opt for random effects model.

Let each study having an effect of T_i. In a random effects model, we can decompose this effect into two components, the true effect that the study with the same specifications as i comes from, θ_i, and a within-study error ε_i:

$$T_i = \theta_i + \varepsilon_i$$

And the random effects model assumes that the θ_i varies from study to study, having a true parameter μ, plus a between-study error, ξ_i:

$$T_i = \mu + \xi_i + \varepsilon_i$$

And the random effects model estimates the parameter μ, under the challenge of estimating both the within-and-between-study sampling errors.

Another crucial assumption in the meta-analysis is the independence between the results (Harrer et al. (2019), Cheung (2019), Veroniki et al. (2016), Borenstein et al. (2011)). This assumption states that for our findings be consistent and efficient, the coefficients used in the meta-analysis have to come from different sources of variation. However, in the political economy literature, authors frequently use similar datasets, and almost all papers fit more than one model for the same variable. While our short dataset contains 44 estimates, our full dataset has 148 coefficients. This because the papers report an average of 4.7741935 coefficients. Between robustness tests, multiple dependent and independent variables, and the papers that share similar datasets, the independence assumption is violated. To correct for this problem, we use a multi-level random effects model (Cheung (2014)). The main difference from the single-level random effects model is that we add two extra levels of dependence: the participants and the studies levels. All these levels are assumed to absorb the dependence in the data, leaving for the main coefficient, the independent effect of legislature size on public spending.

There are two levels in the main models. First, we build a common index for papers that share the same dataset specifications. The papers with common indexing are:

Paper IDs	Source of Dependence
3, 42, 132, 165, 439, 441, 467, 505	US States Dataset
408, 208, A258	US Municipalities Dataset
849, 578	US Municipalities Datasetand Same Author in twoDifferent Studies

All the remaining papers receive a unique index. As the number of the papers with these dependences are not very high, and many characteristics within papers vary (e. g., statewise ad-hoc exclusions, start and end points, regions, etc), we show it makes little difference to change from this index to the paper ID. In the case of the full dataset, the results change considerably, because authors fit several models within the same paper. In the case In any case, we use multi-level random effects for all the estimated models in this paper.

To study the possibility of XXXX

In all empirical estimates, we use the package `meta`, and the package `dmetar`, described in (Harrer et al. 2019)(`https://bookdown.org/MathiasHarrer/Doing_Meta_Analysis_in_R/random.html`). To empirically implement the random effects model, we need to choose a method to estimate the true effect size variance, τ^2, which in our formulation, represents the variance of ξ_i. We selected the **Restricted Maximum Likelihood Estimator**, as the literature regards it the most precise when analysing continuous measures, such as we have in our data (Veroniki et al. (2016)).

We combined the three independent variables (N, $\log(N)$, and K) with our dependent variables of interest (Expenditure Per Capita, Log of Expenditure Per Capita, Expenditure as a Percentage of the GDP). This formed a 3×3 table, and in the following pages we present the results for each of these combinations.

G.2 Lower House Size and Expenditure per Capita

```
##
## Multivariate Meta-Analysis Model (k = 15; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed              factor
## sigma^2.1   0.1614  0.4018      8     no           id_level1
## sigma^2.2   0.0000  0.0000     15     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 14) = 215.1021, p-val < .0001
##
```

```
## Model Results:
##
## estimate      se    tval    pval    ci.lb   ci.ub
##   0.0385  0.1590  0.2418  0.8125  -0.3027  0.3796
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot:

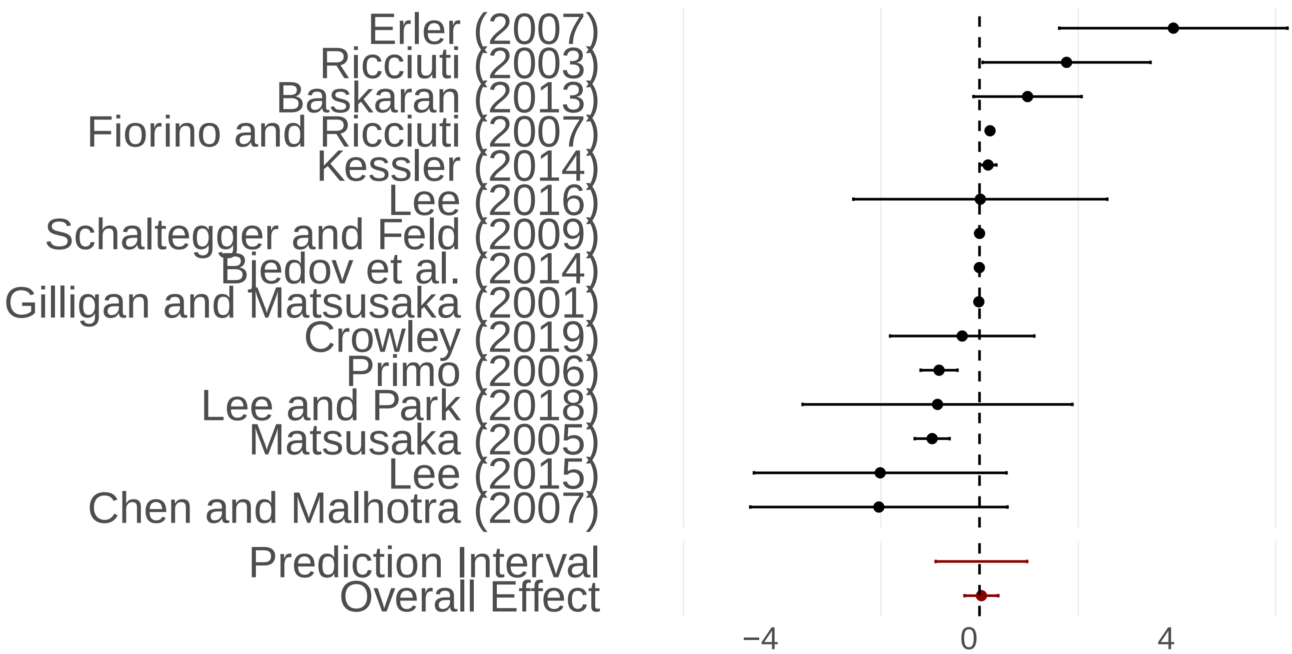


Figure 7: Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

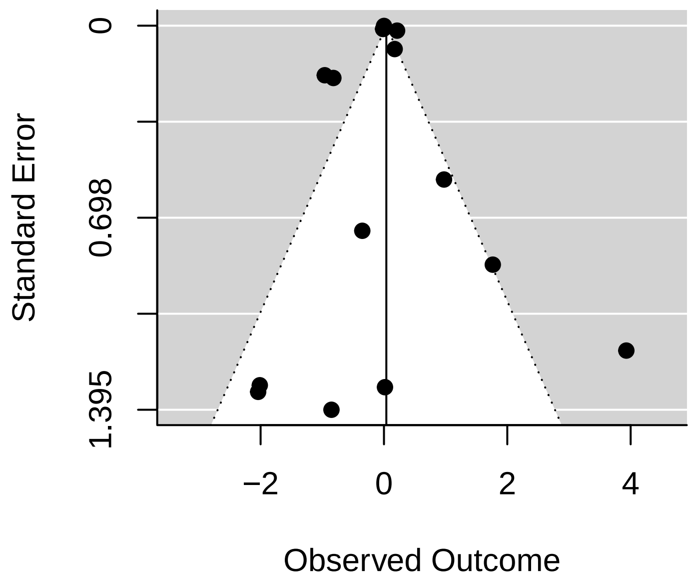


Figure 8: Funnel Plot – Effect of Lower House Size (N) on Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 215.1$.
2. The estimated SMD in the random effects model is $g = 0.04$ ($SE = 0.159$).
3. The prediction interval ranges from -0.89 to 0.97. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.2.1 Electoral System Subgroup Analysis

The *law of 1/n* was created for majoritarian systems. In the theoretical section below, we explain why the argument have potential issues when applied to non-majoritarian electoral systems. We estimated a subgroup analysis using a binary electoral system.

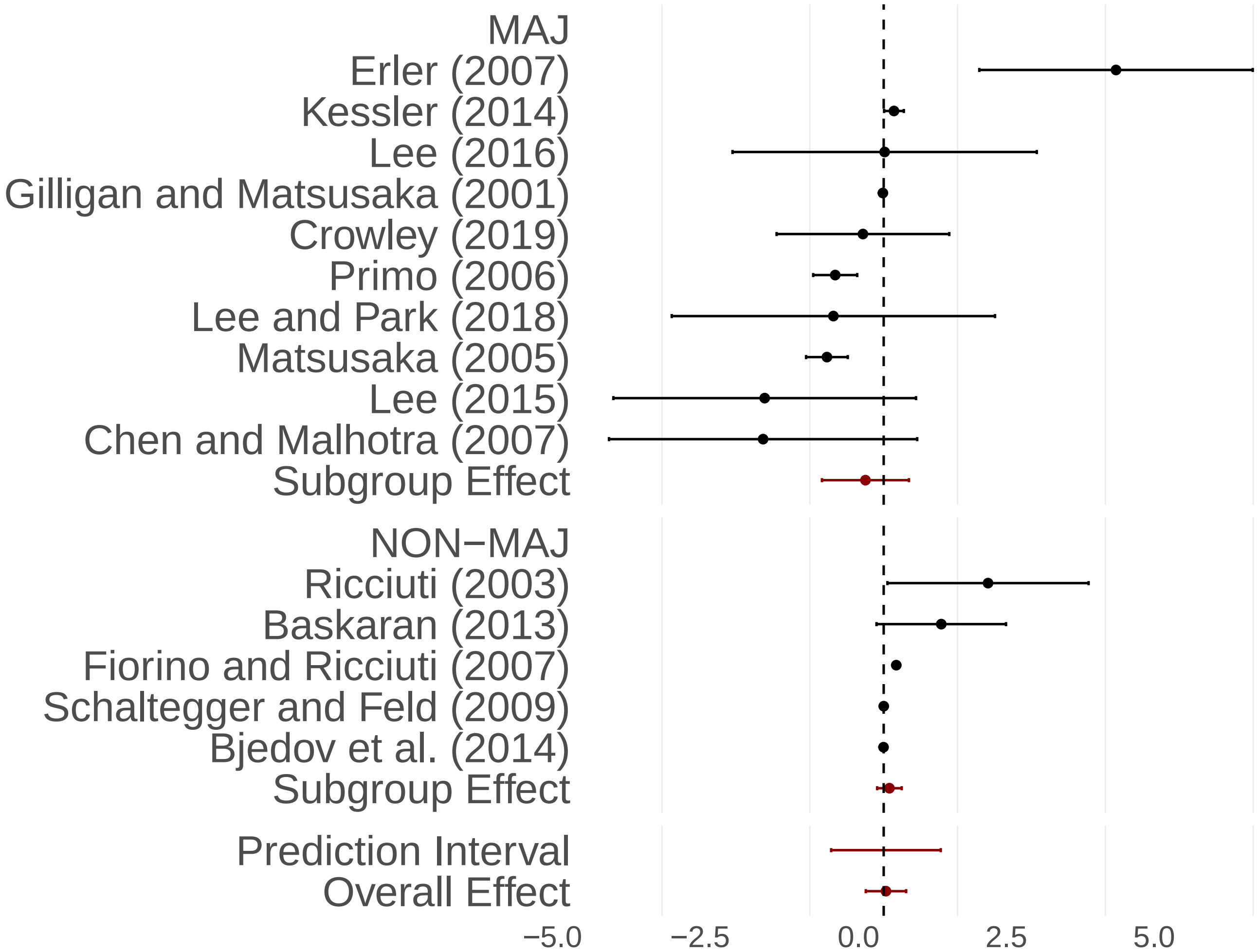


Figure 9: Subgroup Analysis of (N) x (ExpPC), controlling by electoral system

Therefore, we can see that the hypothesis that majoritarian systems produce systematic positive effects was disproved. Both are non-significant, and they reassure us that the absense of effect is not caused by pooling multiple types of electoral systems.

G.3 Log Lower House Size and Expenditure per Capita

There are no studies that have per capita expenditure as the dependent variable and log of lower house size as the treatment variable.

G.4 Upper House Size and Expenditure per Capita

Now, we look into the upper house size (K). In this model, we investigate the effect of upper house size on expenditure per capita (ExpPC).

```
##
## Multivariate Meta-Analysis Model (k = 9; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed              factor
## sigma^2.1  32.4170  5.6936      4     no           id_level1
## sigma^2.2  52.2149  7.2260      9     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 8) = 42.6588, p-val < .0001
##
## Model Results:
##
## estimate      se    tval    pval    ci.lb    ci.ub
##   3.8171  4.2570  0.8967  0.3961  -5.9995  13.6337
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And the forest plot:

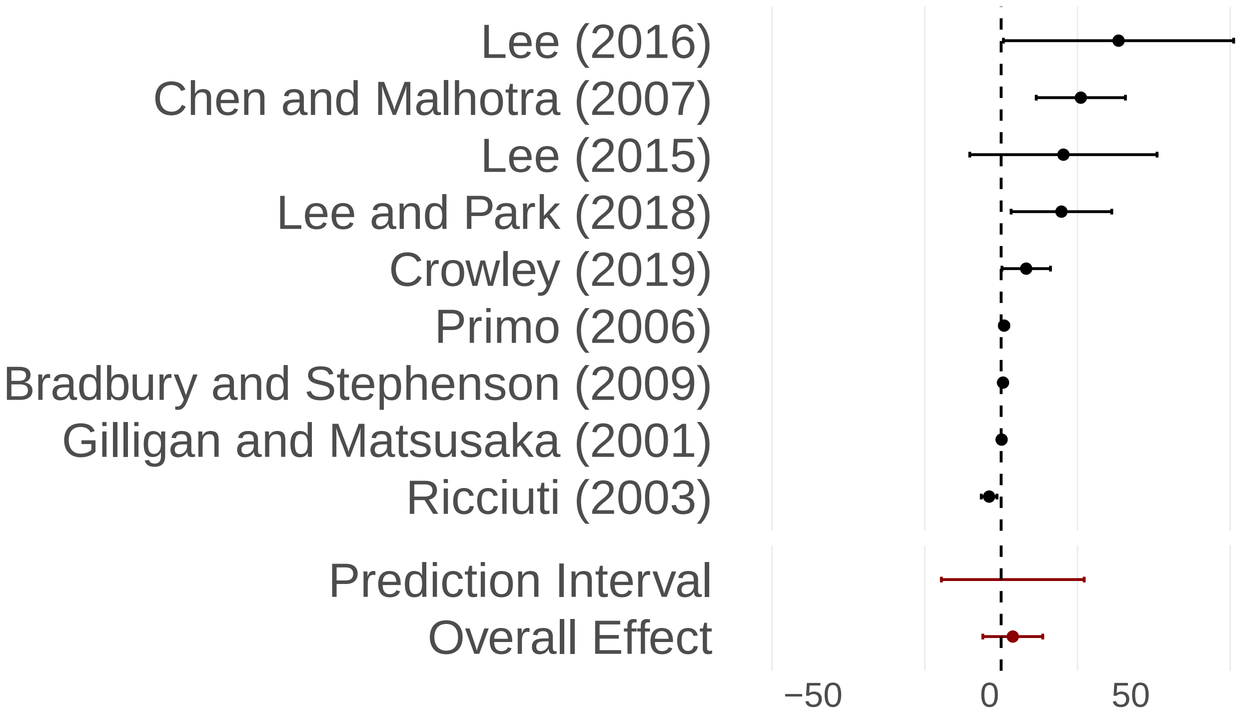


Figure 10: Effect of upper house size (K) on the per capita government expenditure (ExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

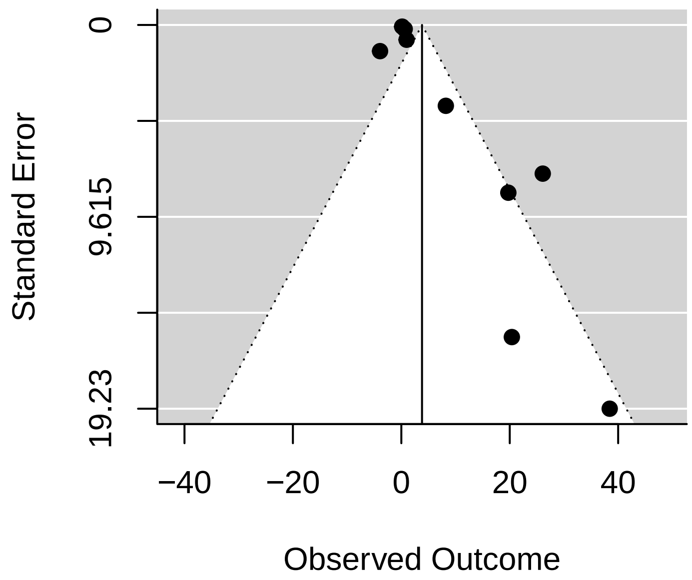


Figure 11: Funnel Plot – Effect of upper house size (K) on per capita government expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 42.66$.
2. The estimated SMD in the random effects model is $g = 3.82$ ($SE = 4.257$).
3. The prediction interval ranges from -19.56 to 27.19. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.5 Lower House Size and Log Expenditure Per Capita

