

Online Appendix to “Publication Bias in Measuring Anthropogenic Climate Change”*

Dominika Reckova and Zuzana Irsova

Charles University, Prague

May 7, 2015

Abstract

This documents contains details of computation and additional results for “Publication Bias in Measuring Anthropogenic Climate Change,” which is to be published in Energy & Environment.

Keywords: Climate sensitivity, climate change, CO_2 , publication bias, meta-analysis

JEL Codes: Q53, Q54, C42

1 Calculating the Standard Errors

Standard techniques for correcting publication bias suppose that the ratio of the effect estimates to their standard errors has a t -distribution, which implies approximately normally distributed estimates of climate sensitivity (Stanley 2005). Therefore, the estimates should not be correlated with their standard errors. With asymmetric distributions this assumption does not necessarily hold, but there is no reason why climate sensitivity estimates should not be distributed symmetrically. None of the collected studies reports the standard error, so we use the confidence interval to calculate it. Assuming standard normal distribution of climate sensitivity estimates we construct the standard errors according to Wooldridge (2012) in the following way:

$$SE_{up} = \frac{up - est}{z}, \quad (1)$$

where SE_{up} denotes the standard error, up represents the upper bound of the confidence interval, est is the estimate of climate sensitivity, and z is the corresponding value for the magnitude of the confidence intervals. In most of the studies, 90% confidence intervals are

*Corresponding author: Dominika Reckova, 91670243@fsv.cuni.cz. Zuzana Irsova acknowledges support from the Czech Science Foundation (grant #15-02411S); Dominika Reckova acknowledges support from the Grant Agency of Charles University (grant #558713).

reported, implying that z equals 1.645. One study reports only 66% confidence intervals and for that we use a z of 0.955. Because the estimates are in most cases asymmetrically distributed we compute two values of the standard error depending on which bound we use for the calculation.

$$SE_{low} = \frac{est - low}{z}, \quad (2)$$

where SE_{low} denotes the standard error and low represents the lower bound of the confidence interval. The assumption of normality is the best choice even if it is inaccurate. Law *et al.* (1994, p. 427) mention that the assumption of normality “is commonly made in social science research under circumstances in which it cannot be known with certainty to be correct.” According Stanley (2001), in the absence of bias normality is a common assumption in meta-analysis. Moreover, Cohen (1983, p. 252) notes that “the failure of normality assumption, unless extreme, bears only marginally on the validity of the conclusions drawn.” Therefore, we consider standard normal distribution of estimates of climate sensitivity to be a good approximation. For assurance, we check whether the possible relationship between the estimates and their standard errors is caused only by huge asymmetry in the distribution using the ratio of the standard errors constructed from “below” and from “above”. The calculated standard errors are summarized in the online appendix.

2 Details about the Studies Collected

One of the studies included does not report what significance level is assumed by the confidence interval and only states that the mean value of the estimate of climate sensitivity “may very likely vary from 0.9 to 2” (Scafetta 2013b). We believe it should be the 90% confidence interval, as that is the most frequent one, so we use a z value of 1.645 in constructing the standard error terms. If we are wrong, the bias caused by this should not be significant, as it appears in just this one case.

Table 1: **List of primary studies used**

Andronova & Schlesinger (2001)	Lindzen & Choi (2011)
Forest <i>et al.</i> (2006)	Murphy <i>et al.</i> (2004)
Frame <i>et al.</i> (2005)	Piani <i>et al.</i> (2005)
Gregory <i>et al.</i> (2002)	Scafetta (2013a)
Hargreaves & Annan (2009)	Scafetta (2013b)
Hegerl <i>et al.</i> (2006)	Schmittner <i>et al.</i> (2011)
Huber (2011)	Webb <i>et al.</i> (2006)
Knutti <i>et al.</i> (2006)	Wigley <i>et al.</i> (2005)

Notes: The search for primary studies was terminated on March 3, 2014.

Lindzen & Choi (2011) report two confidence intervals for one estimate of climate sensitivity. We would have to include this estimate twice if we were to calculate with both intervals. In

order to keep the data as consistent as possible, we use only the 90% confidence interval of the estimate in constructing the standard error (the studies in the data set mostly report a 90% confidence interval).