This model estimates the Log of Per Capita Expenditure as the dependent variable, and the number of lower house legislators as the treatment variable.

```
##
## Multivariate Meta-Analysis Model (k = 5; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed              factor
## sigma^2.1  0.0050  0.0706      5     no           id_level1
## sigma^2.2  0.0050  0.0706      5     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 4) = 50.0612, p-val < .0001
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0543  0.0462  -1.1746  0.3053  -0.1827  0.0741
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot is as follows:

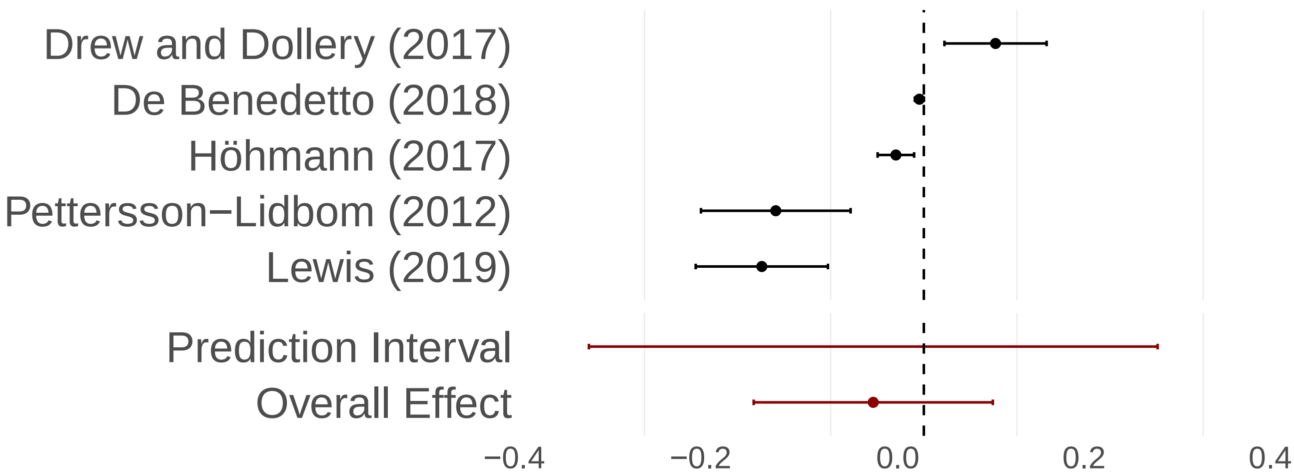


Figure 12: Effect of lower houses size (N) on log of per capita expenditure (logExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

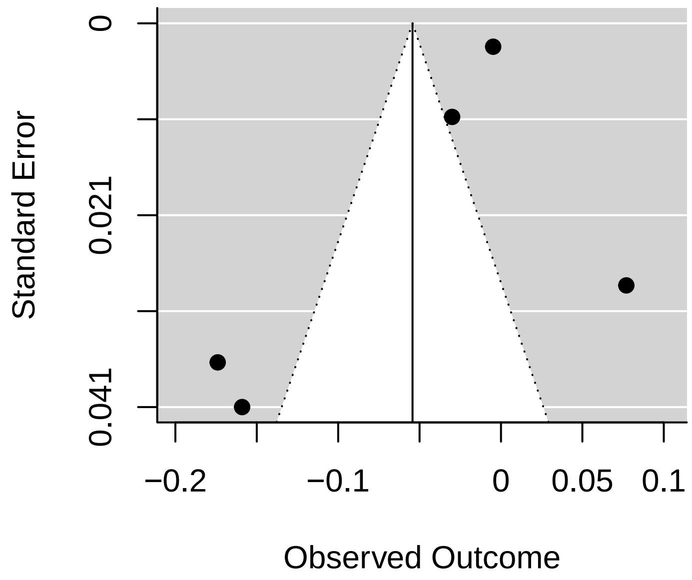


Figure 13: Funnel Plot – Effect of lower houses size (N) on log of per capita expenditure (logExpPC)

Highlights:

1. The results are highly heterogeneous: Q = 50.06.
2. The estimated SMD in the random effects model is g = -0.05 (SE = 0.046).
3. The prediction interval ranges from -0.36 to 0.25. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.6 Log of Lower House Size and Log of Expenditure Per Capita

In this specification, we study the log of per capita expenditure (logExpPC) as a function of the log of lower house size (logN).

```
##
## Multivariate Meta-Analysis Model (k = 4; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed              factor
## sigma^2.1  0.0000  0.0000      2     no           id_level1
## sigma^2.2  0.0058  0.0763      4     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 3) = 14.2923, p-val = 0.0025
##
## Model Results:
##
```

```
## estimate      se    tval    pval    ci.lb    ci.ub
##   0.1815  0.0434  4.1868  0.0248  0.0435  0.3195  *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot is available below:

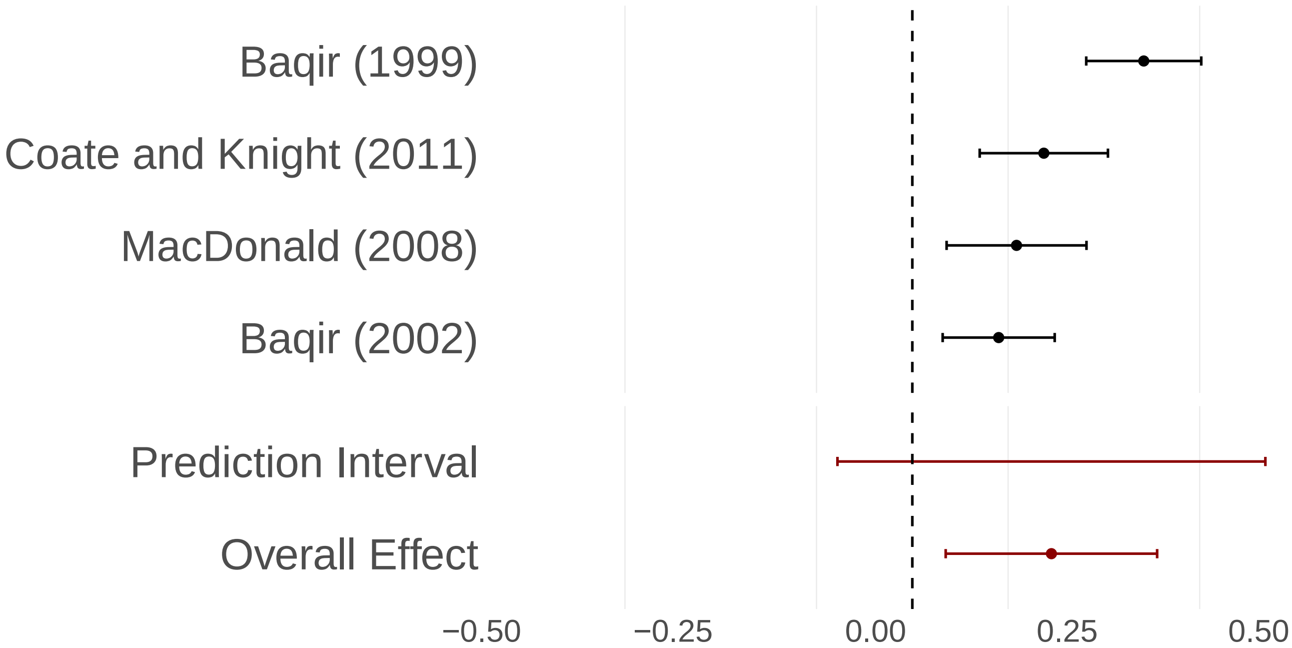


Figure 14: Effect of log lower houses size (logN) on the log of per capita government expenditure (logExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

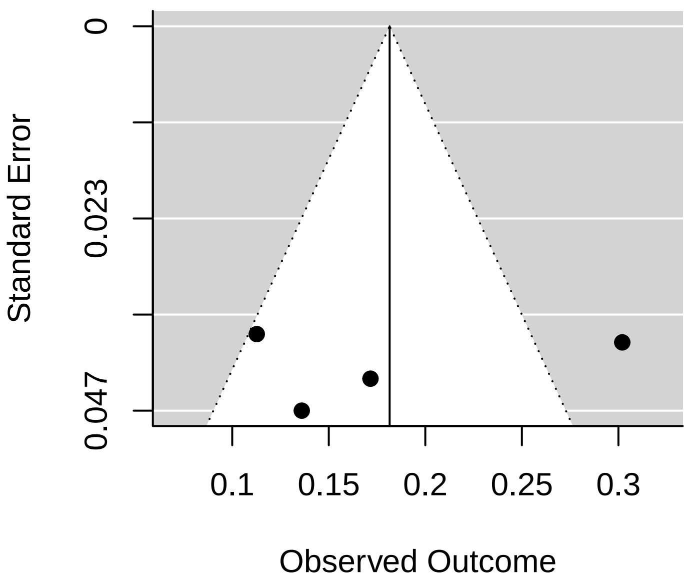


Figure 15: Funnel Plot – Effect of log lower houses size (N) on log of per capita government expenditure (logExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 14.29$.
2. The estimated SMD in the random effects model is $g = 0.18$ ($SE = 0.043$).
3. The prediction interval ranges from -0.1 to 0.46. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.7 Upper House Size and Log of Expenditure Per Capita

No studies correlate the log of per capita expenditure with the size of upper house (K).

G.8 Lower House Size and Expenditure as Percentage of GDP

This model fits the random effects for the percentage of GDP as public expenditure as the main outcome, and the size of lower house as the treatment variable.

```
##
## Multivariate Meta-Analysis Model (k = 5; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed              factor
## sigma^2.1  0.0004  0.0195      5     no            id_level1
## sigma^2.2  0.0004  0.0195      5     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 4) = 30.9717, p-val < .0001
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0083  0.0132  -0.6251  0.5658  -0.0449  0.0284
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Below, you may find the forest plot:

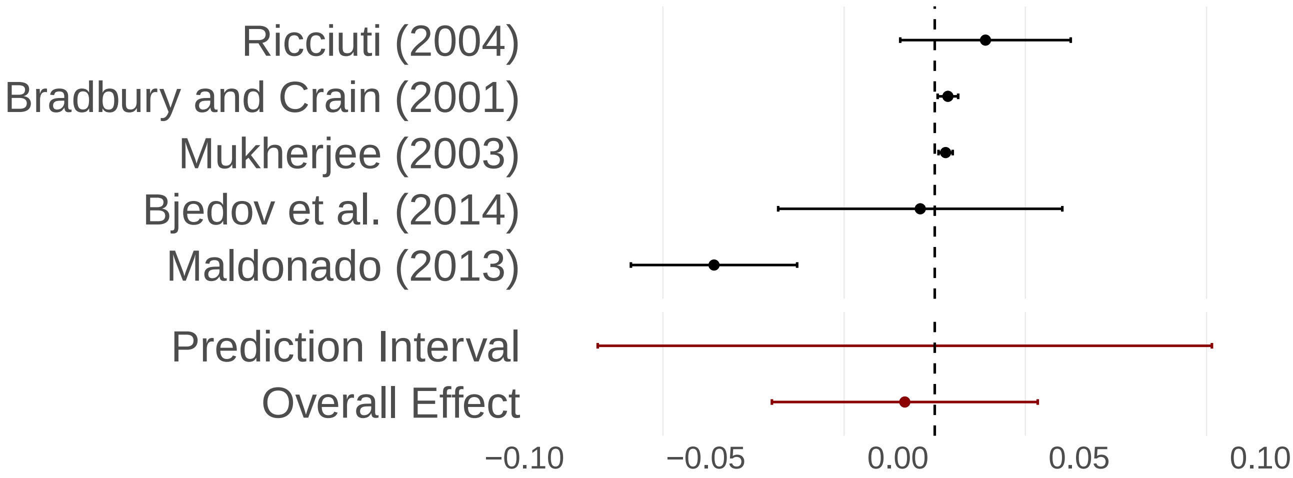


Figure 16: Effect of lower houses size (N) on percentage of public expenditure GDP (PCTGDP)

And to assess the possibility of publication bias, we add funnel plot below:

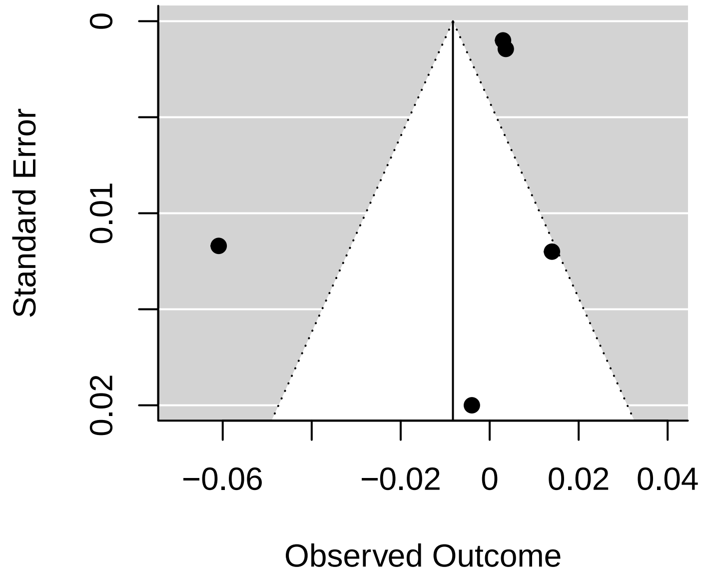


Figure 17: Funnel Plot – Effect of lower houses size (N) on percentage of public expenditure GDP (PCTGDP)

Highlights:

1. The results are highly heterogeneous: Q = 30.97.
2. The estimated SMD in the random effects model is g = -0.01 (SE = 0.013).
3. The prediction interval ranges from -0.09 to 0.08. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.9 Log Lower House Size and Expenditure as Percentage of GDP

This model investigates the percentage of GDP as public expenditure as the dependent variable and the log lower house size (logN) as the treatment variable.

##

```
## Multivariate Meta-Analysis Model (k = 3; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed               factor
## sigma^2.1   2.6578  1.6303      3     no            id_level1
## sigma^2.2   2.6578  1.6303      3     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 2) = 51.6470, p-val < .0001
##
## Model Results:
##
## estimate      se    tval    pval    ci.lb   ci.ub
##   0.0203  1.4854  0.0137  0.9903  -6.3707  6.4114
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot follows below:

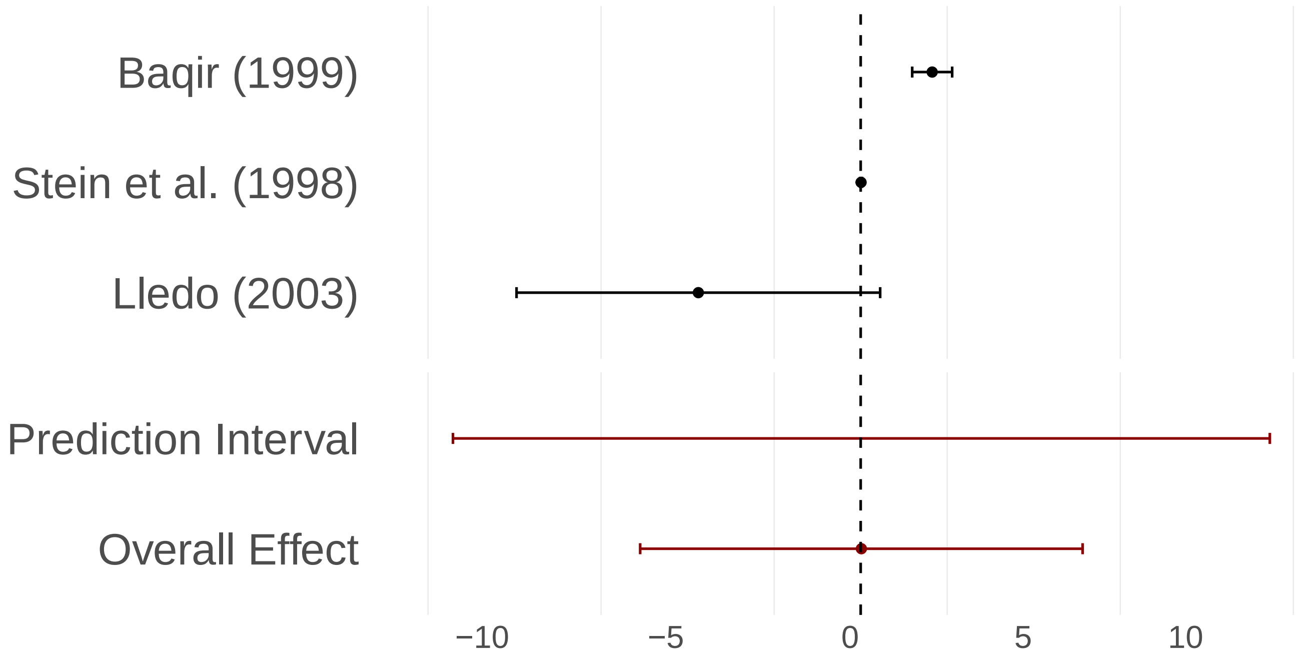


Figure 18: Effect of log lower houses size (logN) on the GDP share of public expenditure (PCTGDP)

And to assess the possibility of publication bias, we add funnel plot below:

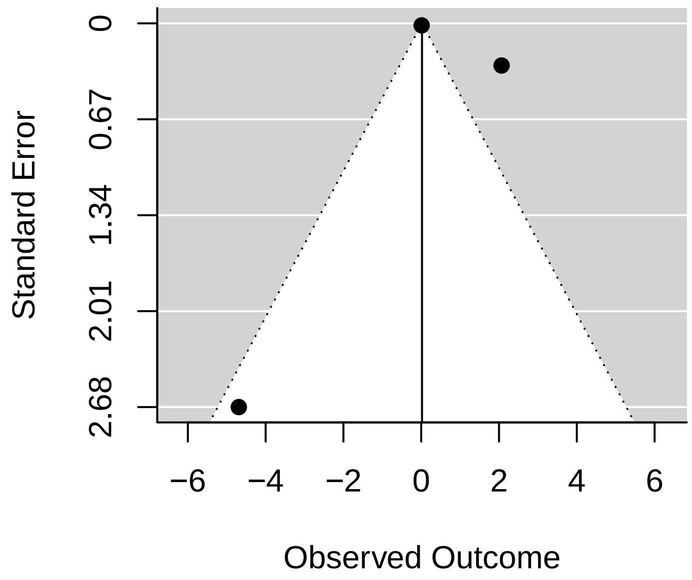


Figure 19: Funnel Plot – Effect of log lower houses size (N) on the GDP share of public expenditure (PCTGDP)

Highlights:

1. The results are highly heterogeneous: $Q = 51.65$.
2. The estimated SMD in the random effects model is $g = 0.02$ ($SE = 1.485$).
3. The prediction interval ranges from -11.78 to 11.82. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.10 Upper House Size and Expenditure as Percentage of GDP

This model looks into the effect of upper house size (K) on the public expenditure share of the GDP (PCTGDP).

```
##
## Multivariate Meta-Analysis Model (k = 3; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.0004  0.0201      3     no            id_level1
## sigma^2.2  0.0004  0.0201      3     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 2) = 14.0739, p-val = 0.0009
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0027  0.0175  -0.1570  0.8896  -0.0781  0.0726
```

```
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot follows below:

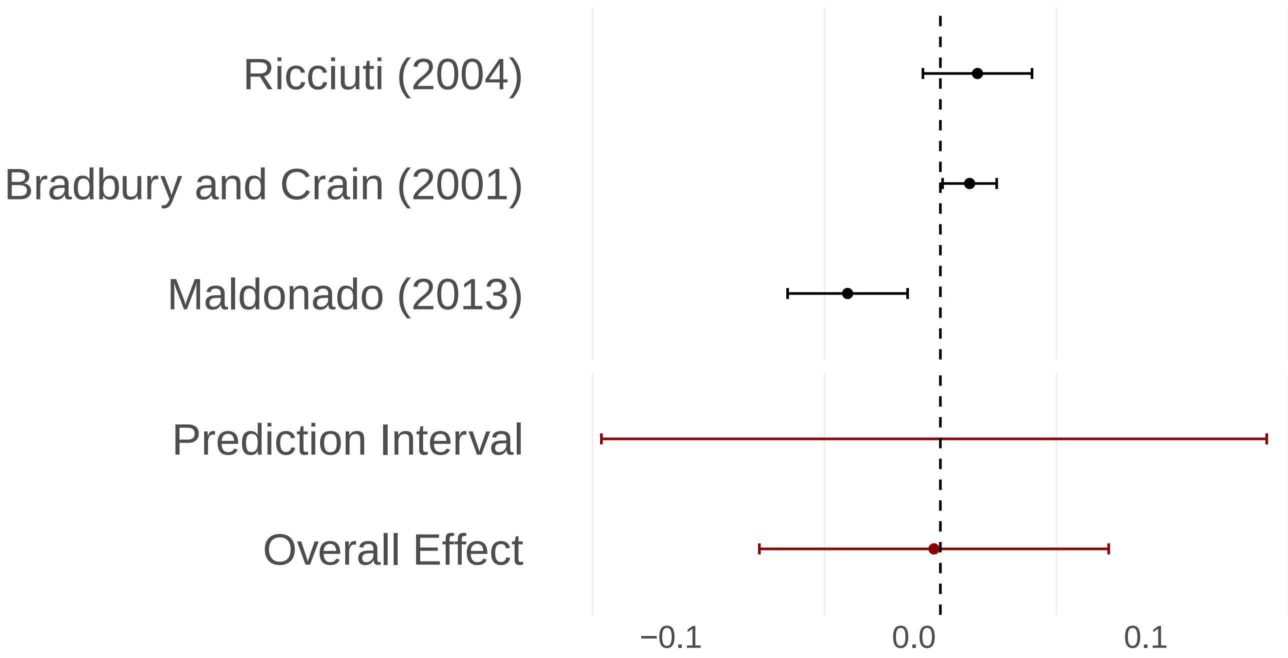


Figure 20: Effect of upper house size (K) on the public expenditure share of the GDP (PCTGDP)

And to assess the possibility of publication bias, we add funnel plot below:

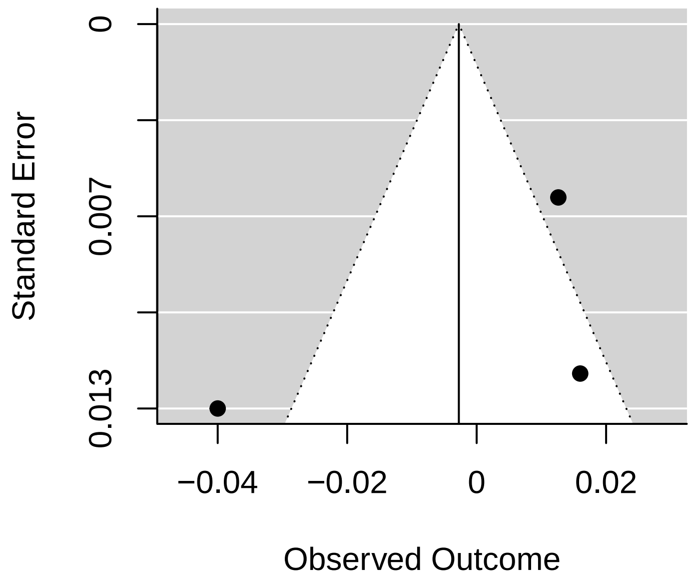


Figure 21: Funnel Plot – Effect of upper house size (K) on the public expenditure share of the GDP (PCTGDP)

Highlights:

1. The results are highly heterogeneous: $Q = 14.07$.
2. The estimated SMD in the random effects model is $g = 0$ ($SE = 0.018$).

3. The prediction interval ranges from -0.15 to 0.14. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.11 Lower House Size and Expenditure per Capita (IV)

```
##
## Multivariate Meta-Analysis Model (k = 4; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.8028  0.8960      3     no            id_level1
## sigma^2.2  0.0000  0.0000      4     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 3) = 46.8325, p-val < .0001
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0105  0.5472  -0.0192  0.9859  -1.7518  1.7308
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And the forest plot:

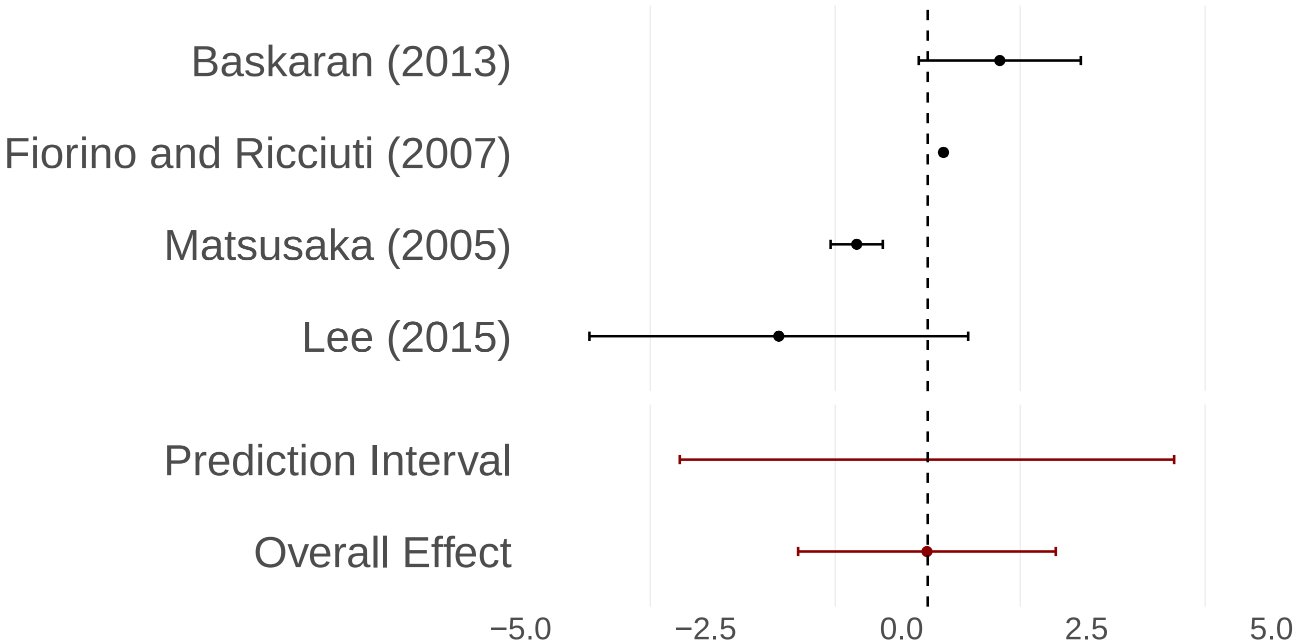


Figure 22: Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

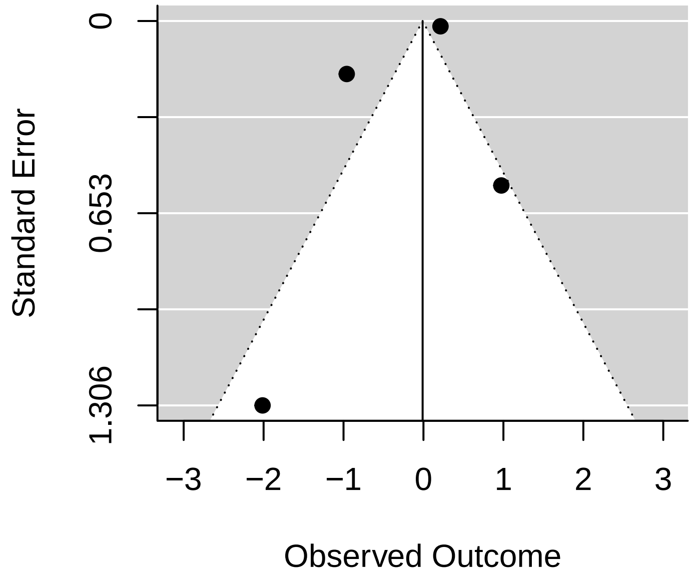


Figure 23: Funnel Plot – Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 215.1$.
2. The estimated SMD in the random effects model is $g = 0.04$ ($SE = 0.159$).
3. The prediction interval ranges from -0.89 to 0.97. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.11.1 Regression Method Subgroup Analysis

Over time, the literature evolved to use causally identified techniques for determine the effect of legislature size on the expenduture per capita. To study whether the method had an effect on the estimated coefficients, we fit a subgroup analysis using the method employed in each paper.

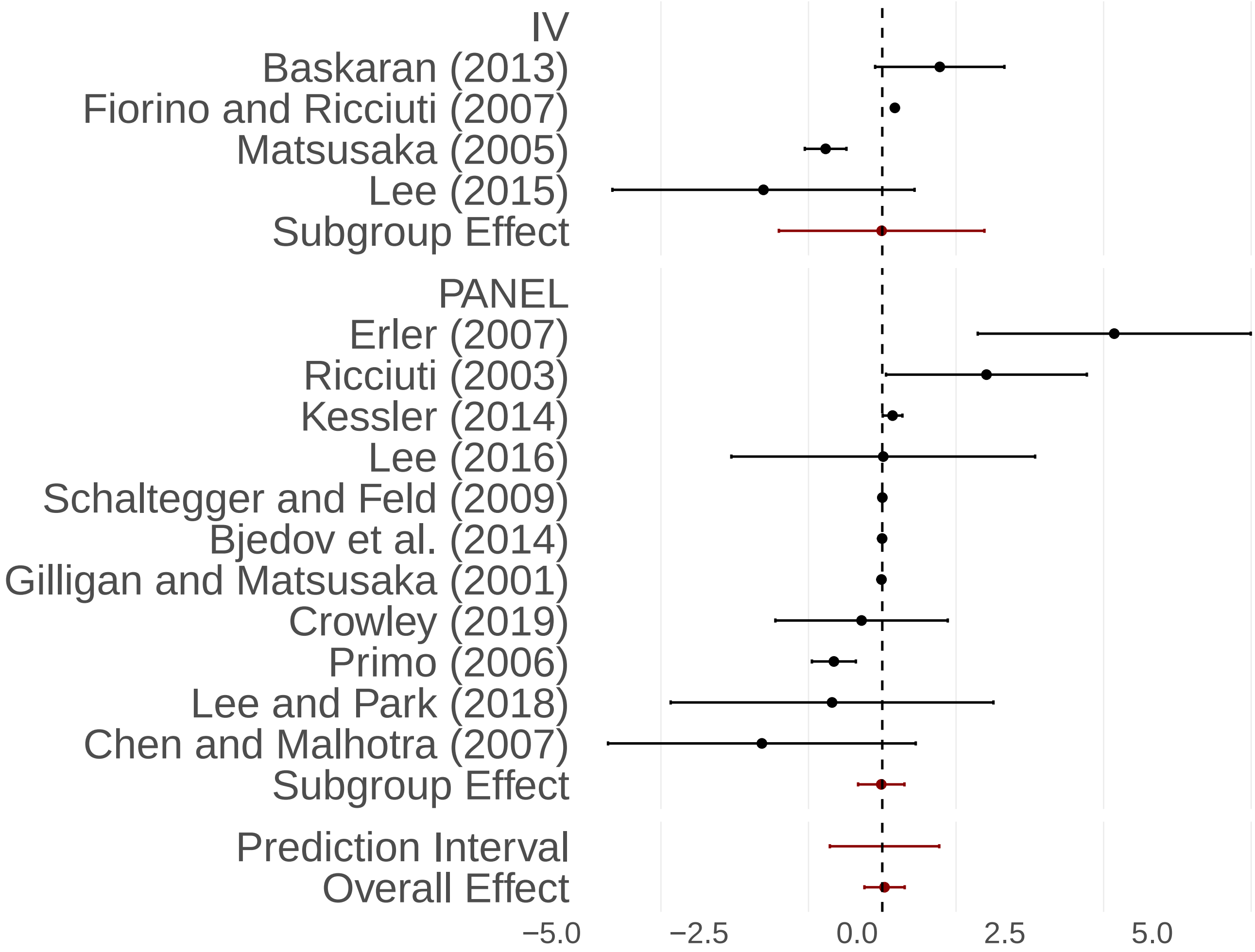


Figure 24: Subgroup Analysis of (N) x (ExpPC), controlling by regression methods

Although all methods generate a null effect, the IV method seems to be well distributed, with two papers with positive effects and two papers negative displaying negative effects. The random effects model for the subgroup is 0.22, which is negative but non-significant. Improve the estimation technique, for the case of IVs, render still a null effect of legislature size on per capita government expenditure.