3 Robustness Checks for the Calculation of Publication Bias

Table 2 compares the results of all the specifications – WLS, FE, and mixed-effects multilevel – using the standard error constructed using the upper limit of the confidence interval of the estimated climate sensitivities. The result should verify the robustness of our analysis with the standard error constructed using the lower tail of the confidence interval of the estimated CS. Both regressions yield a significant coefficient of publication bias at least at the 1% level. The magnitude of the bias based on the upper (lower) limit is 0.84 (2.58) in the case of WLS, 0.78 (2.19) in the case of mixed-effects multilevel, and 0.88 (2.04) in the fixed-effects regression. Therefore, we have good reason to believe that the choice of Se_{low} for implementation in the meta-analysis does not damage its results. We will explain later why significant publication bias of around $|2|$ signals publication selectivity.

Table 2: **Test of publication bias using Se_{up}**

Response variable: t-statistic	Mixed-effects	Clustered OLS	Fixed-effects
Constant (publication bias)	0.78*** (0.245)	0.844*** (0.201)	0.882*** (0.206)
$1/SE_{up}$	2.227*** (0.192)	2.388*** (0.336)	2.327*** (0.275)
mea/SE_{up}	-0.59*** (0.083)	-1.216** (0.421)	-0.645*** (0.115)
Observations	42	42	42
Likelihood-ratio test (χ^2)	2.91**		
R^2		0.679	0.821

Notes: Standard errors are shown in parentheses and clustered at the study level. Null hypothesis for the likelihood-ratio test H_0 : no between-study heterogeneity (that is, mixed-effects multilevel has the same benefit as OLS). ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

The suitability of taking the estimate of climate sensitivity as mix of mean and median estimates should not be overlooked. The effect of the mode and the best estimate can be neglected, since there are only six such estimates in the sample. Some studies report both median and mean estimates, which creates a good subset for testing. These two new samples contain all the mean estimates that are in the original data set, but they also contain an extra 11 median estimates. Table 3 summarizes all the results, showing that there are quite huge differences in the magnitude of the bias depending on whether the mean or median estimate of climate sensitivity is used. The likelihood-ratio test does not reject the null hypothesis in the

model with the median, which suggests that mixed-effects multilevel has no advantage over OLS regression (which means that between-study heterogeneity is present). However, the LR test rejects this hypothesis in the specification with mean estimates, suggesting that mixed-effects multilevel is more appropriate. The likely reason why only the model with median estimates suffers from between-study heterogeneity is that it contains estimates from 11 studies, while the model with mean values contains estimates from only half of them, i.e., from six studies. Concentrating the OLS regression by mean estimation and the multilevel regression by median estimation, the constants in both cases are significant at least at the 1% level, which indicates publication bias. The magnitudes differ: the bias in studies reporting mean estimates is more than twice that in studies reporting the median value.

Table 3: **Test of publication bias on subsets**

Response variable: t-statistic	Mixed-effects multilevel		Clustered OLS	
	mean	median	mean	median
Constant (publication bias)	4.154*** (1.068)	1.847*** (0.537)	4.154*** (0.828)	1.813** (0.616)
1/SE	0.564** (0.288)	1.596*** (0.273)	0.564*** (0.061)	1.663** (0.558)
Observations	25	28	25	28
Studies	6	11	6	11
Likelihood-ratio test (χ^2)	0	3.79**		

Notes: Standard errors are shown in parentheses and clustered at the study level. Null hypothesis for the likelihood-ratio test H_0 : no between-study heterogeneity (that is, mixed-effects multilevel has the same benefit as OLS). *** and ** denote statistical significance at the 1% and 5% level.