G.12 Lower House Size and Log of Expenditure per Capita (RDD)

```
##
## Multivariate Meta-Analysis Model (k = 4; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed             factor
## sigma^2.1  0.0034  0.0583      4     no           id_level1
## sigma^2.2  0.0034  0.0583      4     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 3) = 41.0086, p-val < .0001
```

```
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb    ci.ub
##  -0.0849  0.0433  -1.9594  0.1449  -0.2228  0.0530
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Forest plot:

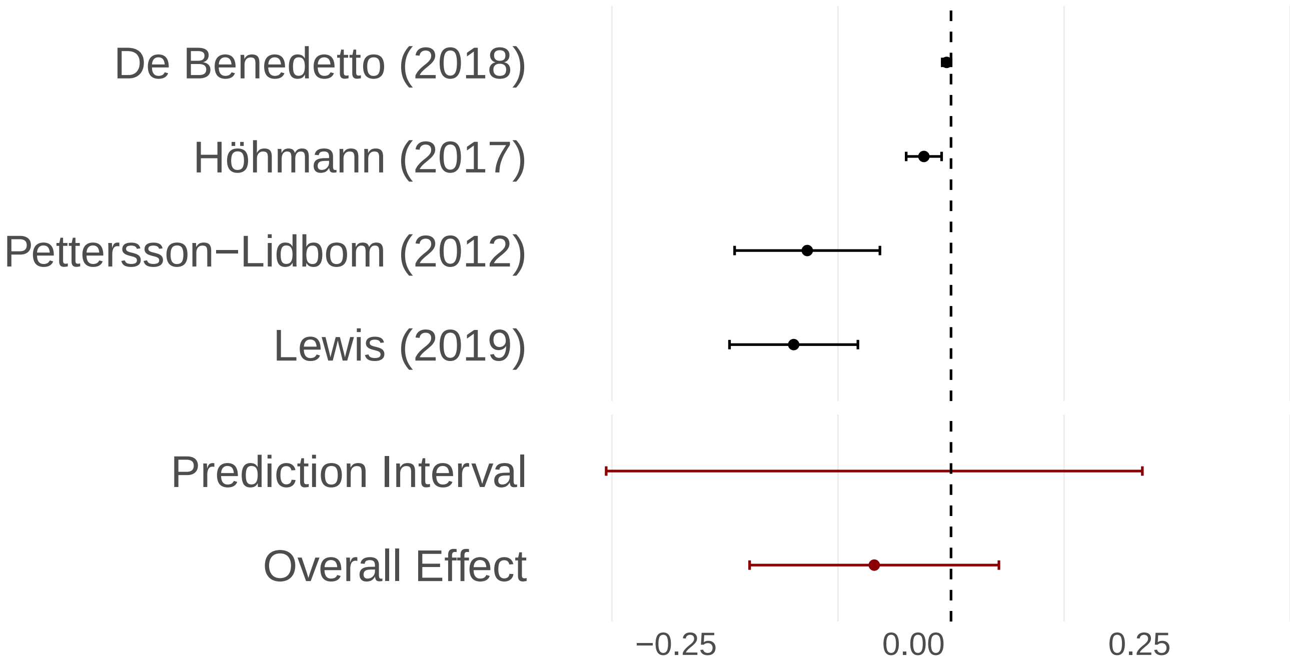


Figure 25: Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: Q = 41.01.
2. The estimated SMD in the random effects model is g = -0.08 (SE = 0.043).
3. The prediction interval ranges from -0.38 to 0.21. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

G.12.1 Regression Method Subgroup Analysis

Over time, the literature evolved to use causally identified techniques for determine the effect of legislature size on the log of expenditure per capita. To study whether the method had an effect on the estimated coefficients, we fit a subgroup analysis using the method employed in each paper.

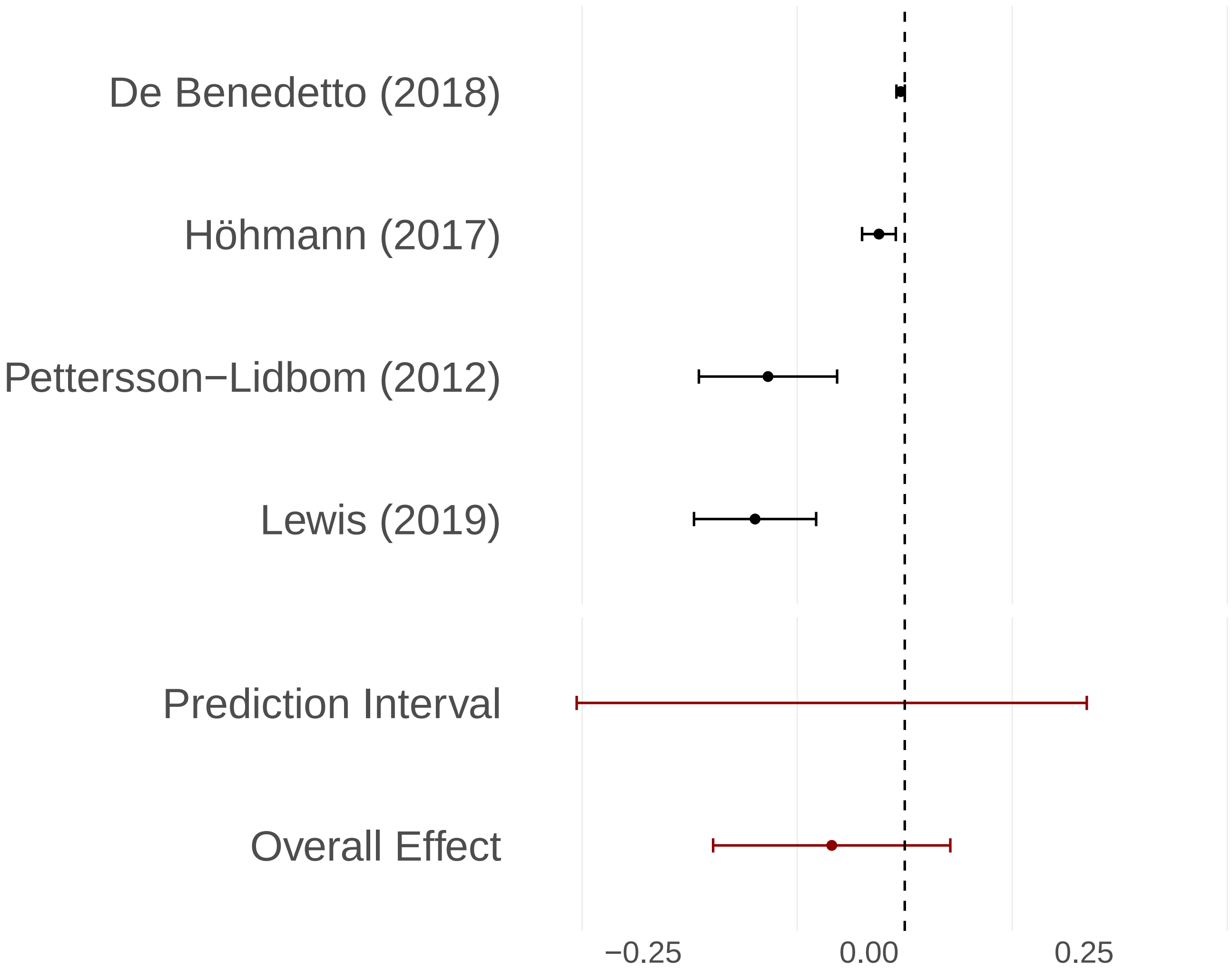


Figure 26: Subgroup Analysis of (N) x (logExpPC), controlling by the regression methods

For the RDD subgroup analysis, we can see a much clearer picture. The subgroup effect is -0.085. This suggests that improving the estimation renders to a negative result that is likely to hold conditional on more papers using the technique displaying the same effect size and sign.

```
## pdf
##   2
```

```
## pdf
##   2
```

H Meta-Analysis (All Coefficients)

H.1 Lower House Size and Expenditure Per Capita

Here we estimate the relationship between expenditure per capita as a dependent variable, and the lower house size as the independent variable.

```
##
## Multivariate Meta-Analysis Model (k = 43; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.4631  0.6805      8     no            id_level1
## sigma^2.2  0.0088  0.0939     43     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 42) = 753.4012, p-val < .0001
##
## Model Results:
##
## estimate      se    tval    pval    ci.lb   ci.ub
##   0.1443  0.2553  0.5651  0.5750  -0.3709  0.6595
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot:

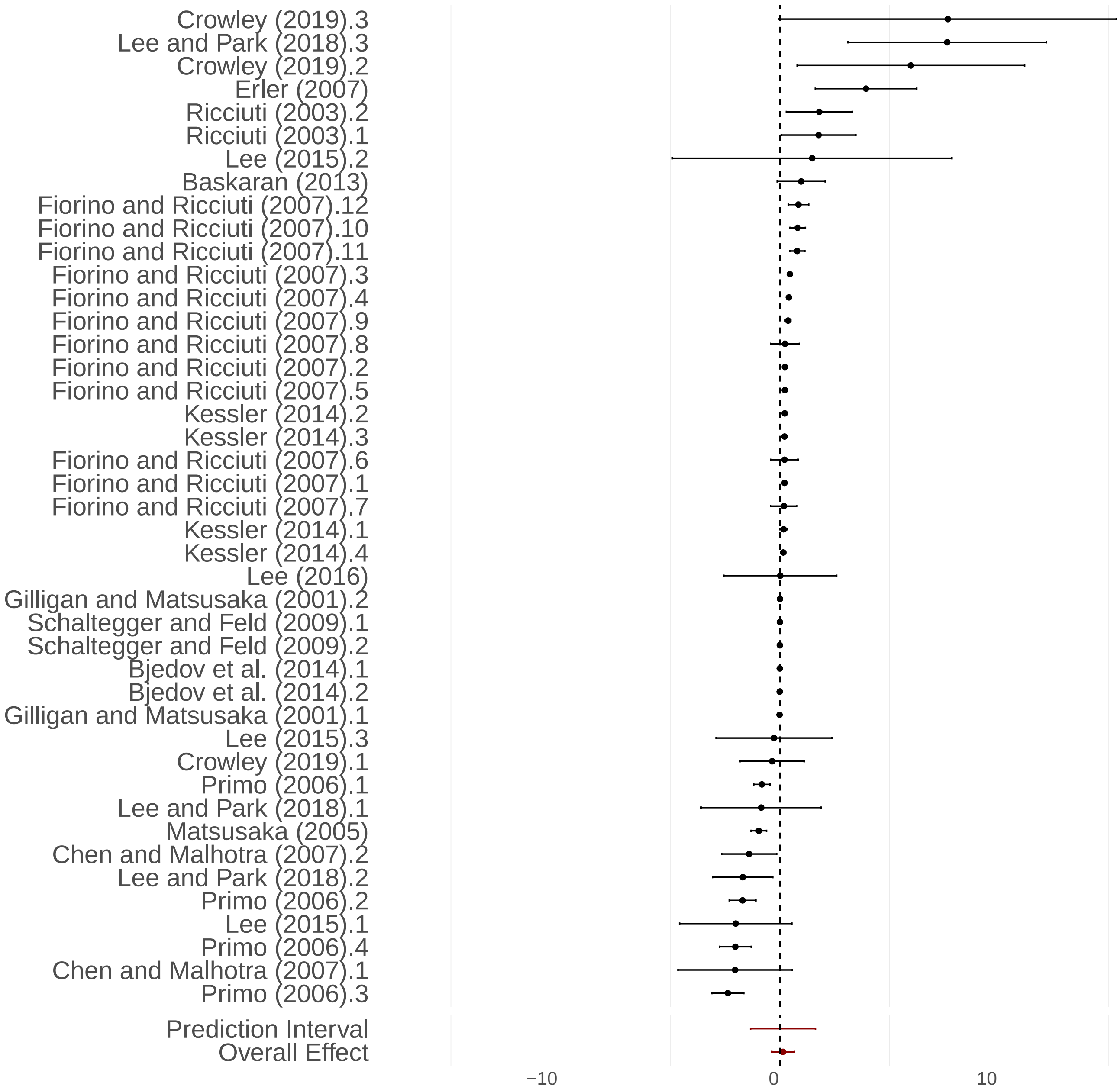


Figure 27: Effect of Lower House Size (N) on Per Capita Expenditure (ExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

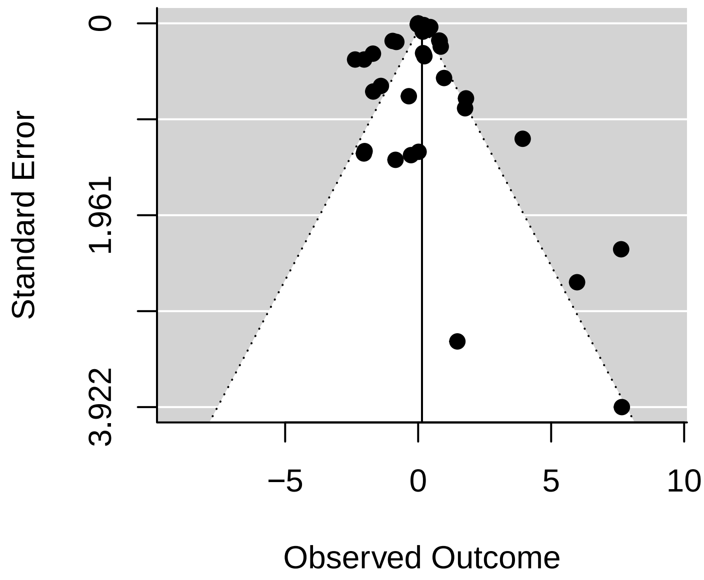


Figure 28: Funnel Plot – Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 753.4$.
2. The estimated SMD in the random effects model is $g = 0.14$ ($SE = 0.255$).
3. The prediction interval ranges from -1.33 to 1.62. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.1.1 Electoral System Subgroup Analysis

The *law of 1/n* was formulated to analyse the budgetary allocation in majoritarian systems. In the theoretical section below, we explain why the argument have potential issues when applied to non-majoritarian electoral systems. We estimated a subgroup analysis using a dummy variable indicating the electoral system included in each model.

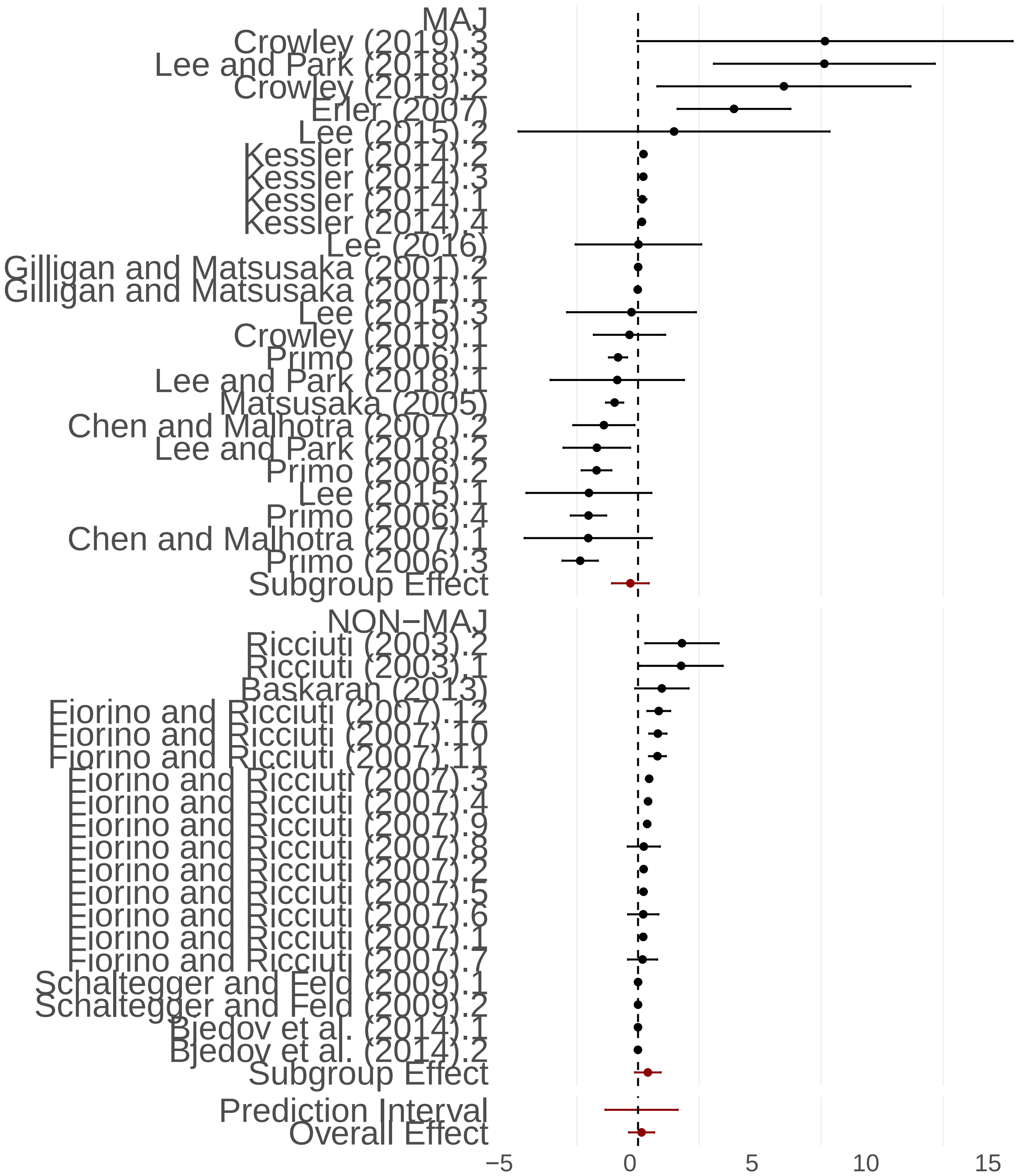


Figure 29: Subgroup Analysis of (N) x (ExpPC), controlling by electoral system

Therefore, we see that majoritarian systems do not have a clear positive effect on budgetary spending. The majoritarian systems in the sample had a random effects model estimate of -0.25, while the random effects model in the non-majoritarian subgroup fitted a value of 0.08. Both are not statistically significant, but they reassure us that the absence of effect is not caused by pooling multiple types of electoral systems.

H.2 Log of Lower House Size and Expenditure Per Capita

There are no studies that have per capita expenditure as the dependent variable and log of lower house size as the treatment variable.