However, the whole sample provides more reliable results, since it contains 48 estimates of climate sensitivity, which means it is almost two times larger than each of the individual subsets. Although it does not include the 11 median estimates, it instead incorporates the mean values and six more estimates from other studies. Moreover, all the specifications correct for differences between the mean and other estimates using the *mea* variable. Its negative sign indicates that the mean estimates should be lower than the median estimates on average (or, except for OLS models, they have higher standard errors on average, which reduces their *t*-statistics and makes them less precise). This matches the data: the averages of the mean and median estimates differ slightly (3.42 and 3.21, respectively) and the averages of their standard errors differ more (1.16 and 0.79, respectively). Consequently, the median estimates have a higher *t*-statistic than the mean estimates on average. We therefore add an interaction term between the standard error and *mea* into equation (1) in the paper to distinguish whether the differences in the mean and median estimates imply variance in publication bias or variance in the magnitude of climate sensitivity (Stanley *et al.* 2008). The first row in Table 4 refers to

specification (1) and indicates that the added interaction term is statistically insignificant. The interaction term, however, is highly correlated with the standard error of climate sensitivity and the two together are significant. After weighting by the standard errors of CS (which means the interaction term changes to *mea*) the “interaction” term becomes statistically significant at least at the 5% level in all models (WLS, fixed-effects, mixed-effects). Its sign is negative in all cases, which reduces the magnitude of the publication bias of the studies using mean estimates. However, the results are not consistent with the analysis of the subsets, where the selectivity in studies using mean estimates of climate sensitivity seems to be higher. To sum up, there is no solid evidence to suggest that the magnitude of publication bias varies between mean and median estimates.

Table 4: **Test of differences in publication bias between mean and median estimates**

Response variable:	OLS	WLS	FE	ME
	Estimate of CS		t-statistic	
SE* <i>mea</i>	-0.078 (0.195)			
<i>mea</i>		-0.962** (0.373)	-3.112*** (0.029)	-1.152*** (0.46)

Notes: ME denotes mixed-effects multilevel, OLS ordinary least squares, and FE fixed-effects regression. Standard errors are shown in parentheses and clustered at the study level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

Table 5: **Multivariate meta-regression**

Response variable:	Mixed-effects	Clustered OLS	Fixed-effects
t-statistic			
Constant (publication bias)	1.929*** (0.344)	2.352*** (0.179)	1.764*** (0.119)
1/SE	1.74*** (0.187)	1.476*** (0.309)	2.255*** (0.099)
<i>mea</i> /SE	-1.152*** (0.184)	-0.873*** (0.276)	-1.676*** (0.089)
Ice	0.901** (0.452)	0.844*** (0.186)	0.941*** (0.136)
Observations	48	48	48
Likelihood-ratio test (χ^2)	7.61***		
R^2		0.788	0.659

Notes: Standard errors are shown in parentheses and clustered at the study level. Null hypothesis for the likelihood-ratio test H_0 : no between-study heterogeneity (that is, mixed-effects multilevel has the same benefit as OLS). ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

The studies employ distinct characteristics and data sets, which may themselves lead to systematically different results and magnitudes for publication bias. Although it is not the main aim of this paper, we try to find out whether some aspects of primary studies can influence the differences in outcomes between individual estimates (that is, publication bias). With the stepwise regression, only *mea*, *ice*, and *cloud* were chosen as possible drivers out of the 14 variables. However, the fixed-effects model omits *cloud* because of collinearity. Therefore, the final model contains only one extra variable compared to the previous specifications. The results in Table 5 again signal serious publication selectivity and put the true climate sensitivity in the range of 1.47–2.26. This serves as a robustness check of the analysis, since the results do not differ. Selectivity seems to be higher in the 10 studies using data about ice surface (it increases β_0 by approximately 0.9), but some studies do not report all the characteristics used to estimate climate sensitivity, hence we cannot take this result as a rule.

4 Additional Tables

Table 6: **Summary statistics of regression variables**

Variable	Observations	Mean	Std. dev.	Min	Max
Climate sensitivity	48	3.274	1.847	0.7	10.4
Mean estimate of CS	25	3.417	2.462	0.7	10.4
Median estimate of CS	28	3.139	1.026	1.38	6.1
Mode estimate of CS	2	2.9	0	2.9	2.9
Best estimate of CS	5	2.82	0.75	1.54	3.4
constructed <i>t</i> -statistic	48	4.316	1.86	2.043	11.475
<i>low</i> (confidence interval)	48	1.689	0.596	0.3	2.9
<i>up</i> (confidence interval)	42	5.796	3.171	1	17.8
Se_{low}	48	0.975	0.983	0.061	5.046
Se_{up}	42	6.695	32.139	0.182	218.28
Publication year	48	2007.813	3.535	2001	2013
No. of citations of study	48	124.646	186.317	2	918
No. of models in study	48	9.417	21.576	1	128