H.3 Upper House Size and Expenditure Per Capita

Now we investigate the effect of the upper house size (K) on government spending. In the model below, we evaluate the relationship between upper house size and expenditure per capita (ExpPC).

```
##
## Multivariate Meta-Analysis Model (k = 31; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed              factor
## sigma^2.1  19.2324  4.3855      4     no           id_level1
## sigma^2.2   5.3579  2.3147     31     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 30) = 150.2534, p-val < .0001
##
## Model Results:
##
## estimate      se    tval    pval    ci.lb   ci.ub
##   1.1563  2.3581  0.4904  0.6274  -3.6596  5.9722
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And the forest plot:

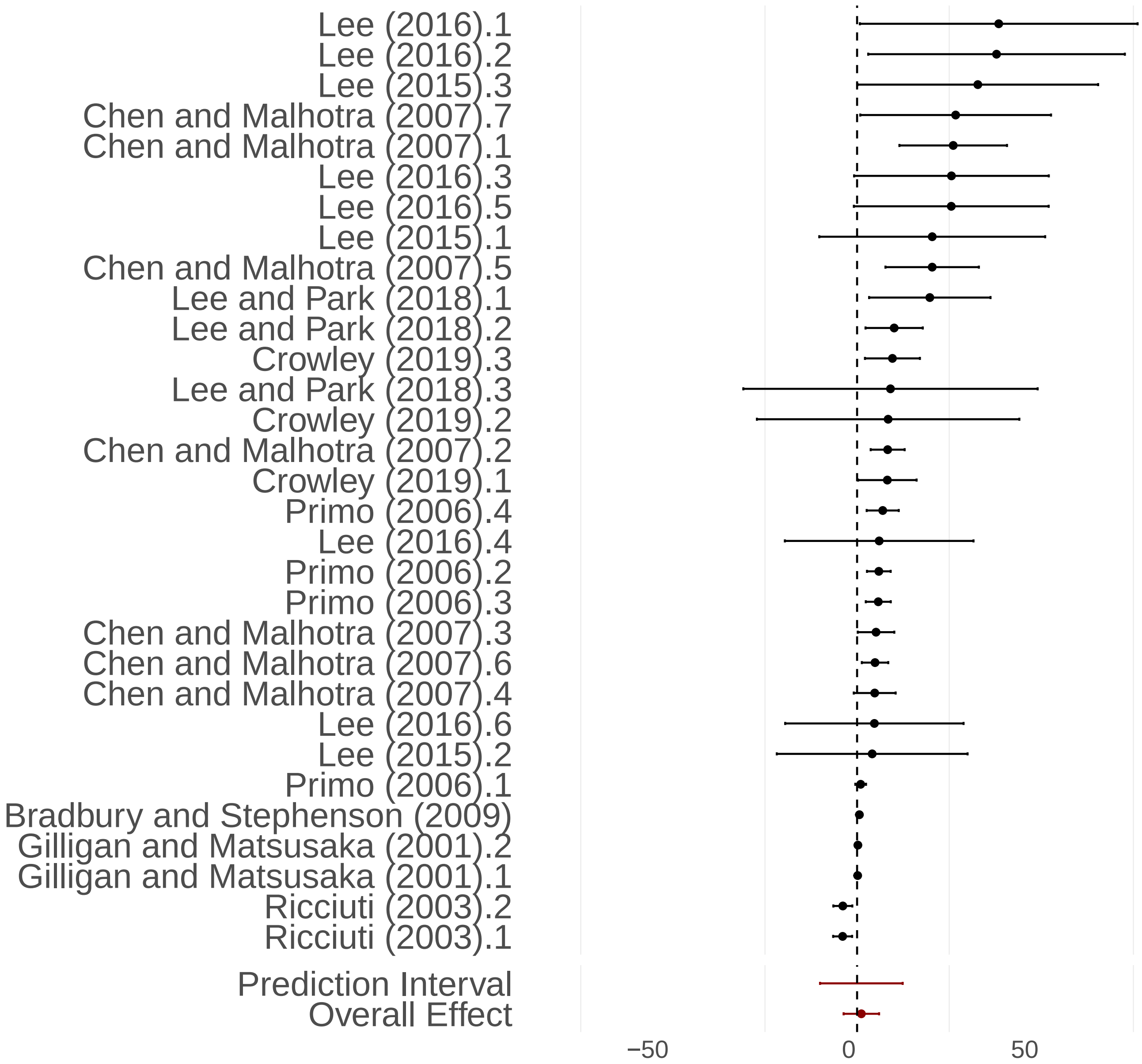


Figure 30: Effect of upper house size (K) on the per capita government expenditure (ExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

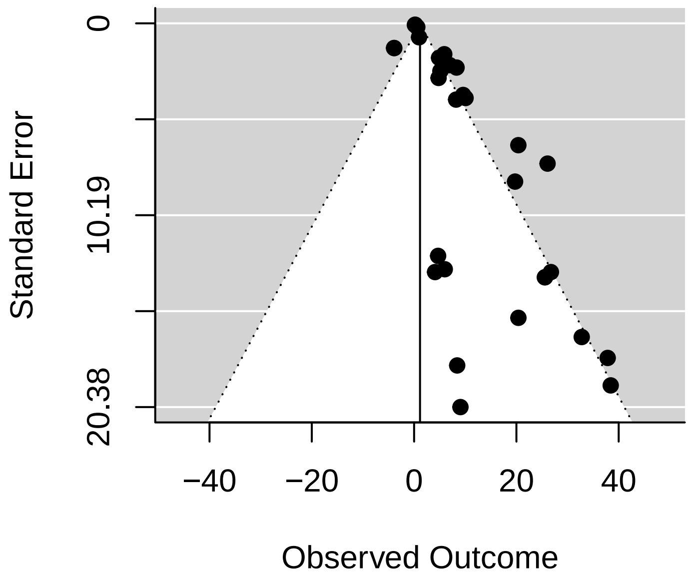


Figure 31: Funnel Plot – Effect of upper houses size (K) on Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 150.25$.
2. The estimated SMD in the random effects model is $g = 1.16$ ($SE = 2.358$).
3. The prediction interval ranges from -10.06 to 12.37. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.4 Lower House Size and Log of Expenditure Per Capita

This model estimates the log of per capita expenditure as the dependent variable, and the number of lower house legislators as the treatment variable.

```
##
## Multivariate Meta-Analysis Model (k = 17; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.0000  0.0000      5     no            id_level1
## sigma^2.2  0.0121  0.1101     17     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 16) = 233.7588, p-val < .0001
##
## Model Results:
##
```

```
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0408  0.0277  -1.4717  0.1605  -0.0995  0.0180
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot is shown below:

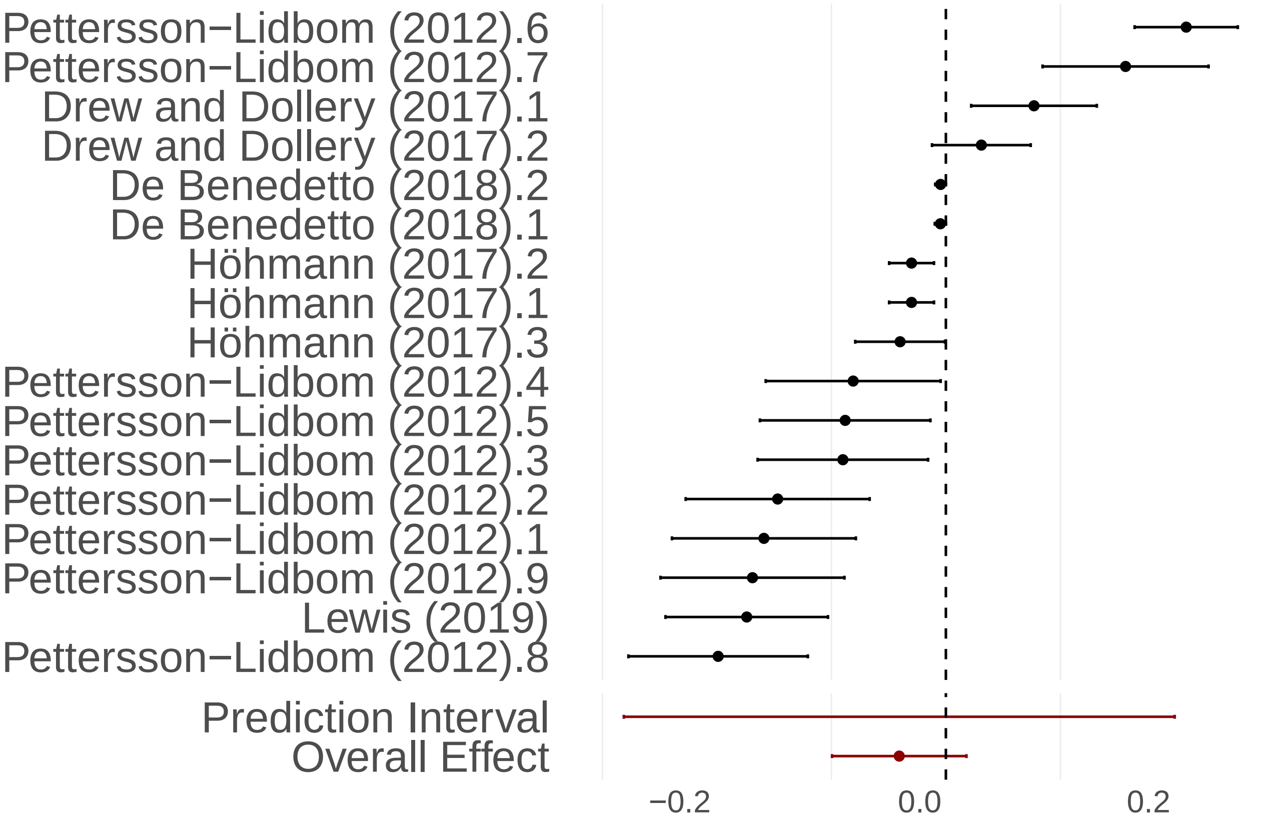


Figure 32: Effect of lower houses size (N) on log of per capita expenditure (logExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

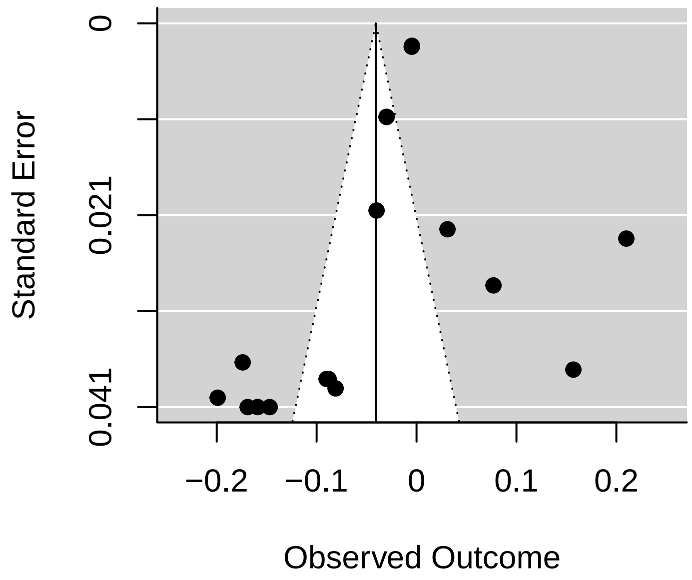


Figure 33: Funnel Plot – Effect of lower houses size (N) on log of Per Capita Expenditure (logExpPC)

Highlights:

1. The results are highly heterogeneous: Q = 233.76.
2. The estimated SMD in the random effects model is g = -0.04 (SE = 0.028).
3. The prediction interval ranges from -0.28 to 0.2. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.5 Log of Lower House Size and Log of Expenditure Per Capita

In this specification, we study the log of per capita expenditure (logExpPC) as a function of the log of lower house size (logN).

```
##
## Multivariate Meta-Analysis Model (k = 16; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.0037  0.0608      2     no            id_level1
## sigma^2.2  0.0015  0.0392     16     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 15) = 43.3297, p-val = 0.0001
##
## Model Results:
##
```

```
## estimate      se    tval    pval   ci.lb   ci.ub
##   0.2230  0.0454  4.9143  0.0002  0.1263  0.3197  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot:

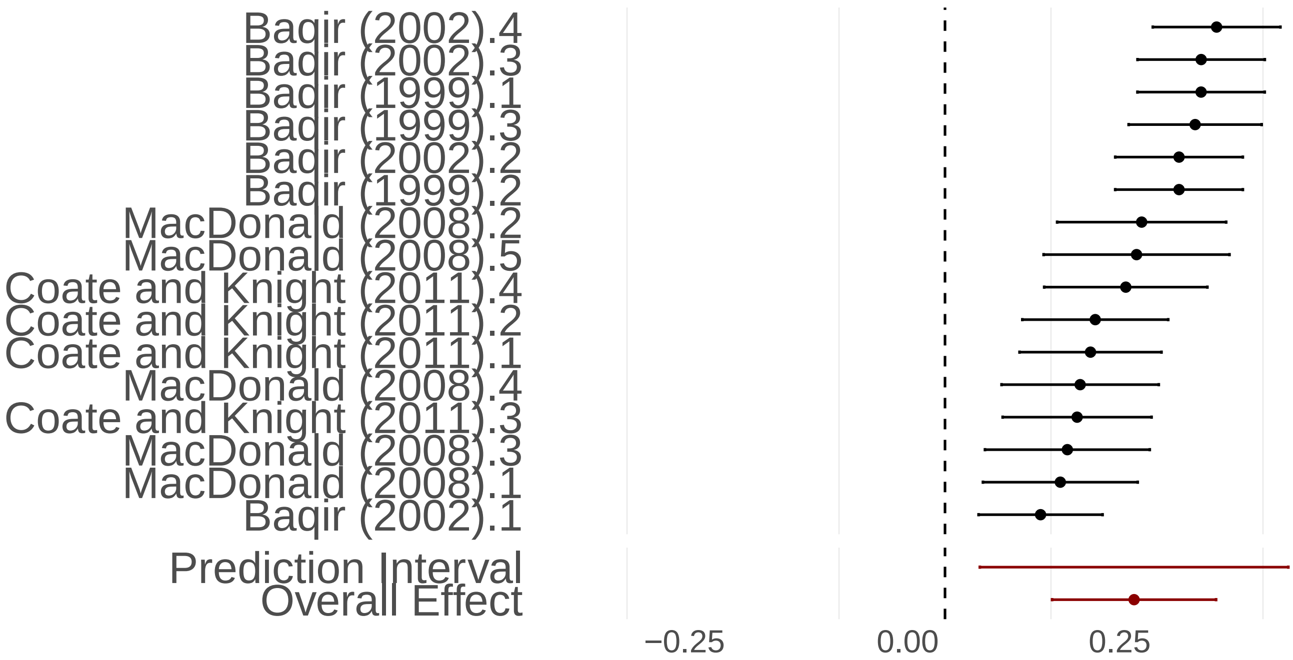


Figure 34: Effect of log lower houses size (logN) on the log of per capita government expenditure (logExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

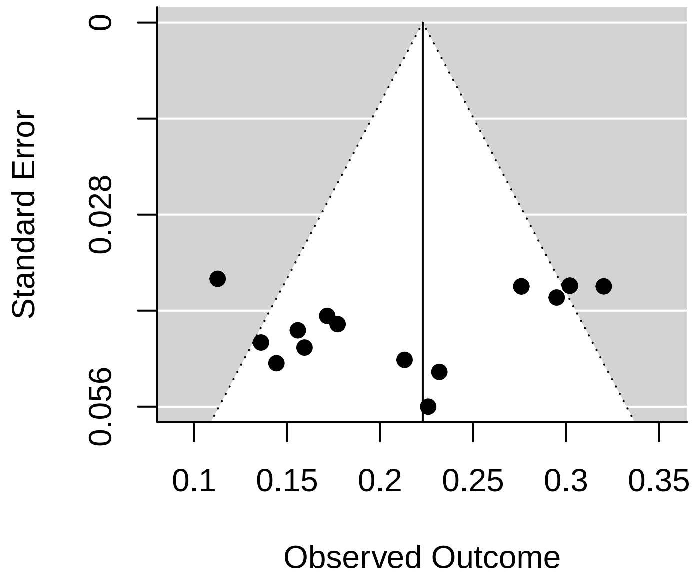


Figure 35: Funnel Plot – Effect of log of lower houses size (logN) on log of Per Capita Expenditure (logExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 43.33$.
2. The estimated SMD in the random effects model is $g = 0.22$ ($SE = 0.045$).
3. The prediction interval ranges from 0.04 to 0.4. Therefore, it does not emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.6 Upper House Size and Log of Expenditure Per Capita

No studies related the log of per capita expenditure with the size of upper house (K).

H.7 Lower House Size and Expenditure as Percentage of GDP

This model fits the random effects for the percentage of GDP as public expenditure as the main outcome, and the size of lower house as the treatment variable.

```
##
## Multivariate Meta-Analysis Model (k = 21; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.0007  0.0260      5     no            id_level1
## sigma^2.2  0.0001  0.0107     21     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 20) = 1314.5409, p-val < .0001
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0046  0.0125  -0.3692  0.7158  -0.0306  0.0214
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Here is the forest plot:

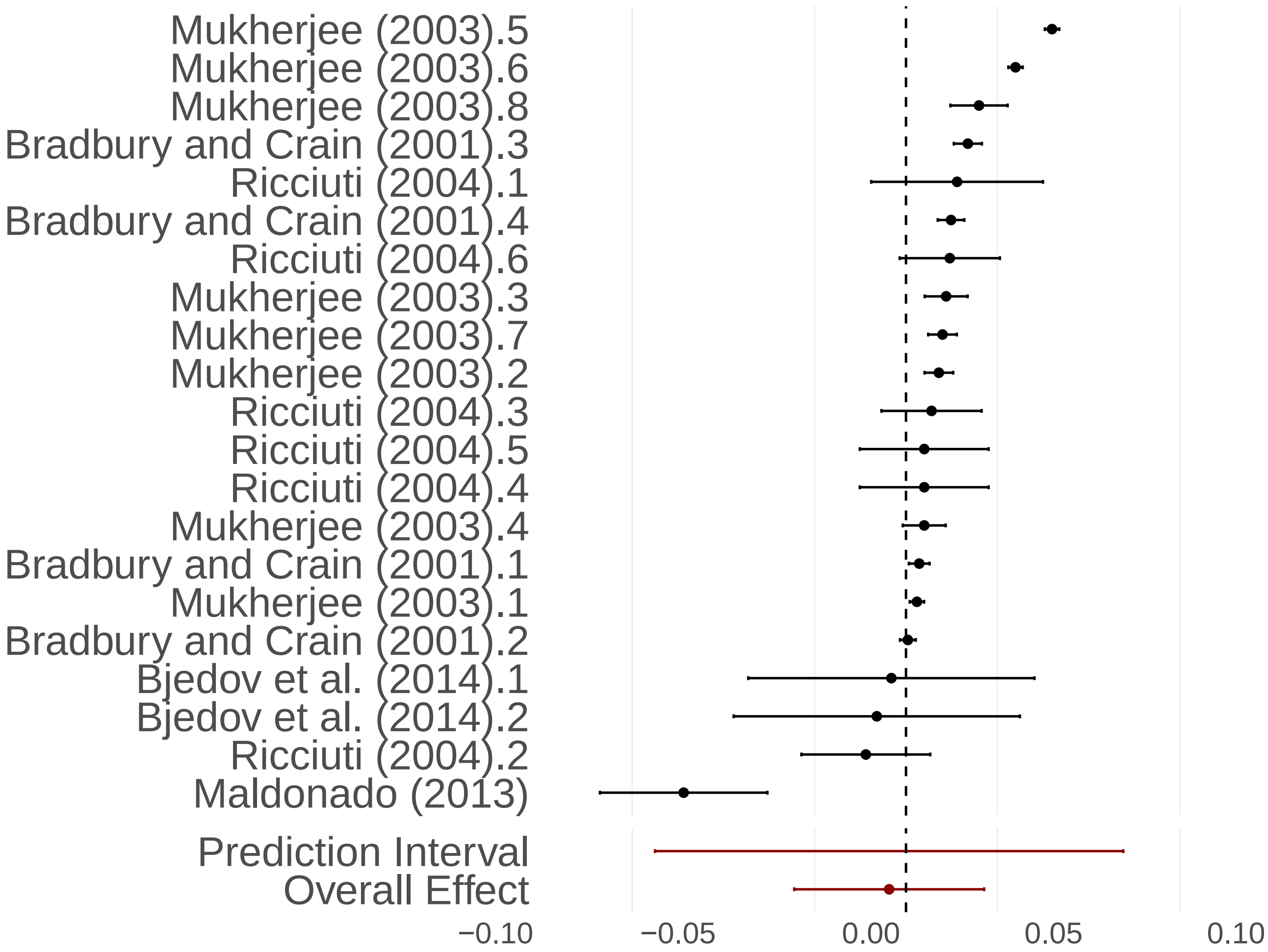


Figure 36: Effect of lower houses size (N) on percentage of public expenditure GDP (PCTGDP)

And to assess the possibility of publication bias, we add funnel plot below:

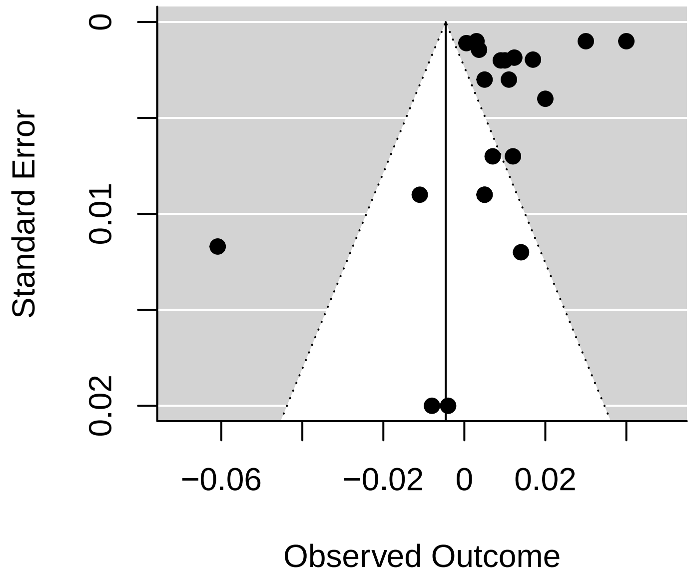


Figure 37: Funnel Plot – Effect of lower houses size (N) on percentage of public expenditure GDP (PCTGDP)

Highlights:

1. The results are highly heterogeneous: $Q = 1314.54$.

2. The estimated SMD in the random effects model is $g = 0$ ($SE = 0.012$).
3. The prediction interval ranges from -0.07 to 0.06. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.8 Log of Lower House Size and Expenditure as Percentage of GDP

This meta-regression investigates the percentage of GDP as public expenditure as the dependent variable and the natural logarithm of lower house size ($\log(N)$) as the treatment variable.

```
##
## Multivariate Meta-Analysis Model (k = 6; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed              factor
## sigma^2.1  5.8712  2.4231      3     no           id_level1
## sigma^2.2  0.0000  0.0000      6     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 5) = 163.0025, p-val < .0001
##
## Model Results:
##
## estimate      se    tval    pval    ci.lb   ci.ub
##   0.0300  1.5497  0.0193  0.9853  -3.9537  4.0136
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The forest plot:

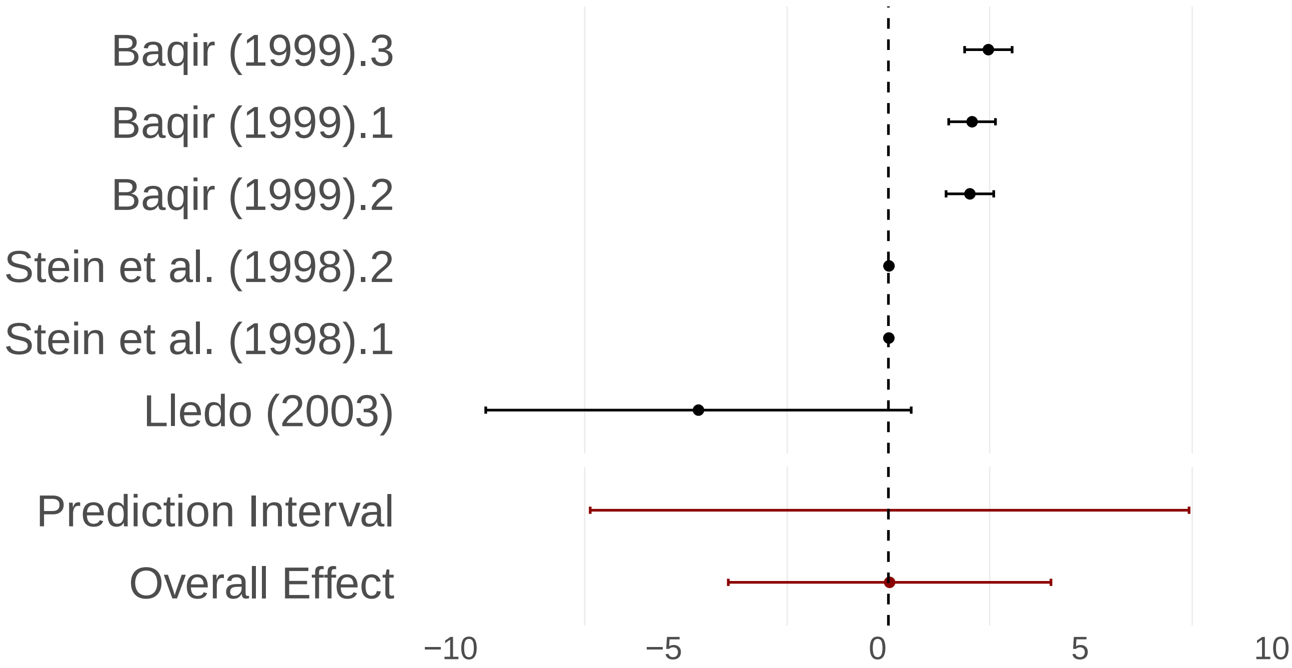


Figure 38: Effect of log lower houses size (logN) on the GDP share of public expenditure (PCTGDP)

And to assess the possibility of publication bias, we add funnel plot below:

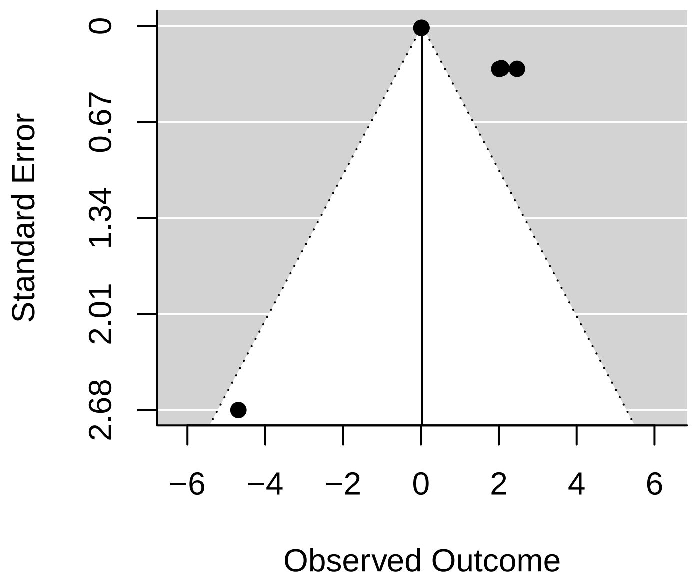


Figure 39: Funnel Plot – Effect of log of lower houses size (logN) on log of Per Capita Expenditure (logExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 163$.
2. The estimated SMD in the random effects model is $g = 0.03$ ($SE = 1.55$).
3. The prediction interval ranges from -7.36 to 7.42. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.9 Upper House Size and Expenditure as Percentage of GDP

This model looks into the effect of upper house size (K) on the public expenditure share of the GDP (PCTGDP).

```
##
## Multivariate Meta-Analysis Model (k = 14; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.0006  0.0240      3     no            id_level1
## sigma^2.2  0.0001  0.0077     14     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 13) = 65.0192, p-val < .0001
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb   ci.ub
##  -0.0057  0.0148  -0.3856  0.7060  -0.0376  0.0262
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And the forest plot:

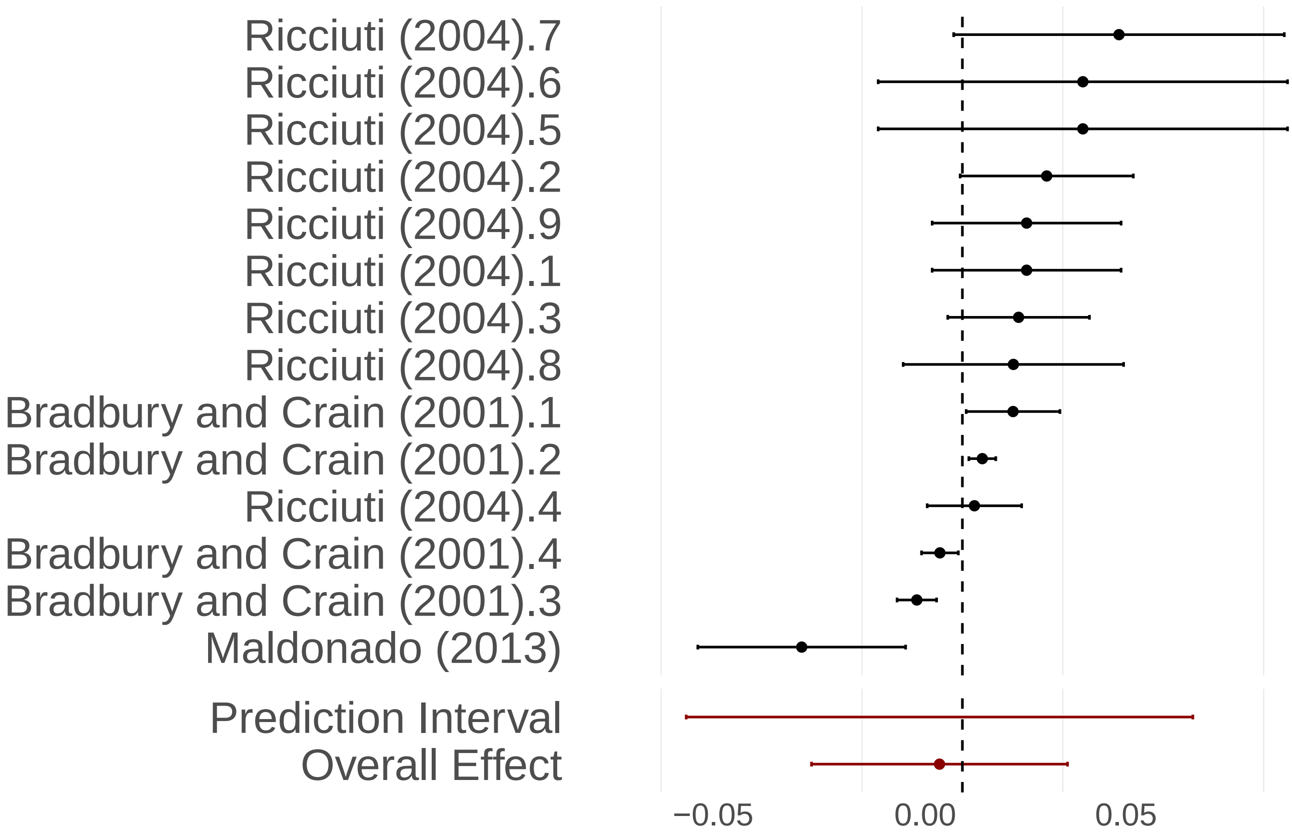


Figure 40: Effect of upper house size (K) on the public expenditure share of the GDP (PCTGDP)

And to assess the possibility of publication bias, we add funnel plot below:

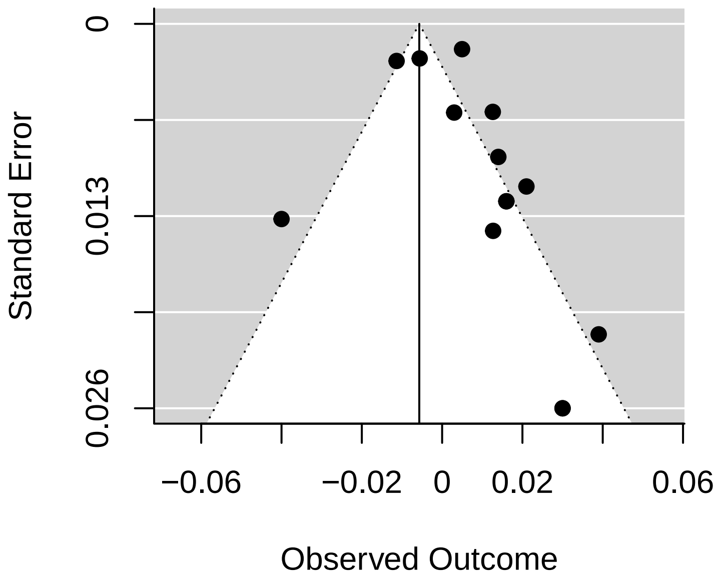


Figure 41: Funnel Plot – Effect of upper houses size (K) on the public expenditure share of GDP (PCTGDP)

Highlights:

1. The results are highly heterogeneous: Q = 65.02.
2. The estimated SMD in the random effects model is g = -0.01 (SE = 0.015).
3. The prediction interval ranges from -0.07 to 0.06. Therefore, it emcompasses zero.

4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.10 Lower House Size and Expenditure per Capita (IV)

```
##
## Multivariate Meta-Analysis Model (k = 9; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed              factor
## sigma^2.1   0.8114  0.9008      3     no           id_level1
## sigma^2.2   0.0141  0.1188      9     no  id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 8) = 94.2338, p-val < .0001
##
## Model Results:
##
## estimate      se    tval    pval    ci.lb   ci.ub
##   0.0398  0.5526  0.0720  0.9443  -1.2345  1.3141
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And the forest plot:

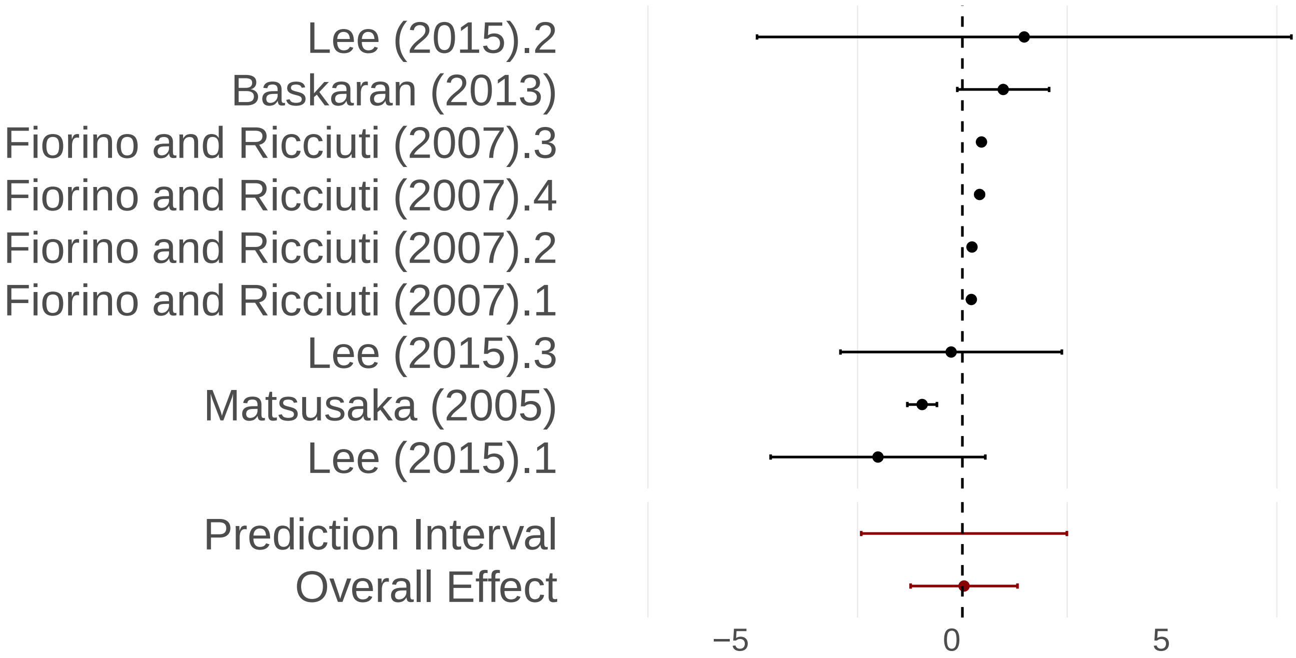


Figure 42: Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

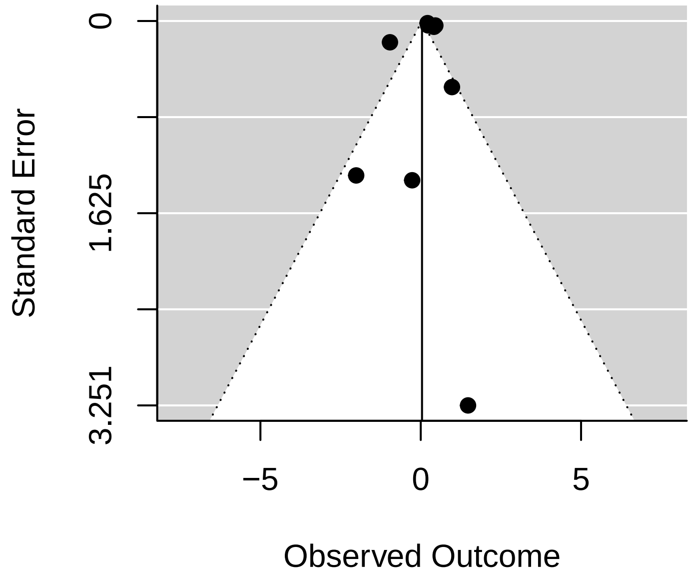


Figure 43: Funnel Plot – Effect of lower houses size (N) on Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: $Q = 94.23$.
2. The estimated SMD in the random effects model is $g = 0.04$ ($SE = 0.553$).
3. The prediction interval ranges from -2.41 to 2.49. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

H.11 Lower House Size and Log of Expenditure per Capita (RDD)