Notes: 11 studies report both mean and median estimates of climate sensitivity. In these cases, only the mean estimate is included in the data set for this meta-analysis (i.e., the climate sensitivity variable contains 17 median estimates), except for the specification where all the median estimates collected are used. Similarly, the climate sensitivity variable contains only the four best estimates. The *t*-statistics are computed in the following way: $cs_i/Se(cs_i)$, with the use of the standard error of the CS estimate constructed from the lower limit of the reported confidence intervals. The search for primary studies was terminated on March 3, 2014.

Table 7: **List of dummy variables and their description**

Variable	Description	Number of studies that use it
ASA	Aerosol forcing	17
solar	Solar irradiation	32
cloud	Cloud feedback	15
ozone	Ozone forcing	29
volcanic	Volcanic forcing	10
ice	Information about the ice sheet	10
mo	The study uses models for generating data	19
mea	The estimate of CS is the mean	25
medi	The estimate of CS is the median	28

Notes: 11 studies report both mean and median estimates of climate sensitivity. In these cases, only the mean estimate is included in the data set for this meta-analysis (i.e., the data set contains 17 median estimates), except for the specification where all the median estimates collected are used. The search for primary studies was terminated on March 3, 2014.

Table 8: **Summary statistics of collected estimates of climate sensitivity**

Variable	Observations	Mean	Std. dev.	Min	Max
Median estimates of CS used in climate sensitivity variable	17	3.212	0.921	1.5	6.1
Median estimate of CS	28	3.139	1.026	1.38	6.1
Mean estimate of CS	25	3.417	2.462	0.7	10.4
Mode estimate of CS	2	2.9	0	2.9	2.9
Best estimate of CS	4	2.82	0.75	1.54	3.4
Climate sensitivity	48	3.274	1.847	0.7	10.4

Notes: The climate sensitivity variable contains the estimates included in the data set for the meta-analysis. 11 studies report both mean and median estimates of climate sensitivity. In these cases, only the mean estimate is included in the data set (i.e., the climate sensitivity variable contains 17 median estimates), except for the specification where all the median estimates collected are used. Similarly, the climate sensitivity variable contains only the four best estimates. The search for primary studies was terminated on March 3, 2014.

Table 9: **Summary statistics of standard errors**

Standard error of:	Observations	Mean	Std. dev.	Min	Max
Median estimates of CS used in the climate sensitivity variable	17	0.794	0.562	0.304	2.736
Median estimate of CS	28	0.861	0.607	0.298	2.827
Mean estimate of CS	25	1.165	1.264	0.061	5.046
Mode estimate of CS	2	0.547	0.086	0.486	0.608
Best estimate of CS	4	0.78	0.115	0.669	0.942
Climate sensitivity (all together)	48	0.975	0.983	0.061	5.046

Notes: The climate sensitivity variable contains the estimates included in the data set for the meta-analysis. 11 studies report both mean and median estimates of climate sensitivity. In these cases, only the mean estimate is included in the data set (i.e., the climate sensitivity variable contains 17 median estimates), except for the specification where all the median estimates collected are used. Similarly, the climate sensitivity variable contains only the four best estimates. The search for primary studies was terminated on March 3, 2014.

Table 10: **Differences in publication bias between mean and median estimates of climate sensitivity**

Response variable: t-statistic	ME	Clustered OLS	Clustered FE
Constant (publication bias)	3.716*** (0.331)	3.668*** (0.365)	4.829*** (0.103)
1/SE	0.614*** (0.064)	0.618*** (0.08)	0.596*** (0.047)
mea	-1.152** (0.46)	-0.962** (0.373)	-3.114*** (0.029)
Observations	48	48	48
R^2		0.602	0.421
Likelihood-ratio test (χ^2)	5.93***		

Notes: Standard errors are shown in parentheses and clustered at the study level. ME denotes mixed-effects multilevel, OLS ordinary least squares, and FE fixed-effects regression. Null hypothesis for the likelihood-ratio test H_0 : no between-study heterogeneity (that is, mixed-effects multilevel has the same benefit as OLS). *** and ** denote statistical significance at the 1% and 5% level.