```
##
## Multivariate Meta-Analysis Model (k = 11; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed               factor
## sigma^2.1   0.0051  0.0712      4     no             id_level1
## sigma^2.2   0.0000  0.0000     11     no   id_level1/id_level2
##
## Test for Heterogeneity:
## Q(df = 10) = 74.4929, p-val < .0001
##
## Model Results:
##
## estimate      se     tval    pval    ci.lb    ci.ub
##  -0.0747  0.0369  -2.0237  0.0705  -0.1569  0.0075  .
```

```
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And the forest plot:

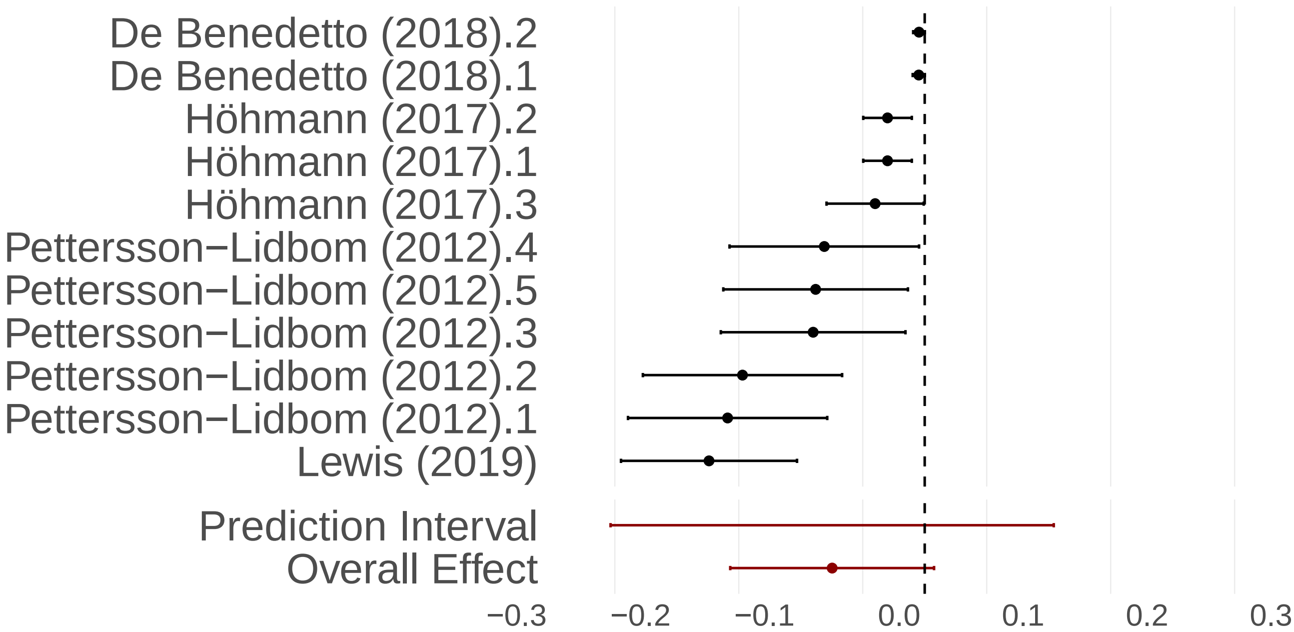


Figure 44: Effect of lower houses size (N) on log of Per Capita Expenditure (logExpPC)

And to assess the possibility of publication bias, we add funnel plot below:

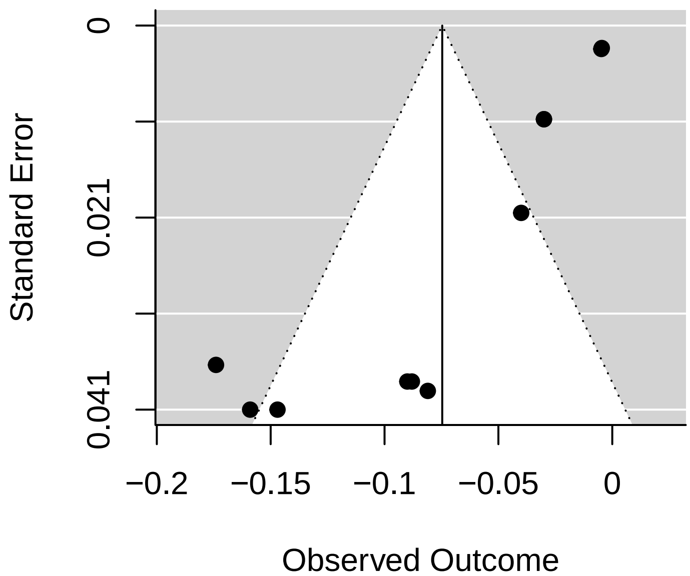


Figure 45: Funnel Plot – Effect of lower houses size (N) on log of Per Capita Expenditure (ExpPC)

Highlights:

1. The results are highly heterogeneous: Q = 74.49.
2. The estimated SMD in the random effects model is g = -0.07 (SE = 0.037).

3. The prediction interval ranges from -0.25 to 0.1. Therefore, it emcompasses zero.
4. The Egger et al. (1997) test rejected the hypothesis of publication bias.

I Meta-Regressions

I.1 Meta-Regressions for Expenditure as a Percentage of the GDP

In this section, we show the coefficients for our meta-regressions. We start with expenditure as a percentage of GDP as the dependent variable.

```
##
## Mixed-Effects Model (k = 11; tau^2 estimator: REML)
##
##   logLik  deviance       AIC       BIC      AICc
##   6.7485  -13.4970    0.5030   -2.2310  112.5030
##
## tau^2 (estimated amount of residual heterogeneity):     0.0002 (SE = 0.0002)
## tau (square root of estimated tau^2 value):             0.0149
## I^2 (residual heterogeneity / unaccounted variability): 92.93%
## H^2 (unaccounted variability / sampling variability):   14.14
## R^2 (amount of heterogeneity accounted for):            99.92%
##
## Test for Residual Heterogeneity:
## QE(df = 5) = 23.7235, p-val = 0.0002
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 5) = 7.2901, p-val = 0.0240
##
## Model Results:
##
##                   estimate      se     tval    pval    ci.lb    ci.ub
## intrcpt             9.9763  3.9450   2.5288  0.0526  -0.1647  20.1174   .
## indepvar2logN      -0.0159  0.0359  -0.4420  0.6769  -0.1083   0.0765
## indepvar2N         -0.0055  0.0175  -0.3123  0.7674  -0.0506   0.0396
## year               -0.0039  0.0020  -2.0202  0.0993  -0.0090   0.0011   .
## elecsys2Non-Maj    -2.0593  0.3804  -5.4132  0.0029  -3.0372  -1.0814  **
## methodPANEL         0.0025  0.0202   0.1245  0.9058  -0.0493   0.0543
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As we have considerable heterogeneity in our sample, we run a permutation test to ensure the validity of our estimates. The results follow below.

```
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 5) = 7.2901, p-val* = 0.0490
##
## Model Results:
##
##                  estimate      se     tval   pval*    ci.lb    ci.ub
## intrcpt            9.9763  3.9450   2.5288  0.0100  -0.1647  20.1174  **
## indepvar2logN     -0.0159  0.0359  -0.4420  0.6440  -0.1083   0.0765
## indepvar2N        -0.0055  0.0175  -0.3123  0.7630  -0.0506   0.0396
## year              -0.0039  0.0020  -2.0202  0.0390  -0.0090   0.0011   *
## elecsys2Non-Maj   -2.0593  0.3804  -5.4132  0.0820  -3.0372  -1.0814   .
## methodPANEL        0.0025  0.0202   0.1245  0.8780  -0.0493   0.0543
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We have the following results for the meta-regressions of Expenditure as a Percentage of GDP:

1. Compared with `K`, models with `N` and `logN` find significantly negative coefficients.
2. Year has null effect.
3. Unpublished papers tend to have higher coefficients than published papers.
4. Passing from `Majoritarian` to `Non-Majoritarian`, decreases significantly the effects found in our models.
5. In terms of modelling, passing from `OLS` to `PANEL` increases the detected effects.
6. When passing from `Country` to `Cross-Country`, it has no effect on the estimated coefficients.

Below we also run the meta-regressions adding all coefficients in the papers. The results follow below:

```
##
## Mixed-Effects Model (k = 41; tau^2 estimator: REML)
##
##    logLik   deviance        AIC        BIC       AICc
##   84.0132  -168.0264  -154.0264  -143.1390  -149.8783
##
## tau^2 (estimated amount of residual heterogeneity):     0.0002 (SE = 0.0001)
## tau (square root of estimated tau^2 value):             0.0129
## I^2 (residual heterogeneity / unaccounted variability): 96.03%
## H^2 (unaccounted variability / sampling variability):   25.20
```

```
## R^2 (amount of heterogeneity accounted for):           99.88%
##
## Test for Residual Heterogeneity:
## QE(df = 35) = 1217.8992, p-val < .0001
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 35) = 33.2523, p-val < .0001
##
## Model Results:
##
##                  estimate      se      tval    pval    ci.lb    ci.ub
## intrcpt            8.7105  2.0519    4.2450  0.0002   4.5448  12.8762  ***
## indepvar2logN     -0.0123  0.0156   -0.7880  0.4360  -0.0441   0.0194
## indepvar2N         0.0047  0.0059    0.8035  0.4271  -0.0072   0.0166
## year              -0.0033  0.0010   -3.1979  0.0029  -0.0053  -0.0012   **
## elecsys2Non-Maj   -2.1723  0.1752  -12.4019  <.0001  -2.5279  -1.8167  ***
## methodPANEL       -0.0041  0.0063   -0.6490  0.5206  -0.0169   0.0087
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 35) = 33.2523, p-val* = 0.0010
##
## Model Results:
##
##                  estimate      se      tval   pval*    ci.lb    ci.ub
## intrcpt            8.7105  2.0519    4.2450  0.0030   4.5448  12.8762   **
## indepvar2logN     -0.0123  0.0156   -0.7880  0.3210  -0.0441   0.0194
## indepvar2N         0.0047  0.0059    0.8035  0.3710  -0.0072   0.0166
## year              -0.0033  0.0010   -3.1979  0.0080  -0.0053  -0.0012   **
## elecsys2Non-Maj   -2.1723  0.1752  -12.4019  0.0010  -2.5279  -1.8167  ***
## methodPANEL       -0.0041  0.0063   -0.6490  0.4540  -0.0169   0.0087
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For all the coefficients, we have the following results:

1. Compared with `K`, models with `N` and `logN` tend to have significantly negative coefficients.
2. Year has a positive effect: the younger the publication, the higher the detected coefficient.

3. Unpublished papers tend to have higher coefficients than published papers.
4. Passing from `Majoritarian` to `Non-Majoritarian` significantly decreases the effects found in our models.
5. Regarding statistical models, passing from `OLS` to `PANEL` increases the detected effects.

I.2 Meta-Regressions for Expenditure Per Capita

Here we do the same exercise with expenditure per capita as the main outcome.

```
##
## Mixed-Effects Model (k = 24; tau^2 estimator: REML)
##
##   logLik  deviance       AIC       BIC      AICc
## -51.2403  102.4807  118.4807  125.1464  136.4807
##
## tau^2 (estimated amount of residual heterogeneity):     2.4577 (SE = 1.2115)
## tau (square root of estimated tau^2 value):             1.5677
## I^2 (residual heterogeneity / unaccounted variability): 99.71%
## H^2 (unaccounted variability / sampling variability):   343.92
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 17) = 124.7931, p-val < .0001
##
## Test of Moderators (coefficients 2:7):
## F(df1 = 6, df2 = 17) = 0.1403, p-val = 0.9886
##
## Model Results:
##
##                  estimate        se     tval    pval      ci.lb     ci.ub
## intrcpt          -66.0936  239.2398  -0.2763  0.7857  -570.8454  438.6581
## indepvar2N        -1.0416    1.7620  -0.5911  0.5622    -4.7590    2.6758
## year               0.0325    0.1194   0.2719  0.7890    -0.2195    0.2845
## publishedYes       1.4630    2.6010   0.5625  0.5811    -4.0247    6.9506
## elecsys2Non-Maj    0.4147    1.4962   0.2772  0.7850    -2.7420    3.5713
## methodPANEL        0.5012    2.7942   0.1794  0.8598    -5.3940    6.3964
## methodIV          -0.0682    3.1931  -0.0214  0.9832    -6.8050    6.6686
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As we have considerable heterogeneity in our sample, we run a permutation test to ensure the validity of our estimates. The results follow below.

```
##
## Test of Moderators (coefficients 2:7):
## F(df1 = 6, df2 = 17) = 0.1403, p-val* = 0.9050
##
## Model Results:
##
##                  estimate        se     tval   pval*      ci.lb     ci.ub
## intrcpt          -66.0936  239.2398  -0.2763  0.6920  -570.8454  438.6581
## indepvar2N        -1.0416    1.7620  -0.5911  0.3990    -4.7590    2.6758
## year               0.0325    0.1194   0.2719  0.6910    -0.2195    0.2845
## publishedYes       1.4630    2.6010   0.5625  0.4290    -4.0247    6.9506
## elecsys2Non-Maj    0.4147    1.4962   0.2772  0.6640    -2.7420    3.5713
## methodPANEL        0.5012    2.7942   0.1794  0.8080    -5.3940    6.3964
## methodIV          -0.0682    3.1931  -0.0214  0.9700    -6.8050    6.6686
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We have the following results for the meta-regressions of Expenditure Per Capita:

1. Compared with `K`, models with `N` tend to detect significantly smaller effects.
2. Year has null effect.
3. `Majoritarian`, when compared to `Non-Majoritarian` electoral systems, significantly increase per capita expenditure.
4. Regarding statistical models, passing from `OLS` to `PANEL` or `IV` increases the detected effects.

We also run the meta-regressions adding all coefficients in the papers. The results follow below:

```
##
## Mixed-Effects Model (k = 74; tau^2 estimator: REML)
##
##    logLik   deviance        AIC        BIC       AICc
## -189.5073   379.0146   395.0146   412.6521   397.4973
##
## tau^2 (estimated amount of residual heterogeneity):     3.6491 (SE = 0.8732)
## tau (square root of estimated tau^2 value):             1.9103
## I^2 (residual heterogeneity / unaccounted variability): 99.94%
## H^2 (unaccounted variability / sampling variability):   1765.58
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
```

```
## QE(df = 67) = 568.5327, p-val < .0001
##
## Test of Moderators (coefficients 2:7):
## F(df1 = 6, df2 = 67) = 3.3232, p-val = 0.0063
##
## Model Results:
##
##                  estimate        se     tval    pval      ci.lb    ci.ub
## intrcpt          -300.7463  150.1894  -2.0024  0.0493  -600.5257  -0.9669    *
## indepvar2N         -3.7466    0.9420  -3.9771  0.0002    -5.6270  -1.8663  ***
## year                0.1502    0.0751   2.0004  0.0495     0.0003   0.3001    *
## publishedYes        2.3118    1.7208   1.3434  0.1837    -1.1230   5.7466
## elecsys2Non-Maj     0.7810    1.0298   0.7584  0.4509    -1.2746   2.8366
## methodPANEL         0.4206    1.1576   0.3634  0.7175    -1.8899   2.7312
## methodIV           -0.0401    1.1343  -0.0354  0.9719    -2.3041   2.2239
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Test of Moderators (coefficients 2:7):
## F(df1 = 6, df2 = 67) = 3.3232, p-val* = 0.0100
##
## Model Results:
##
##                  estimate        se     tval   pval*      ci.lb    ci.ub
## intrcpt          -300.7463  150.1894  -2.0024  0.0200  -600.5257  -0.9669   *
## indepvar2N         -3.7466    0.9420  -3.9771  0.0100    -5.6270  -1.8663  **
## year                0.1502    0.0751   2.0004  0.0300     0.0003   0.3001   *
## publishedYes        2.3118    1.7208   1.3434  0.1300    -1.1230   5.7466
## elecsys2Non-Maj     0.7810    1.0298   0.7584  0.2900    -1.2746   2.8366
## methodPANEL         0.4206    1.1576   0.3634  0.6000    -1.8899   2.7312
## methodIV           -0.0401    1.1343  -0.0354  0.9200    -2.3041   2.2239
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

With all coefficients, the results of the effect sizes on the Expenditure Per Capita regressions are the following:

1. Compared with `K`, models with `N` tend to detect significantly smaller effects.
2. Year has now a positive effect on coefficient sizes.