Table 11: List of constructed standard errors

ID study	Estimate of CS	Lower limit	Upper limit	z	Se_{low}	Se_{up}
2	2.3	1.2	5.2	1.96	0.669	1.763
3	3.2	2.2	4.3	1.96	0.608	0.669
3	3.3	2.2	4.6	1.96	0.669	0.79
3	3.4	2.3	4.4	1.96	0.669	0.608
3	3.3	2.2	4.4	1.96	0.669	0.669
3	3.1	1.9	4.7	1.96	0.729	0.973
3	3.4	1.5	6.4	1.96	1.155	1.824
4	2.9	2.1	8.9	1.96	0.486	3.647
4	2.9	1.9	4.7	1.96	0.608	1.094
5	3.3	2.2	6.8	1.96	0.669	2.128
6	6.1	1.6	-	1.96	2.736	-
7	1.43	0.94	2.04	1.96	0.298	0.371
7	3.46	1.9	6.02	1.96	0.948	1.556
7	7.53	2.88	17.8	1.96	2.827	6.243
7	3.4	1	9.3	1.96	1.459	3.587
8	2.9	1.9	5.3	1.96	0.608	1.459
8	3.5	2.4	5.4	1.96	0.669	1.155
10	3.8	2.3	6.3	1.96	0.912	1.52
10	3.3	2.1	7.1	1.96	0.729	2.31
11	2.83	1.28	6.32	1.96	0.942	2.122
11	1.54	0.3	7.73	1.96	0.754	3.763
11	3.03	1.79	5.21	1.96	0.754	1.325
12	1.5	1	2.3	1.96	0.304	0.486
13	3.5	2.6	4.5	1.96	0.547	0.608
13	2.4	1.7	3.4	1.96	0.426	0.608
16	2.6	1.4	6.1	1.96	0.729	2.128
16	3.4	1.2	8.6	1.96	1.337	3.161
17	3.4	2.9	4	1.96	0.304	0.365
17	4	2.6	5.4	1.96	0.851	0.851
17	3.6	1.7	6.5	1.96	1.155	1.763
17	1.8	1.3	2.3	1.96	0.304	0.304
17	3.3	2.2	5.1	1.96	0.669	1.094
18	2.2	1.7	2.6	0.955	0.524	0.419
18	2.2	1.4	2.8	0.955	0.838	0.628
18	2.1	1.3	2.7	1.96	0.486	0.365
18	3.4	2.2	4.6	1.96	0.729	0.729
19	0.7	0.6	1	1.96	0.061	0.182
19	8.1	1.6	-	1.96	3.951	-
19	1.7	0.9	8	1.96	0.486	3.83
19	7.9	2.2	-	1.96	3.465	-
19	2.2	1.1	-	1.96	0.669	-
19	2.5	1.5	8.7	1.96	0.608	3.769
19	2.7	1.3	-	1.96	0.851	-
19	10.4	2.1	-	1.96	5.046	-
19	2.2	1.3	6.4	1.96	0.547	2.553
19	2.4	1.3	14.7	1.96	0.669	7.477
19	1.7	1	8.8	1.96	0.426	4.316
20	1.35	0.9	2	1.96	0.274	0.395