3. `Majoritarian`, when compared to `Non-Majoritarian` electoral systems, significantly increase per capita expenditure.
4. Regarding statistical models, passing from `OLS` to `PANEL` decreases the detected effects.
5. All other coeffients were not significant.

I.3 Meta-Regressions for Log of Expenditure Per Capita

Lastly, we run the model with the natural logarithm of expenditure per capita.

```
##
## Mixed-Effects Model (k = 9; tau^2 estimator: REML)
##
##   logLik  deviance       AIC       BIC      AICc
##   3.6143   -7.2286    6.7714    0.4617  118.7714
##
## tau^2 (estimated amount of residual heterogeneity):     0.0047 (SE = 0.0047)
## tau (square root of estimated tau^2 value):             0.0689
## I^2 (residual heterogeneity / unaccounted variability): 85.20%
## H^2 (unaccounted variability / sampling variability):   6.76
## R^2 (amount of heterogeneity accounted for):            78.89%
##
## Test for Residual Heterogeneity:
## QE(df = 3) = 29.9437, p-val < .0001
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 3) = 6.3328, p-val = 0.0798
##
## Model Results:
##
##                 estimate       se     tval    pval     ci.lb    ci.ub
## intrcpt           1.5149  18.5417   0.0817  0.9400  -57.4930  60.5228
## indepvar2logN     0.0906   0.1183   0.7663  0.4993   -0.2857   0.4669
## year             -0.0007   0.0092  -0.0720  0.9472   -0.0301   0.0287
## publishedYes     -0.1364   0.0606  -2.2511  0.1098   -0.3292   0.0564
## methodPANEL       0.0390   0.1156   0.3371  0.7582   -0.3289   0.4068
## methodRDD        -0.1594   0.1387  -1.1495  0.3337   -0.6008   0.2820
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As we have considerable heterogeneity in our sample, we run a permutation test to ensure the validity of our estimates. The results follow below.

```
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 3) = 6.3328, p-val* = 0.0750
##
## Model Results:
##
##                estimate       se     tval   pval*     ci.lb    ci.ub
## intrcpt          1.5149  18.5417   0.0817  0.9400  -57.4930  60.5228
## indepvar2logN    0.0906   0.1183   0.7663  0.5140   -0.2857   0.4669
## year            -0.0007   0.0092  -0.0720  0.9500   -0.0301   0.0287
## publishedYes    -0.1364   0.0606  -2.2511  0.1240   -0.3292   0.0564
## methodPANEL      0.0390   0.1156   0.3371  0.7840   -0.3289   0.4068
## methodRDD       -0.1594   0.1387  -1.1495  0.3260   -0.6008   0.2820
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For the meta-regressions of Log of Expenditure Per Capita we find no significant results.

Below we also run the meta-regressions adding all coefficients in the papers. The results follow below:

```
##
## Mixed-Effects Model (k = 33; tau^2 estimator: REML)
##
##   logLik  deviance       AIC       BIC      AICc
##  30.3747  -60.7493  -46.7493  -37.6785  -40.8546
##
## tau^2 (estimated amount of residual heterogeneity):     0.0046 (SE = 0.0016)
## tau (square root of estimated tau^2 value):             0.0682
## I^2 (residual heterogeneity / unaccounted variability): 97.15%
## H^2 (unaccounted variability / sampling variability):   35.11
## R^2 (amount of heterogeneity accounted for):            81.46%
##
## Test for Residual Heterogeneity:
## QE(df = 27) = 125.5351, p-val < .0001
##
## Test of Moderators (coefficients 2:6):
## F(df1 = 5, df2 = 27) = 21.9242, p-val < .0001
##
## Model Results:
##
```

```
##                estimate      se     tval    pval     ci.lb    ci.ub
## intrcpt       -11.4625  9.3360  -1.2278  0.2301  -30.6185   7.6935
## indepvar2logN    0.1695  0.0489   3.4675  0.0018    0.0692   0.2697   **
## year             0.0058  0.0046   1.2455  0.2236   -0.0037   0.0153
## publishedYes    -0.0784  0.0388  -2.0198  0.0534   -0.1581   0.0012    .
## methodPANEL     -0.1395  0.0468  -2.9808  0.0060   -0.2355  -0.0435   **
## methodRDD       -0.2151  0.0530  -4.0569  0.0004   -0.3239  -0.1063  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

With all coefficients, the results of the effect sizes on the Log of Expenditure Per Capita Regressions are the following:

1. In terms of the modelling, passing from `OLS` to `PANEL` or `RDD` decreases the detected effects.
2. All other coefficients remained insignificant.

J Robustness: Meta-Regressions (All Coefficients)

In this section, we aggregate all the coefficients and run a multivariate meta-regression, controlling for:

1. The type of the dependent variable in the study (expenditure per capita, log of the expenditure per capita, and share of government expenditure in the GDP)
2. The type of the independent variable in the study (N, K, $log(N)$);
3. The electoral system (Majoritarian, Proportional Representation, and Mixed).

The results follow below, and show null effects for all variables, including the intercept.

```
##
## Mixed-Effects Model (k = 44; tau^2 estimator: REML)
##
##   logLik  deviance       AIC       BIC      AICc
## -67.0973  134.1947  158.1947  176.1528  173.7947
##
## tau^2 (estimated amount of residual heterogeneity):     0.1953 (SE = 0.0676)
## tau (square root of estimated tau^2 value):             0.4420
## I^2 (residual heterogeneity / unaccounted variability): 99.96%
## H^2 (unaccounted variability / sampling variability):   2290.44
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
```

```
## QE(df = 33) = 255.2630, p-val < .0001
##
## Test of Moderators (coefficients 2:11):
## F(df1 = 10, df2 = 33) = 0.2581, p-val = 0.9862
##
## Model Results:
##
##                  estimate      se     tval    pval      ci.lb    ci.ub
## intrcpt          -23.1869  58.6034  -0.3957  0.6949  -142.4165  96.0426
## depvar2logExpPC   -0.2960   0.6192  -0.4780  0.6358    -1.5559   0.9639
## depvar2PCTGDP     -0.0108   0.5001  -0.0217  0.9828    -1.0282   1.0065
## indepvar2logN      0.2944   0.7140   0.4123  0.6828    -1.1583   1.7470
## indepvar2N        -0.1580   0.3991  -0.3958  0.6948    -0.9699   0.6540
## year               0.0118   0.0292   0.4029  0.6896    -0.0477   0.0713
## publishedYes      -0.2413   0.4893  -0.4931  0.6252    -1.2367   0.7542
## elecsys2Non-Maj   -0.0691   0.4303  -0.1606  0.8734    -0.9446   0.8064
## methodPANEL       -0.0194   0.3881  -0.0500  0.9604    -0.8091   0.7702
## methodIV          -0.2113   0.6624  -0.3189  0.7518    -1.5589   1.1363
## methodRDD          0.0380   0.7459   0.0509  0.9597    -1.4796   1.5555
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As we have considerable heterogeneity in our sample, we run a permutation test to ensure the validity of our estimates. The results follow below.

```
##
## Test of Moderators (coefficients 2:11):
## F(df1 = 10, df2 = 33) = 0.2581, p-val* = 0.7980
##
## Model Results:
##
##                  estimate      se     tval   pval*      ci.lb    ci.ub
## intrcpt          -23.1869  58.6034  -0.3957  0.5760  -142.4165  96.0426
## depvar2logExpPC   -0.2960   0.6192  -0.4780  0.4650    -1.5559   0.9639
## depvar2PCTGDP     -0.0108   0.5001  -0.0217  0.9760    -1.0282   1.0065
## indepvar2logN      0.2944   0.7140   0.4123  0.5580    -1.1583   1.7470
## indepvar2N        -0.1580   0.3991  -0.3958  0.5440    -0.9699   0.6540
## year               0.0118   0.0292   0.4029  0.5670    -0.0477   0.0713
## publishedYes      -0.2413   0.4893  -0.4931  0.4570    -1.2367   0.7542
## elecsys2Non-Maj   -0.0691   0.4303  -0.1606  0.8100    -0.9446   0.8064
## methodPANEL       -0.0194   0.3881  -0.0500  0.9400    -0.8091   0.7702
```

```
## methodIV          -0.2113   0.6624  -0.3189  0.6510    -1.5589   1.1363
## methodRDD          0.0380   0.7459   0.0509  0.9480    -1.4796   1.5555
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In the main text, we selected coefficients based on the regressions that had most observations and presented a full model (with fixed effects or intermediate bandwidth in RDD). We also run the meta-regressions adding all coefficients in the papers. The results follow below:

```
##
## Mixed-Effects Model (k = 148; tau^2 estimator: REML)
##
##    logLik   deviance        AIC        BIC       AICc
## -246.7124   493.4247   517.4247   552.4645   519.9408
##
## tau^2 (estimated amount of residual heterogeneity):     0.1145 (SE = 0.0178)
## tau (square root of estimated tau^2 value):             0.3384
## I^2 (residual heterogeneity / unaccounted variability): 99.98%
## H^2 (unaccounted variability / sampling variability):   4748.85
## R^2 (amount of heterogeneity accounted for):            23.43%
##
## Test for Residual Heterogeneity:
## QE(df = 137) = 2279.7730, p-val < .0001
##
## Test of Moderators (coefficients 2:11):
## F(df1 = 10, df2 = 137) = 1.4247, p-val = 0.1756
##
## Model Results:
##
##                  estimate       se     tval    pval     ci.lb    ci.ub
## intrcpt          -24.0263  28.8429  -0.8330  0.4063  -81.0611  33.0085
## depvar2logExpPC   -0.3475   0.2400  -1.4480  0.1499   -0.8221   0.1271
## depvar2PCTGDP     -0.1267   0.1971  -0.6425  0.5216   -0.5165   0.2632
## indepvar2logN      0.4057   0.3109   1.3050  0.1941   -0.2090   1.0204
## indepvar2N        -0.1264   0.1657  -0.7628  0.4469   -0.4542   0.2013
## year               0.0122   0.0144   0.8485  0.3976   -0.0163   0.0407
## publishedYes      -0.2703   0.2257  -1.1977  0.2331   -0.7166   0.1760
## elecsys2Non-Maj    0.1178   0.2063   0.5709  0.5690   -0.2901   0.5257
## methodPANEL       -0.1267   0.1344  -0.9425  0.3476   -0.3925   0.1391
## methodIV          -0.0553   0.2761  -0.2001  0.8417   -0.6012   0.4907
```

```
## methodRDD         -0.0882   0.2753  -0.3202  0.7493   -0.6325   0.4562
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Test of Moderators (coefficients 2:11):
## F(df1 = 10, df2 = 137) = 1.4247, p-val* = 0.0020
##
## Model Results:
##
##                  estimate       se     tval   pval*     ci.lb    ci.ub
## intrcpt          -24.0263  28.8429  -0.8330  0.2370  -81.0611  33.0085
## depvar2logExpPC   -0.3475   0.2400  -1.4480  0.0400   -0.8221   0.1271  *
## depvar2PCTGDP     -0.1267   0.1971  -0.6425  0.2930   -0.5165   0.2632
## indepvar2logN      0.4057   0.3109   1.3050  0.0540   -0.2090   1.0204  .
## indepvar2N        -0.1264   0.1657  -0.7628  0.2480   -0.4542   0.2013
## year               0.0122   0.0144   0.8485  0.2260   -0.0163   0.0407
## publishedYes      -0.2703   0.2257  -1.1977  0.0950   -0.7166   0.1760  .
## elecsys2Non-Maj    0.1178   0.2063   0.5709  0.3820   -0.2901   0.5257
## methodPANEL       -0.1267   0.1344  -0.9425  0.1530   -0.3925   0.1391
## methodIV          -0.0553   0.2761  -0.2001  0.7580   -0.6012   0.4907
## methodRDD         -0.0882   0.2753  -0.3202  0.6210   -0.6325   0.4562
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

K Session Information

```
## R version 4.0.3 (2020-10-10)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Catalina 10.15.7
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRblas.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
```

```
## [1] grid      stats     graphics  grDevices utils     datasets  methods
## [8] base
##
## other attached packages:
##  [1] dmetar_0.0.9000     compareGroups_4.5.0 broom_0.7.5
##  [4] pander_0.6.3        stargazer_5.2.2     magick_2.5.2
##  [7] kableExtra_1.3.4    ggpubr_0.4.0        gridExtra_2.3
## [10] gridGraphics_0.5-0  knitr_1.31          data.table_1.14.0
## [13] devtools_2.3.2      usethis_1.6.3       readxl_1.3.1
## [16] metafor_2.4-0       Matrix_1.2-18       meta_4.18-0
## [19] forcats_0.5.0       stringr_1.4.0       dplyr_1.0.5
## [22] purrr_0.3.4         readr_1.4.0         tidyr_1.1.3
## [25] tibble_3.1.0        ggplot2_3.3.3       tidyverse_1.3.0
##
## loaded via a namespace (and not attached):
##   [1] uuid_0.1-4          backports_1.2.1     systemfonts_1.0.1
##   [4] splines_4.0.3       digest_0.6.27       htmltools_0.5.1.1
##   [7] fansi_0.4.2         magrittr_2.0.1      Rsolnp_1.16
##  [10] memoise_1.1.0       cluster_2.1.0       openxlsx_4.2.3
##  [13] remotes_2.2.0       modelr_0.1.8        officer_0.3.17
##  [16] svglite_2.0.0       prettyunits_1.1.1   colorspace_2.0-0
##  [19] rvest_1.0.0         ggrepel_0.9.1       haven_2.3.1
##  [22] xfun_0.22           callr_3.5.1         crayon_1.4.1
##  [25] jsonlite_1.7.2      lme4_1.1-26         survival_3.2-7
##  [28] glue_1.4.2          gtable_0.3.0        webshot_0.5.2
##  [31] kernlab_0.9-29      car_3.0-10          pkgbuild_1.1.0
##  [34] DEoptimR_1.0-8      prabclus_2.3-2      abind_1.4-5
##  [37] scales_1.1.1        DBI_1.1.0           rstatix_0.6.0
##  [40] Rcpp_1.0.6          viridisLite_0.3.0   magic_1.5-9
##  [43] foreign_0.8-80      mclust_5.4.7        stats4_4.0.3
##  [46] netmeta_1.3-0       truncnorm_1.0-8     httr_1.4.2
##  [49] fpc_2.2-9           ellipsis_0.3.1      modeltools_0.2-23
##  [52] mice_3.13.0         farver_2.1.0        pkgconfig_2.0.3
##  [55] flexmix_2.3-17      nnet_7.3-14         dbplyr_2.0.0
##  [58] utf8_1.2.1          labeling_0.4.2      tidyselect_1.1.0
##  [61] rlang_0.4.10        munsell_0.5.0       cellranger_1.1.0
##  [64] tools_4.0.3         cli_2.3.1           generics_0.1.0
##  [67] evaluate_0.14       yaml_2.2.1          processx_3.4.5
##  [70] fs_1.5.0            robustbase_0.93-7   zip_2.1.1
##  [73] nlme_3.1-149        xml2_1.3.2          compiler_4.0.3
##  [76] rstudioapi_0.13     curl_4.3            testthat_3.0.0
```

```
##  [79] ggsignif_0.6.0      reprex_0.3.0        statmod_1.4.35
##  [82] stringi_1.5.3       HardyWeinberg_1.7.1 highr_0.8
##  [85] ps_1.6.0            desc_1.2.0          gdtools_0.2.3
##  [88] lattice_0.20-41     poibin_1.5          nloptr_1.2.2.2
##  [91] vctrs_0.3.6         CompQuadForm_1.4.3  pillar_1.5.1
##  [94] lifecycle_1.0.0     cowplot_1.1.0       flextable_0.6.4
##  [97] R6_2.5.0            MuMIn_1.43.17       rio_0.5.16
## [100] writexl_1.3.1       codetools_0.2-16    sessioninfo_1.1.1
## [103] boot_1.3-25         MASS_7.3-53         assertthat_0.2.1
## [106] pkgload_1.1.0       chron_2.3-56        rprojroot_2.0.2
## [109] withr_2.4.1         diptest_0.75-7      parallel_4.0.3
## [112] hms_0.5.3           class_7.3-17        minqa_1.2.4
## [115] rmarkdown_2.7.3     carData_3.0-4       lubridate_1.7.9.2
## [118] base64enc_0.1-3     tinytex_0.30
```

References

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Egger, M., Smith, G. D., Schneider, M., and Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *Bmj*, 315(7109):629–634. Cited on pages 16, 18, 20, 22, 23, 25, 27, 28, 30, 34, 38, 40, 42, 44, 45, 48, 49 and 51.

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