References

- ANDRONOVA, N. G. & M. E. SCHLESINGER (2001): “Objective estimation of the probability density function for climate sensitivity.” *Journal of Geophysical Research: Atmospheres (1984–2012)* **106(D19)**: pp. 22605–22611.
- COHEN, J. (1983): “The cost of dichotomization.” *Applied Psychological Measurement* **7**: pp. 249–253.
- FOREST, C. E., P. H. STONE, & A. P. SOKOLOV (2006): “Estimated pdfs of climate system properties including natural and anthropogenic forcings.” *Geophysical Research Letters* **33(1)**: p. L01705.
- FRAME, D., B. BOOTH, J. KETTLEBOROUGH, D. STAINFORTH, J. GREGORY, M. COLLINS, & M. ALLEN (2005): “Constraining climate forecasts: The role of prior assumptions.” *Geophysical Research Letters* **32(9)**.
- GREGORY, J., R. STOUFFER, S. RAPER, P. STOTT, & N. RAYNER (2002): “An observationally based estimate of the climate sensitivity.” *Journal of Climate* **15(22)**.
- HARGREAVES, J. & J. ANNAN (2009): “Comment on” aerosol radiative forcing and climate sensitivity deduced from the last glacial maximum to holocene transition”, by p. chylek and u. lohmann, geophys. res. lett., 2008.” *Climate of the Past* **5(2)**.
- HEGERL, G. C., T. J. CROWLEY, W. T. HYDE, & D. J. FRAME (2006): “Climate sensitivity constrained by temperature reconstructions over the past seven centuries.” *Nature* **440(7087)**: pp. 1029–1032.
- HUBER, M. (2011): *The Earth’s energy balance and its changes: Implications for past and future temperature change*. Ph.D. thesis, ETH.
- KNUTTI, R., G. A. MEEHL, M. R. ALLEN, & D. A. STAINFORTH (2006): “Constraining climate sensitivity from the seasonal cycle in surface temperature.” *Journal of Climate* **19(17)**.
- LAW, K. S., F. L. SCHMIDT, & J. E. HUNTER (1994): “Nonlinearity of range corrections in meta-analysis: Test of an improved procedure.” *Journal of Applied Psychology* **79(3)**: pp. 425–438.
- LINDZEN, R. S. & Y.-S. CHOI (2011): “On the observational determination of climate sensitivity and its implications.” *Asia-Pacific Journal of Atmospheric Sciences* **47(4)**: pp. 377–390.
- MURPHY, J. M., D. M. SEXTON, D. N. BARNETT, G. S. JONES, M. J. WEBB, M. COLLINS, & D. A. STAINFORTH (2004): “Quantification of modelling uncertainties in a large ensemble of climate change simulations.” *Nature* **430(7001)**: pp. 768–772.
- PIANI, C., D. FRAME, D. STAINFORTH, & M. ALLEN (2005): “Constraints on climate change from a multi-thousand member ensemble of simulations.” *Geophysical Research Letters* **32(23)**.
- SCAFETTA, N. (2013a): “Discussion on climate oscillations: Cmp5 general circulation models versus a semi-empirical harmonic model based on astronomical cycles.” *Earth-Science Reviews* **126**: pp. 321–357.
- SCAFETTA, N. (2013b): “Solar and planetary oscillation control on climate change: hind-cast, forecast and a comparison with the cmp5 gcms.” *Energy & Environment* **24(3)**: pp. 455–496.
- SCHMITTNER, A., N. M. URBAN, J. D. SHAKUN, N. M. MAHOWALD, P. U. CLARK, P. J. BARTLEIN, A. C. MIX, & A. ROSELL-MELE (2011): “Climate sensitivity estimated from temperature reconstructions of the last glacial maximum.” *Science* **334(6061)**: pp. 1385–1388.
- STANLEY, T. D. (2001): “Wheat from chaff: Meta-analysis as quantitative literature review.” *Journal of economic perspectives* pp. 131–150.
- STANLEY, T. D. (2005): “Beyond publication bias.” *Journal of Economic Surveys* **19(3)**: pp. 309–345.
- STANLEY, T. D., C. DOUCOLIAGOS, & S. B. JARRELL (2008): “Meta-regression analysis as the socio-economics of economics research.” *The Journal of Socio-Economics* **37(1)**: pp. 276–292.
- WEBB, M., C. SENIOR, D. SEXTON, W. INGRAM, K. WILLIAMS, M. RINGER, B. MCAVANEY, R. COLMAN, B. SODEN, R. GUDGEL *et al.* (2006): “On the contribution of local feedback mechanisms to the range of climate sensitivity in two gcm ensembles.” *Climate Dynamics* **27(1)**: pp. 17–38.
- WIGLEY, T., C. AMMANN, B. SANTER, & S. C. RAPER (2005): “Effect of climate sensitivity on the response to volcanic forcing.” *Journal of Geophysical Research: Atmospheres (1984–2012)* **110(D9)**.

WOOLDRIDGE, J. (2012): *Introductory econometrics: A modern approach*. Cengage Learning.